DEVELOPMENTAL ROBOTICS

From Babies to Robots

Angelo Cangelosi
and Matthew Schlesinger

Developmental Robotics

Intelligent Robotics and Autonomous Agents

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To my parents Vita and Salvatore (AC)
To Angie, Nick, and Natalie (MS)

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Foreword

Linda B. Smith

The dominant method of science is analysis and simplification. This was clearly articulated by Descartes in 1628: In studying any phenomenon, simplify it to its essential components, dissecting away everything else. This approach is motivated by the belief that complicated systems will be best understood at the lowest possible level. By reducing explanations to the smallest possible entities, the hope is that we will find entities that are simple enough to fully analyze and explain. The spectacular success of this methodology in modern science is undeniable. Unfortunately, it has not given us an understanding of how systems made up of simple elements can operate with sufficient complexity to be autonomous agents. Building artificial agents who can act and adapt in complex and varying environments requires a different kind of science, one that is principally about integration and complexity rather than analysis and simplification. The theoretical task of understanding of developmental process in biological systems also requires a science of integration.

Developmental robotics is based on the premise that principles of developmental process are the key to engineering adaptive and fluid intelligence. Although the promise of this idea is not yet fully realized, remarkable progress has been made over the last decade and half. This book presents the current state of the art. In so doing, the authors also make a case for deeper collaborations between developmental roboticists and developmental psychologists. At present the ties are weak. We are working on related problems, reading the same literatures, sometimes participating in joint conferences, but only rarely actually collaborating in a sustained way. I firmly believe that remarkable gains could be made in both fields through programmatic research by teams of researchers in human development and robotics. For developmental psychology, the promise is both better theory and new ways to test theories by manipulating the pathways and experiences using artificial developing intelligent systems. Accordingly, in this foreword, I highlight seven fundamental aspects of the human developmental process that might be better understood through developmental robotics.

1. *Extended immaturity.* Development, like evolution and culture, is a process that creates complexity by accumulating change. At any moment, the developing agent is a product of all previous developments, and any new change begins with and must build on those previous developments. Biological systems that are flexibly smart have relatively long periods of immaturity. Why is this? Why and how does "slow accumulative" intelligence yield higher and more abstract forms of cognition? One possibility is that a slow accumulative system —one that does not settle too fast—can acquire the massive amounts of experience that yield multiple layers of knowledge at multiple granularities. A second related possibility concerns what developmentalists sometimes call "readiness" and what recent research in robotics has called "learning progression."[1] As learning progresses, new structures and new ways of learning emerge so that that the same experiences later in development have different effects on the learning system than those experiences earlier in development. If these ideas are correct, then the developmental pathway itself may be part of the explanation as to why human intelligence has the properties that it does. It simply may not be possible to shortcut development—to try to build just the adult system—and achieve fluid and adaptive intelligence that characterizes biologically developing systems.

2. *Activity.* Learning experiences do not passively "happen" to infants. Piaget[2] described a pattern of infant activity that is highly illustrative of this point. He placed a rattle in a four-month-old infant's hands. As the infant moved the rattle, it would both come into sight and also make a noise, arousing and agitating the infant and causing more body motions, and thus causing the rattle to move into and out of sight and to make more noise. The infant has no prior knowledge of the rattle but discovers—through activity—the task and goal of rattle shaking. As the infant accidentally moves the rattle, and sees and hears the consequences, the infant will become captured by the activity—moving and shaking, looking and listening—and incrementally through this repeated action

gain intentional control over the shaking of the rattle and the goal of making noise. Action and exploration creates opportunities for learning and new tasks to be conquered. This role of action is well covered in this book and is an area in which developmental robotics is clearly demonstrating its relevance to theories of development.

3. *Overlapping tasks.* Developing organisms do not solve just one task; they solve many overlapping tasks. Consider again the rattle example. The infant's shaking of the rattle couples auditory, motor, and visual systems creating and changing the specialized regions in the brain and the connections between them.[4] But these same systems and functional connections enter into many other behaviors and so achievements in shaking rattles may extend to influence means-end reasoning and or the processing of multimodal synchronicities. Developmental theory deeply needs a way to explore how multimodal and multitask experiences create an abstract, general purpose, and inventive intelligence. This is also an area in which developmental robotics is ready to make big contributions.

4. *Degeneracy.* Degeneracy as it is used in computational neuroscience[3] refers to complex systems in which individual components may contribute to many different functions and in which there is more than one route to the same functional end. Degeneracy is believed to promote robustness in developmental outcomes. Because functionally redundant pathways can compensate for one another, they provide a kind of insurance against pathway failure. Robotic models may exploit these principles to build systems that are robust and that can succeed—over the long term and in multiple tasks—even given breakdowns in some components. Such robotic models also offer a rigorous way to test the implications of multicausality and complex systems of causes may constrain developmental outcome.

5. *Cascades.* Developmental theorists often refer to the far reach of early developments on later ones in terms of the "developmental cascade." These cascades often evident in the perturbed patterns of atypical development also characterize typical development and such seemingly distinct domains of intelligence as sitting and visual object representation and walking and language input.[4] Here is the deeper theoretical question: Are the facts of these cascades—the way earlier developments start the pathway for quite different later

developments—relevant to how and why human intelligence has the properties that it does? Developmental robotics may not only advance the engineering of robots by taking on this question, but also provide a platform for understanding how the integrative nature the complex pathways that characterize human cognitive development are essential to human intelligence.

6. *Ordered tasks.* Biologically developing systems typically confront classes of experiences and tasks in a particular sequence and there is a large theoretical and experimental literature on the cascading developmental consequences of altering that natural order of sensorimotor development in animals.[5] Human infants travel through a systematic of set of changing environments in the first two years of life as they proceed to rolling over, reaching, sitting steadily, crawling, and walking. The series of changes in motor skills in the first two years of human life provide strong and most likely evolutionarily selected gates on experience. The consequences and importance of ordered experiences and the significance of perturbations in that ordering have not been theoretically well specified in humans nor systematically pursued in developmental robotics; this is an important next frontier.

7. *Individualism.* It is the individual that develops. The history of the species may be in the intrinsic biology and environment may contain conspecifics who scaffold development but each developing organism has to travel the path. Because developmental pathways are degenerate, because development builds on itself, because intrinsic biologies and environments are inherently unique, different developing agents may come to comparable functional skills through different paths. This is a theoretically important idea to understanding both the robustness and variability in human intelligence and perhaps also a foundational idea for building multifunctional adaptive robots that can be intelligent in whatever environment they find themselves in.

This book is an excellent steppingstone to future advances in developmental science.

Notes

1. Gottlieb, J., P. Y. Oudeyer, M. Lopes, and A. Baranes, "Information-Seeking, Curiosity, and Attention: Computational and Neural Mechanisms," *Trends in Cognitive Science* 17 (11) (2013): 585–593.

2. J. Piaget, *The Origins of Intelligence in the Child*, trans. M. Cook (New York: International Universities Press, 1952. (Original work published in 1936.)

3. O. Sporns, *Networks of the Brain* (Cambridge, MA: MIT Press, 2011).

4. L. Byrge, O. Sporns, and L. B. Smith, “Developmental Process Emerges from Extended Brain-Body-Behavior Networks,” *Trends in Cognitive Science* (in press); L. B. Smith, “It’s All Connected: Pathways in Visual Object Recognition and Early Noun Learning,” *American Psychologist* 68 (8) (2014): 618.

5. G. Turkewitz, and P. A. Kenny, “Limitations on Input as a Basis for Neural Organization and Perceptual Development: A Preliminary Theoretical Statement,” *Developmental Psychobiology* 15 (4) (1982): 357–368.

Preface

Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's? If this were then subjected to an appropriate course of education one would obtain the adult brain.
—Alan Turing, "Computing Machinery and Intelligence"

The idea that the human child can be used as a template for designing an intelligent machine is rooted in the early days of modern artificial intelligence (AI). Alan Turing was part of a large community of researchers in the interdisciplinary field of cognitive science, which included Marvin Minsky, Jean Piaget, Noam Chomsky, and Herbert Simon, who collectively argued that the same principles could be used to study both biological organisms and "artificial" or man-made systems. Nevertheless, over the next fifty years the concept of *child-inspired* AI failed to gain widespread appeal, and instead made only sporadic progress. By 2000, however, a critical mass of researchers had formed in psychology, computer science, linguistics, robotics, neuroscience, and a number of other related disciplines, and as we highlight in chapter 1, two new scientific communities were established (autonomous mental development; epigenetic robotics) and two conference series (IEEE ICDL: IEEE International Conference on Development and Learning; EpiRob: International Workshop on Epigenetic Robotics) and an international IEEE journal (*IEEE Transactions in Autonomous Mental Development*) were subsequently launched, all devoted to the study of developmental robotics.

It is now just over a decade later, and the two groups have merged into a unified research community (see icdl-epirob.org). The time is right for a comprehensive volume that not only surveys the previous dozen years of work in the interdisciplinary field of developmental robotics, but more important, also articulates the core principles that shape and guide the discipline.

There are three key goals that we pursued while writing our book. First, much of the decision making about what to include (as well as the technical level at which it was presented) followed the premise that the book should be *broadly accessible*. In particular, whether the reader is an engineer or a philosopher, an anthropologist or a neuroscientist, a developmental psychologist or a roboticist, our objective was to ensure that a wide audience could read and comfortably digest what is often relatively complex material. On this note, we also envisioned that our text would be a good fit for both advanced undergraduate students and graduate students in the engineering, biological, and social sciences, as well as the humanities.

Our second goal was to deliberately take a *behavior-centered approach*, which means we focused on robotics research that could be mapped in a relatively direct way to comparable studies with human infants and children. In other words, we highlight here robotics work (or more broadly speaking, computational models) that either seeks to directly simulate and replicate a specific developmental study, or more generally, to capture a well-defined developmental phenomenon (e.g., the emergence of crawling, first words, face perception, etc.).

This lays the foundation for our third goal, which was to demonstrate the *collaborative, interdisciplinary nature of developmental robotics*. Thus, an important benefit gained by focusing on embodied, perceiving, acting, autonomous agents is that we can then illustrate a variety of examples in which ongoing work in the developmental sciences is informed by parallel efforts in robotics, engineering, and computer science, and vice versa. As part of this goal, in each chapter we strategically selected and profiled a specific human-developmental study, and where possible, also presented a comparable robotics study that was intentionally designed to simulate the same task, behavior, or developmental phenomenon. We hope that by juxtaposing these analogous studies of natural and artificial organisms, we can make a clear and convincing case that humans and machines indeed have much to learn from each other!

Acknowledgments

This volume is the result not only of the effort of the two authors, but also the contribution from the wider community of collaborators in our own labs, and within the broader international community of developmental robotics.

Many colleagues kindly and patiently offered to go through some sections of the draft manuscript, especially to make sure that our description of their models and experiments was correct and clear. In particular, we would like to thank the following colleagues for their review and feedback on specific sections of chapter 2 (and for providing images of their own baby robots): Gordon Cheng, Paul Baxter, Minoru Asada, Yasuo Kuniyoshi, Hiroshi Ishiguro, Hisashi Ishihara, Giorgio Metta, Vadim Tikhanoff, Hideki Kozima, Kerstin Dautenhahn, William De Braekeleer (Honda Motor Europe), Oliver Michel (Cyberobotics), Jean-Christophe Baillie and Aurea Sequeira (Aldebaran Robotics), and Masahiro Fujita (SONY Corporation). Lisa Meeden provided feedback on chapter 3, and Daniele Caligiore reviewed parts of chapter 5. Verena Hafner, Peter Dominey, Yukie Nagai, and Yiannis Demiris reviewed sections of chapter 6. Chapter 7 was reviewed by Anthony Morse (who contributed box 7.2), Caroline Lyon, Joe Saunders, Holger Brandl, Christian Goerick, Vadim Tikhanoff, and Pierre-Yves Oudeyer (extra thanks to Pierre-Yves for kindly providing feedback on many other chapters). Marek Rucinki (who contributed box 8.2) and Stephen Gordon provided feedback on chapter 8. Kerstin Dautenhahn and Tony Belpaeme reviewed the section on assistive robotics in chapter 9. Moreover, the recommendation and feedback from the three referees was invaluable to improve the final version of the monograph. We are also grateful to many colleagues who gave us the original image files of many of the figures in the book (their names are acknowledged in the figure captions).

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And finally, we extend a big and heartfelt thank you to our families for their patience when we had to steal time from them to work on this book. We hope they will agree that this was, after all, "time well spent" and that they might even enjoy reading all about baby robots.

1 Growing Babies and Robots

Human development is one of the most fascinating phenomena in nature. Babies are born as helpless individuals, with simple motor and cognitive skills not even sufficient to allow them to survive and fend for themselves without the support of their parents and caregivers. However, within a few years, they reach a sophisticated level of mental development. A ten-year-old child can play chess and computer games, solve increasingly complex math problems, master one or more languages, build a theory of mind of self and others, cooperate altruistically with peers and adults, excel at gym exercises, and use complex tools and machines. These slow but impressive developmental changes pose a series of key questions on the understanding of human development: What are the mechanisms that allow the child to develop autonomously such mental capabilities? How does the social and physical environment, with which the child interacts, shape and scaffold the child's developing cognitive skills and knowledge? What is the relative contribution of *nature* (i.e., genes) and *nurture* (i.e., environment) in the development of human intelligence? What do qualitative stages during development, and body and brain maturational changes tell us about the mechanisms and principles supporting development?

Developmental psychology is the discipline that aims at understanding the child's autonomous mental development, through field and laboratory experiments with children of different ages and varying cultural backgrounds, and through comparative psychology studies. These empirical investigations lead to the definition of theories and hypotheses of motor, cognitive, and social development and to the identification of general developmental principles underlying the acquisition of mental capabilities.

Such a growing set of empirical data and theoretical knowledge on human development, in addition to benefiting human sciences such as psychology, philosophy, and cognitive science, can have tremendous technological implications. If we understand the underlying principles and mechanisms of the development of natural cognition in human babies through social interaction, we can use this knowledge to inform the design of cognitive capabilities in artificial agents such as robots. Such principles and mechanisms can be implemented in the cognitive architecture of robots and tested through developmental experiments with robots. This is the aim of developmental robotics, and this volume will explore the current achievements and challenges in the design of autonomous mental development via social interaction in robots and the benefit of a mutual interaction between developmental psychologists and developmental roboticists.

1.1 Developmental Theories of Nature and Nurture

One of the oldest, and endless, debates in psychology, as well as in philosophy, is the contribution of nature and nurture in the development of human intelligence. The baby's prolonged interaction with its physical and social environment is essential to, and significantly influences, its full mental development. At the same time, the baby's genome plays a fundamental role both in the physical and cognitive development of the child. Some traits, especially physical body characteristics, but also cognitive skills such as color perception, can be strongly determined by the baby's own genes, with little influence of environmental phenomena.

This debate has led to various developmental psychology theories on the role of nature versus nurture (Croker 2012). Nativist theories tend to stress the fact that children are born with innate, domain-specific knowledge, which is the result of direct influence of the genes on mental development, with little or no influence from the environment. One of the best-known nativist theories is Chomsky's hypothesis on the language acquisition device and universal grammar (Chomsky 1957; Pinker 1994; see also Pinker and Bloom 1990). This nativist theory proposes that children are born with innate knowledge of linguistic and syntactic principles, whose parameters are then fine-tuned through experience of the language of their parents. In other fields, Leslie (1994) hypothesized that children are born with a theory of mind, and Wynn (1998) that they have innate knowledge of math concepts. On the opposite end, empiricist theories stress the importance of the social and cultural environment in cognitive development. This is the case of Vygotsky's (1978) sociocultural theory, where the role of adults and peers is essential to guide the child to exploit her "zone of proximal development," meaning, the space of the infant's potential capabilities.

Similarly, Bruner's socio-cognitive theory of development (Bruner and Haste 1987) stresses the importance of social interaction and interpersonal communication in the various stages of learning. Tomasello (2003) proposes an empiricist theory of language development based on the principle of constructivist and emergent development, whereby the child constructs her own language competence through interaction with other language-speaking agents.

Within these extremes, Piaget (1971) has proposed one of the most influential theories in developmental psychology that combines the contribution of nature and nurture mechanisms. The key tenet of Piaget's theory is that a child goes through different *stages* of development, where at each stage the infant develops qualitatively different and increasingly complex *schemas*, the building block of intelligence. These stages are influenced by maturational constraints, determined by genetic influence, and called "epigenetic" in Piaget's theory (ibid.). However, the child goes through a process of *adaptation*, where the contribution of the external environment is important in the adaptation of existing schemas to new knowledge (assimilation) and the modification and creation of new schemas (accommodation). Piaget proposed four key stages of development of mental capabilities, with a particular focus on the development of thinking capabilities and the origin of abstract thought schemas in sensorimotor knowledge. In the Sensorimotor Stage (Stage 1, 0–2 years old), the child starts with the acquisition of sensorimotor schemas, which initially consist of motor reflexes. In the Preoperational Stage (Stage 2, 2–7 years old), children acquire egocentric symbolic representations of objects and actions, which allow them to represent objects even when these are not visible (object permanence task, when the child understands that a moving object reappears after hiding behind an obstacle). In the subsequent Concrete Operational Stage (Stage 3, 7–11 years old) children can adopt other people's perspectives on object representation and perform mental transformation operations on concrete objects (e.g., liquid conservation task). This finally leads to the Formal Operational Stage (Stage 4, 11+ years old) with the acquisition of full abstract thinking capabilities and complex problem-solving skills. Piaget's theory and stages will be further described in chapter 8, on the models of abstract knowledge.

Another theory that considers the simultaneous contribution of biological and environmental factors is Thelen and Smith's (1994) dynamic systems theory of development. This considers the complex dynamic interaction of various neural, embodiment, and environmental factors in the self-organization of cognitive strategies (see section 1.3.1 for more details).

The nature/nurture debate and nativist/empiricist theories have significantly influenced other fields interested in intelligence, specifically in artificial intelligence and robotics. When building artificial cognitive systems, as with adaptive agents in artificial intelligence and with cognitive robots in robotics, it is possible to use a nativist approach. This implies that the agent's cognitive architecture is fully predefined by the researcher, and does not change significantly during the agent's interaction with the environment. On the other end, the utilization of a more empiricist approach in artificial intelligence and robotics requires the definition of a series of adaptation and learning mechanisms that allow the agent to gradually develop its own knowledge and cognitive system through interaction with other agents and human users. The developmental robotics approach presented in this volume mostly follows a balanced nativist/empiricist approach to robot design as it puts a great emphasis on the development of the robot's capability during interaction with the environment, as well as on the maturational and embodiment factors that constrain development. In particular, Piaget's theory, in addition to being the most influential theory in developmental psychology, has strongly influenced the field of developmental robotics, including the use of the term "epigenetic" in the "Epigenetic Robotics" conference title series. This is because Piaget's theory emphasizes the sensorimotor bases of mental development and the balanced biological and environmental approach.

Together with Piaget, another well-known developmental psychologist, Lev Vygotsky, has also significantly influenced the field of developmental robotics. Vygotsky's theory puts much emphasis on the role of social environment on mental development and on the effects that the social and physical environment have on the *scaffolding* of the child's cognitive system during development (Vygotsky 1978). His insights have therefore contributed to social learning and human-robot imitation studies, and to the developmental robotics theory of scaffolding (Asada *et al.* 2009; Otero *et al.* 2008; Nagai and Rohlfing 2009).

In the following sections, after defining developmental robotics and presenting a brief historical overview, we will discuss the main defining characteristics and principles of this approach, which combines the dynamic interaction of biological and cultural phenomena in the autonomous mental development of robots.

1.2 Definition and Origins of Developmental Robotics

Developmental robotics is the *interdisciplinary approach to the autonomous design of behavioral and cognitive capabilities in artificial agents (robots) that takes direct inspiration from the developmental principles and mechanisms observed in the natural cognitive systems of children.* In particular, the main idea is that the robot, using a set of intrinsic developmental principles regulating the real-time interaction between its body and brain and its environment, can autonomously acquire an increasingly complex set of sensorimotor and mental capabilities.

Developmental robotics relies on a highly interdisciplinary effort of empirical developmental sciences such as developmental psychology, neuroscience, and comparative psychology; and computational and engineering disciplines such as robotics and artificial intelligence. Developmental sciences provide the empirical bases and data to identify the general developmental principles, mechanisms, models, and phenomena guiding the incremental acquisition of cognitive skills. The implementation of these principles and mechanisms into a robot's control architecture and the testing through experiments where the robot interacts with its physical and social environment simultaneously permits the validation of such principles and the actual design of complex behavioral and mental capabilities in robots. Developmental psychology and developmental robotics mutually benefit from such a combined effort.

Historically, developmental robotics traces its origins to the years 2000–2001, in particular in coincidence with two scientific workshops that, for the first time, gathered together scientists interested in developmental psychology principles in both humans and robots. These workshops had been preceded by some work and publications advocating an explicit link between human development and robotics, such as in Sandini, Metta, and Konczak (1997); Brooks *et al.* (1998); Scassellatti (1998); and Asada *et al.* (2001).

The first event was the Workshop on Development and Learning (WDL) organized by James McClelland, Alex Pentland, Juyang (John) Weng, and Ida Stockman and held on April 5–7, 2000, at Michigan State University, in East Lansing, Illinois. This workshop subsequently led to the establishment of the annual International Conference on Development and Learning (ICDL). At the WDL the term “developmental robotics” was publicly used for the first time. In addition, the workshop contributed to the coinage of the term “autonomous mental development,” to stress the fact that robots develop mental (cognitive) capabilities in an autonomous way (Weng *et al.* 2001). Autonomous mental development has in fact become a synonym for developmental robotics, and is the name of the main scientific journal in this field, *IEEE Transactions on Autonomous Mental Development.*

The second event to contribute to the birth of developmental psychology as a scientific discipline was the First International Workshop on Epigenetic Robotics: Modeling Cognitive Development in Robotic Systems, which again led to the establishment of the subsequent Epigenetic Robotics (EpiRob) conference series. This workshop was organized by Christian Balkenius and Jordan Zlatev, and was held at Lund University (Sweden) September 17–19, 2001. The workshops borrowed the term “epigenetic” from Piaget. As noted earlier, in Piaget’s Epigenetic Theory of human development, the child’s cognitive system develops as a result of the interaction between genetic predispositions and the organism’s interaction with the environment. As such the choice of the term “epigenetic robotics” was justified by Piaget’s stress on the importance of the role of interaction with the environment, and in particular on the sensorimotor bases of higher-order cognitive capabilities. Moreover, this early definition of epigenetic robotics also complemented Piaget’s sensorimotor bases of intelligence with Lev Vygotsky’s emphasis on social interaction (Zlatev and Balkenius 2001).

In addition to the term “developmental robotics” used in this volume and in other review publications (e.g., Metta *et al.* 2001; Lungarella *et al.* 2003; Vernon, von Hofsten, and Fadiga 2010; Oudeyer 2012), and the related term “cognitive developmental robotics” used in Asada *et al.* (2001, 2009), in the literature other names have been proposed to refer to the same approach and interdisciplinary field. Some authors prefer the term “autonomous mental development” (Weng *et al.* 2001), while others use the term “epigenetic robotics” (Balkenius *et al.* 2001; Berthouze and Ziemke 2003).

The use of these different terms mostly reflects historical factors, as discussed, rather than real semantic differences. As a matter of fact, in 2011 the two communities of the ICDL conference series (preferring the term “autonomous mental development”) and of the EpiRob series (preferring the term “epigenetic robotics”) joined forces to organize the first joint International Conference on Developmental and Learning and on Epigenetic Robotics (IEEE ICDL-EpiRob). This joint conference, continued since 2011, has become the common home for developmental robotics research, with a web presence on http://www.icdl-epirob.org, through the activities of the IEEE Technical Committee on Autonomous Mental Development, which coordinate such joint efforts.

1.3 Principles of Developmental Robotics

The field of developmental robotics has been strongly influenced by developmental psychology theories, as seen in section 1.1. As discussed, developmental robotics models follow an approach based on the coupled interaction of both nativist and empiricist phenomena, though with a stronger emphasis on environmental and social factors. The consideration of the influence of biological and genetic factors includes the effects of maturational phenomena in both the agent’s body and brain, the exploitation of embodiment constraints for the acquisition of sensorimotor and mental capabilities, and the role of intrinsic motivation and the instinct to imitate and learn from others. Empiricist and constructivist phenomena considered in developmental robotics research include a focus on situated learning and the contribution of both the social and physical environment in shaping development, and of an online, open-ended and cumulative acquisition of cognitive skills. Moreover, both biological and environmental factors are coupled in an intricate and dynamic way resulting in stage-like qualitative changes of cognitive strategies dependent on a nonlinear dynamical system interaction of genetic, embodiment, and learning phenomena.

A series of general principles can be identified that reflect the numerous factors and processes implicated in the design of autonomous mental development in robots and that have guided developmental robotics practice. These principles can be grouped as shown in table 1.1, and will then be briefly analyzed in the following subsections.

1.3.1 Dynamical Systems Development

An important concept taken from mathematics and physics, and which has significantly influenced general theories of human development, is that of *dynamical systems*. In mathematics, a dynamical system is characterized by complex changes, over time, in the phase state, and which are the result of the self-organization of multifaceted interactions between the system's variables. The complex interaction of nonlinear phenomena results in the production of unpredictable states of the system, often referred to as *emergent* states. This concept has been borrowed by developmental psychologists, and in particular by Thelen and Smith (1994; Smith and Thelen 2003), to explain child development as the emergent product of the intricate and dynamic interaction of many decentralized and local interactions related to the child's growing body and brain and her environment. Thus Thelen and Smith have proposed that the development of a child should be viewed as change within a complex dynamic system, where the growing child can generate novel behaviors through her interaction with the environment, and these behavioral states vary in their stability within the complex system.

Table 1.1

Principles and characteristics of developmental robotics

	Principles	Characteristics
1	Development as a dynamical system	Decentralized system Self-organization and emergence Multicausality Nested timescales
2	Phylogenetic and ontogenetic interaction	Maturation Critical period Learning
3	Embodied and situated development	Embodiment Situatedness Enaction Morphological computation Grounding
4	Intrinsic motivation and social learning	Intrinsic motivation Value systems Imitation
5	Nonlinear, stage-like development	Qualitative stages U-shaped phenomena
6	Online, open-ended, cumulative learning	Online learning Cumulative Cross-modality Cognitive bootstrapping

One key concept in this theory is that of *multicausality*, for example, in the case when one behavior, such as crawling and walking, is determined by the simultaneous and dynamic consequences of various phenomena at the level of the brain, body, and environment. Thelen and Smith use the example of the dynamic changes in crawling and walking motor behaviors as an example of multicausality changes in the child's adaptation to the environment, in response to body growth changes. When the child's body configuration produces sufficient strength and coordination to support its body through the hands and knee posture, but not to support upright walking, the child settles for a crawling strategy to locomote in the environment. But when the infant's body growth results in stronger and more stable legs, the standing and walking behavior emerges as the stable developmental state, which as a consequence destabilizes, and gradually replaces, the pattern of crawling. This demonstrates that rather than following a predetermined, top-down genetic-controlled developmental trajectory that first controls crawling and then walking, the locomotion behavior is the result of self-organizing dynamics of decentralized factors such as the child’s changing body (stronger legs and better balance) and its adaptation to the environment. This illustrates the principle of multicausality, as there are many parallel factors causing varying behavioral strategies.

Another key concept in Thelen and Smith’s dynamic systems view of development is that of *nested timescales*, in other words, neural and embodiment phenomena acting at different timescales, and all affecting development in an intricate, dynamic way. For example the dynamics of the very fast timescale of neural activity (milliseconds) is nested within the dynamics of the other slower timescales such as reaction time during action (seconds or hundreds of milliseconds), learning (after hours or days), and physical body growth (months).

One of the best-known developmental psychology examples used by Thelen and Smith to demonstrate the combined effects of the concepts of multicausality and nested timescales is that of the A-not-B error. This example is inspired by Piaget’s object permanence experiment, when one toy is repeatedly hidden under a lid at a location A (right) during the first part of the experiment. Toward the end of the task, the experimenter hides the same toy in the location B (left) for a single trial, and then asks the child to reach for the object. While infants older than twelve months have no problem in reaching for the toy in its correct location B, unexpectedly most eight-to-ten-month-old infants produce the curious error of looking for the object in location A. This error is only produced when there is a short delay between hiding and reaching. While psychologists such as Piaget have used explanations based on age (stage) differences linked to qualitative changes in the capability to represent objects and space, a computational simulation of the dynamic system model (Thelen *et al.* 2001) has demonstrated that there are many decentralized factors (multicausality) and timing manipulations (nested timing) affecting such a situation. These for example depend on the time delay between hiding and reaching, the properties of the lids on the table, the saliency of the hiding event, the past activity of the infant, and her body posture. The systematic manipulation of these factors results in the appearance, stopping, and modulation of the A-not-B errors.

The use of a dynamical systems approach as a theory of development, and the general dynamic linking of body, neural, and environmental factors, have had significant influence in developmental robotics research, as well in other fields of robotics and cognitive systems (Beer 2000; Nolfi and Floreano 2000). This theory has been applied for example to developmental robotics models of early motor development, as in Mori and Kuniyoshi's (2010) simulation on the self-organization of body representation and general movements in the fetus and newborn (section 2.5.3). Also a developmental robotics model of early word learning (Morse, Belpaeme, *et al.* 2010) uses a setup similar to the A-not-B error to investigate dynamics interactions between embodiment factors and higher-order language development phenomena (section 7.3).

1.3.2 Phylogenetic and Ontogenetic Interaction

Discussion of the dynamical systems approach has already stressed the importance of different timescales during development, including the ontogenetic phenomena of *learning*, over a timescale of hours or days, and *maturational* changes, occurring for periods of months or years. An additional, slower, timescale to consider when studying development is that of the phylogenetic time dimension, that is, the effect of evolutionary changes in development. Therefore the additional implication of the interaction between ontogenetic and phylogenetic phenomena should be considered in robotics models of development.

In this section we will discuss the importance of maturational changes, as these more closely relate to phylogenetic changes. The effect of cumulative changes due to learning new behaviors and skills will be discussed in sections 1.3.5 and 1.3.6.

Maturation refers to changes in the anatomy and physiology of the child's brain and body, especially during the first years of life. Maturational phenomena related to the brain include the decrease of brain plasticity during early development, and phenomena like the gradual hemispheric specialization and the pruning of neurons and connections (Abitz *et al.* 2007). Brain maturation changes have also been evoked to explain the critical periods in learning. Critical periods are stages (window of time) of an organism's lifespan during which the individual is more sensitive to external stimulation and more efficient at learning. Moreover, after a critical period has ended, learning becomes difficult or impossible to achieve. The best know example of critical period (also known as the sensitive period) in ethology is Konrad Lorenz's study on imprinting, that is, the attachment of ducklings to their mother (or to Lorenz!), which is only possible within the first few hours of life and has a long-lasting effect. In vision research, Hubel and Wiesel (1970) demonstrated that the cat's visual cortex can only develop its receptive fields if the animal is exposed to visual stimuli in the first few months of life, and not when there is total visual deprivation by covering the kitten's eyes. In developmental psychology, the best-studied critical period is that for language learning. Lenneberg (1967) was one of the first to propose the critical period hypothesis for language development that claims that the brain changes occurring between the age of two and seven years, specifically for the hemispheric specialization gradually leading to lateralization of the linguistic function in the left hemisphere, are responsible for the problems in learning language after this age. The critical period hypothesis has also been proposed to explain the limitation in the acquisition of a second language after puberty (Johnson and Newport 1989). Although this hypothesis is still debated in the literature, there is general agreement that brain maturation changes significantly affect language learning beyond the period of puberty.

Maturation in the body of the child is more evident given the significant morphological changes a child goes through from birth to adolescence. These changes naturally affect the motor development of the child, as in Thelen and Smith's analysis of crawling and walking. Morphological changes occurring during development also have implication for the exploitation of embodiment factors, as discussed in section 1.3.3, on the morphological computation effects of embodiment.

Some developmental robotics models have explicitly addressed the issue of brain and body maturation changes. For example, the study by Schlesinger, Amso, and Johnson (2007) models the effects of neural plasticity in the development of object perception skills (section 4.5). The modeling of body morphology development is also extensively discussed in chapter 4 on motor development.

The ontogenetic changes due to maturation and learning have important implications for the interaction of development with phylogenetic changes due to evolution. Body morphology and brain plasticity variations can in fact be explained as evolutionary adaptations of the species to changing environmental context. These phenomena have been analyzed, for example, in terms of genetic changes affecting the timing of ontogenetic phenomena, known as heterochronic changes (McKinney and McNamara 1991). Heterochronic classifications are based on the comparison of ontogenies that differ for the onset of growth, the offset of growth, and the rate of growth of an organ or a biological trait. Namely, the terms “predisplacement” and “postdisplacement” refer respectively to an anticipated and a postponed onset of morphological growth, “hypermorphosis” and “progenesis” refer respectively to a late and an early offset of growth, and “acceleration” and “neoteny” refer respectively to a faster and a slower rate of growth. Heterochronic changes have been used to explain the complex interaction between nature and nurture in models of development, an in Elman et al.’s (1996) proposal that the role of genetic factors in development is to determine the architectural constraints, which subsequently control learning. Such constraints can be explained in terms of brain adaptation and neurodevelopmental and maturational events.

The interaction between ontogenetic and phylogenetic factors has been investigated through computational modeling. For example, Hinton and Nowlan (1987) and Nolfi, Parisi, and Elman (1994) have developed simulation models explaining the effects of learning in evolution, as for the Baldwin effect. Cangelosi (1999) has tested the effects of heterochronic changes in the evolution of neural network architectures for simulated agents. Furthermore, the modeling of the evolution of varying body and brain morphologies in response to phylogenetic and ontogenetic requirements is also the goal of the “evo-devo” computational approach. This aims at simulating the simultaneous effects of developmental and evolutionary adaptation in body and brain morphologies (e.g., Stanley and Miikkulainen 2003; Kumar and Bentley 2003; Pfeifer and Bongard 2007). Developmental robotics models normally are based on robots with fixed morphologies and cannot directly address the simultaneous modeling of phylogenetic changes and their interaction with ontogenetic morphological changes. However, various epigenetic robotics models take into consideration the evolutionary origins of the ontogenetic changes of learning and maturation, especially for studies including changes in brain morphology.

1.3.3 Embodied, Situated, and Enactive Development

Growing empirical and theoretical evidence exists on the fundamental role of the body in cognition and intelligence (*embodiment*), the role of interaction between the body and its environment (*situatedness*), and the organism's autonomous generation of a model of the world through sensorimotor interactions (*enaction*). This embodied, situated, and enactive view stresses the fact that the body of the child (or of the robot, with its sensors and actuators), and its interaction with the environmental context determines the type of representations, internal models, and cognitive strategies learned. As Pfeifer and Scheier (1999, 649) claim, "intelligence cannot merely exist in the form of an abstract algorithm but requires a physical instantiation, a body."

In psychology and cognitive science, the field of embodied cognition (aka grounded cognition) has investigated the behavioral and neural bases of embodiment, specifically for the roles of action, perception, and emotions in the grounding of cognitive functions such as memory and language (Pecher and Zwaan 2005; Wilson 2002; Barsalou 2008). In neuroscience, brain-imaging studies have shown that higher-order functions such as language share neural substrates normally associated with action processing (Pulvermüller 2003). This is consistent with philosophical proposals on the embodied mind (Varela, Thompson, and Rosch 1991; Lakoff and Johnson 1999) and situated and embodied cognition (Clark 1997).

In robotics and artificial intelligence, embodied and situated cognition has also received great emphasis through the approach of embodied intelligence (Pfeifer and Scheier 1999; Brooks 1990; Pfeifer and Bongard 2007; Pezzulo *et al.* 2011). Ziemke (2001) and Wilson (2002) analyze different views of embodiment and their consideration in computational models and psychology experiments. These different views range from considering embodiment as the phenomenon of the "structural coupling" between the body and the environment, to the more restrictive "organismic" embodiment view, based on the autopoiesis of living systems, that is, that cognition actually is what living systems *do* in interaction with their world (Varela, Thompson, and Rosch 1991). Along the same lines, the paradigm of enaction highlights the fact that an autonomous cognitive system interacting in its environment is capable of developing its own understanding of the world and can generate its own models of how the world works (Vernon 2010; Stewart, Gapenne, and Di Paolo 2010).

Embodied and situated intelligence has significantly influenced developmental robotics, and practically any developmental model places great emphasis on the relation between the robot's body (and brain) and the environment. Embodiment effects concern pure motor capabilities (morphological computation) as well as higher-order cognitive skills such as language (grounding). *Morphological computation* (Bongard and Pfeifer 2007) refers to the fact that the organism can exploit the body's morphological properties (e.g., type of joint, length of limbs, passive/active actuators), and the dynamics of the interaction with the physical environment (e.g., gravity) to produce intelligent behavior. One of the best-known examples of this is the passive dynamic walker, that is, bipedal robots that can walk on a slope without any actuator, thus not requiring any explicit control, or bipedal robots only requiring minimal actuation to start movement (McGeer 1990; Collins *et al.* 2005). The exploitation of morphological computation has important implications for energy consumption optimization in robotics, and for the increasing use of compliant actuators and soft robotics material (Pfeifer, Lungarella, and Iida 2012).

On the other end, an example of the role of embodiment in higher-order cognitive functions can be seen in the models of the grounding of words in action and perception (Cangelosi 2010; Morse, Belpaeme, *et al.* 2010, see section 7.3) and the relationship between spatial representation and numerical cognition in psychology and developmental robotics (Rucinski, Cangelosi, and Belpaeme 2011, see section 8.2).

1.3.4 Intrinsic Motivation and Social Learning Instinct

Conventional approaches to designing intelligent agents typically suffer from two limitations. First, the objectives or goals (i.e., the value system) are normally imposed by the model-builder, rather than determined by the agent themselves. Second, learning is often narrowly restricted to performance on a specific, predefined task. In response to these limitations, developmental robotics explores methods for designing *intrinsically motivated* agents and robots. An intrinsically motivated robot explores its environment in a completely autonomous manner, by deciding for itself what it wants to learn and what goals it wants to achieve. In other words, intrinsic motivation enables the agent to construct its own value system.

The concept of intrinsic motivation is inspired by a variety of behaviors and skills that begin to develop in infancy and early childhood, including diverse phenomena such as curiosity, surprise, novelty seeking, and the “drive” to achieve mastery. Oudeyer and Kaplan (2007) propose a framework for organizing research on models of intrinsic motivation, including two major categories: (1) knowledge-based approaches (which are subdivided into novelty-based and prediction-based approaches), and (2) competence-based approaches. Within this framework, a large number of algorithms can be defined and systematically compared.

Novelty-based approaches to intrinsic motivation often utilize mobile robots, which learn about their environments by exploring and discovering unusual or unexpected features. A useful mechanism for detecting novelty is habituation: the robot compares its current sensory state to past experiences, devoting its attention toward situations that are unique or different from those that have already been experienced (e.g., Neto and Nehmzow 2007).

Prediction-based approaches are a second type of knowledge-based intrinsic motivation, as they also rely on accumulated knowledge. However, in this case prediction-based models explicitly attempt to predict future states of the world. A simple example could be a robot that pushes an object toward the edge of the table, and predicts that it will make a sound when it drops on the floor. The rationale of this approach is that incorrect or inaccurate predictions provide a learning signal, that is, they indicate events that are poorly understood, and require further analysis and attention. As an example of this approach, Oudeyer *et al.* (2005) describe the Playground Experiment, in which the Sony AIBO robot learns to explore and interact with a set of toys in its environment.

The third approach to modeling intrinsic motivation is competence based. According to this view, the robot is motivated to explore and develop skills that effectively produce reliable consequences. A key element of the competence-based approach is *contingency detection*: this is the capacity to detect when one’s actions have an effect on the environment. While the knowledge-based approach motivates the agent toward discovering properties of the world, the competence-based approach, in contrast, motivates the agent to discover *what it can do* with the world.

Child development research has shown the presence of social learning capabilities (instincts). This is evidenced for example by observations that newborn babies have an instinct to imitate the behavior of others from the day they are born and can imitate complex facial expressions (Meltzoff and Moore 1983). Moreover, comparative psychology studies have demonstrated that 18-to 24-month-old children have a tendency to cooperate altruistically, a capacity not observed in chimpanzees (Warneken, Chen, and Tomasello 2006).

As we highlight in chapter 3, the development of intrinsic motivation has direct implications for how infants perceive and interact with others. For example, young infants quickly learn that people in their environment respond contingently to their movements and sounds. Thus, babies may be intrinsically motivated to orient toward and interact with other people.

Developmental robotics places a heavy emphasis on social learning, and as demonstrated in the numerous studies discussed in chapter 6, various robotics models of joint attention, imitation, and cooperation have been tested.

1.3.5 Nonlinear, Stage-Like Development

The literature on child psychology has plenty of theories and models proposing a sequence of developmental *stages*. Each stage is characterized by the acquisition of specific behavioral and mental strategies, which become more complex and articulated as the child progresses through these stages. Stages are also linked to specific ages of the child, except for individual differences. Piaget's four stages of development of thought are the prototypical example of a theory of development centered on stages (chapter 8). Numerous other examples of stage-based development exist, and a few will be described in the chapters that follow, as Courage and Howe's (2002) timescale of self-perception (chapter 4), Butterworth's (1991) four stages of joint attention and Leslie's (1994) and Baron-Cohen's (1995) stages of the theory of mind (chapter 6), the sequential acquisition of lexical and syntactic skills (chapter 8), and the stages of numerical cognition and of rejection behavior (chapter 9).

In most theories, the transition between stages follows nonlinear, qualitative shifts. Again, in the example of Piaget's four stages, the mental schemas used in each stage are qualitatively different, as they are the results of accommodation processes that change and adapt the schema to new knowledge representations and operations. Another well-known developmental theory based on qualitative changes during development is the Representational-Redescription Model of Karmiloff-Smith (1995). Although Karmiloff-Smith explicitly avoids the definition of age-determined stage models, as in Piaget, her model assumes four levels of development going from the use of implicit representation to different levels of explicit knowledge-representation strategies. When a child learns new facts and knowledge about specific domains, she develops new representations, which are gradually "redescribed" and increase the child's explicit understanding of the world. This has been applied to a variety of knowledge domains such as physics, math, and language.

The nonlinearity of the developmental process and the qualitative shifts in the mental strategies and knowledge representations employed by the child at different stages of development have been extensively investigated through "U-shaped" learning error patterns and with the vocabulary spurt phenomenon. The prototypical case study of the U-shaped phenomenon in child development is in the patterns of errors produced by children during the acquisition of the verb morphology for the English past tense. The (inverted) U-shaped phenomenon consists of the low production of errors at the beginning of learning, which is then followed by an unexpected increase in errors, subsequently followed by an improved performance and low error production again. In the case of the English past tense, initially children produce few errors as they can say the correct past tense for high-frequency irregular verbs, such as "went," and the correct "ed" suffix form for regular verbs. At a later stage, they pass through a stage of "over-regularization," and start producing morphological errors for irregular verbs, as with "goed." Eventually, children can again distinguish the multiple forms of irregular past tenses. This phenomenon has been extensively studied in psychology, and has caused heated debate between the proponents of a rule-based strategy for syntax processing (Pinker and Prince 1988), and the advocates of a distributed representation strategy, which is supported by demonstration that connectionist networks can produce a U-shaped performance by using distributed representations (e.g., Plunkett and Marchman 1996). U-shaped learning phenomena have also been reported in other domains, such as in phonetic perception (Eimas *et al.* 1971; Sebastián-Gallés and Bosch 2009), face imitation (Fontaine 1984), and in Karmiloff-Smith's (1995) explanation of a child’s performance and errors due to the changing representational strategies.

The vocabulary spurt phenomenon in lexical acquisition is another case of nonlinear and qualitative shifts during development. The vocabulary spurt (also called the “naming explosion”) occurs around the eighteen-to twenty-four-month period, when the child goes from an initial pattern of slow lexical learning, with the acquisition of few words per month, to the *fast mapping* strategy, whereby a child can quickly learn tens of words per week by single exposure to the lexical item (e.g., Bloom 1973; Bates *et al.* 1979; Berk 2003). The vocabulary spurt typically happens when a child has learned around 50–100 words. This qualitative change of strategy in word learning has been attributed to a variety of underlying cognitive strategies, including the mastering of word segmentation or improvements in lexical retrieval (Ganger and Brent 2004).

Many developmental robotics studies aim to model the progression of stages during the robot’s development, with some directly addressing the issue of nonlinear phenomena in developmental stages as a result of learning dynamics. For example Nagai *et al.* (2003) explicitly modeled the joint attention stages proposed by Butterworth (1991). However, the model shows that qualitative changes between these stages are the result of gradual changes in the robot’s neural and learning architecture, rather than ad hoc manipulations of the robot’s attention strategies (see section 6.2). Some models have also directly addressed the modeling of U-shaped phenomena, such as in the Morse *et al.* (2011) model of error patterns in phonetic processing.

1.3.6 Online, Open-Ended, Cumulative Learning

Human development is characterized by online, cross-modal, continuous, open-ended learning. *Online* refers to the fact that learning happens while the child interacts with its environment, and not in an offline mode. *Cross-modal* refers to the fact that different modalities and cognitive domains are acquired in parallel by the child, and interact with each other. This is for example evidenced in the interaction of sensorimotor and linguistics skills, as discussed in the embodiment section 1.3.3. *Continuous* and *open-ended* refers to the fact that learning and development do not start and stop at specific stages, but rather constitute a lifelong learning experience. In fact, developmental psychology is often framed within the wider field of the psychology of life cycles, ranging from birth to aging.

Lifelong learning implies that the child *accumulates* knowledge, and thus learning never stops. As seen in the previous sections, such continuous learning and accumulation of knowledge can result in qualitative changes of cognitive strategies, as in the language vocabulary spurt phenomenon, and in Karmiloff-Smith's theory on the transition from implicit to explicit knowledge through the Representational-Redescription model.

One consequence of cumulative, open-ended learning is *cognitive bootstrapping.* In developmental psychology, cognitive bootstrapping has been mostly applied to numerical cognition (Carey 2009; Piantadosi, Tenenbaum, and Goodman 2012). According to this concept, a child acquires knowledge and representation from learned concepts (e.g., numerical quantities and counting routines) and then inductively uses this knowledge to define the meaning of new number words learned subsequently, and with a greater level of efficiency. The same idea can be applied to the vocabulary spurt, in which the knowledge and experience from the slow learning of the first 50–100 words causes a redefinition of the word learning strategy, and to syntactic bootstrapping, by which children rely on syntactic cues and word context in verb learning to determine the meaning of new verbs (Gleitman 1990). Gentner (2010) has also proposed that general cognitive bootstrapping is achieved through the use of analogical reasoning and the acquisition of symbolic relationship knowledge.

Online learning is implemented in developmental robotics, as will be demonstrated in most of the studies presented in the next chapters. However, the application of cross-modal, cumulative, open-ended learning, which can lead to cognitive bootstrapping phenomena, has been investigated less frequently. Most of the current models typically focus on the acquisition of only one task or modality (perception, or phonetics, or semantics, etc.), and few consider the parallel development, and interaction, between modalities and cognitive functions. Thus a truly online, cross-modal, cumulative, open-ended developmental robotics model remains a fundamental challenge to the field.

The presentations of various examples of developmental robotics models and experiments will show how most of the preceding principles guide and inform the design of the cognitive architecture and the experimental setups of developmental robots.

1.4 Book Overview

In this introductory chapter we have defined developmental robotics and discussed its grounding in developmental psychology theories. The discussion of the main principles at the basis of developmental robotics has also highlighted the common defining characteristics of such an approach.

In chapter 2 we provide further introductory material, in particular a working definition of robots and a look at the different types of android and humanoid robots. Chapter 2 also includes an overview of sensor and actuator technology for humanoid robotics and the primary baby robot platforms used in developmental robotics, as well as the simulation tools.

In the experiment-focused chapters 3–8 we look in detail at how developmental robotics models and experiments have explored the realization of various behavioral and cognitive capabilities (motivation, perception, action, social, linguistic, and abstract knowledge). Then we consider the achievements and challenges in these areas. Each of these chapters begins with a concise overview of the main empirical findings and theoretical positions in developmental psychology. Although each overview is aimed at readers who are not familiar with the child psychology literature, at the same time it provides the specific empirical grounding and reference work pertaining to the individual developmental issues modeled in the robotics studies described in the rest of each chapter. Each experiment-focused chapter then discusses seminal experiments demonstrating the achievement of developmental robotics in modeling autonomous mental development. These examples explicitly address key issues in child psychology research. Moreover, most experimental chapters include boxes that provide technical and methodological details on exemplar psychology and robotics experiments, and highlight methodological implications in developmental robotics and their direct correspondence to child psychology studies.

Of these six experimental chapters, chapter 3 specifically concerns the developmental robotics models of intrinsic motivation and curiosity, looking in particular at the neural, conceptual, and computational bases of novelty, prediction, and competence. Chapter 4 discusses the models of perceptual development, concentrating in detail on the models of face recognition, perception of space, robot's self-perception, and recognition of objects and of motor affordances. Chapter 5 analyzes motor development models contemplating both manipulation (i.e., reaching and grasping) and locomotion capabilities (i.e., crawling and walking). In chapter 6 we look at the developmental work of social learning, with emphasis on the models of joint attention, imitation learning, cooperation and shared plans, and robot's theory of mind. Chapter 7 focuses on language and analyzes the development of phonetic babbling, the grounded acquisition of words and meaning, and the development of syntactic processing skills. Chapter 8 focuses on developmental robotics models of abstract knowledge, with a discussion of number learning models, abstracts concepts, and reasoning strategies.

Finally, the concluding chapter 9 reflects on the achievements in developmental robotics common to the different cognitive areas, and looks ahead to consider future research directions and developments in the field.

Additional Reading

Thelen, E., and L. B. Smith. *A Dynamic Systems Approach to the Development of Cognition and Action.* Cambridge, MA: MIT Press, 1994.

This is a seminal book on theoretical developmental psychology that, in addition to its impact in child psychology, has greatly inspired developmental robotics, and in general dynamical systems approaches to cognitive modeling. The volume provides the original and detailed account of the dynamical systems approach to development briefly introduced in section 1.3.1.

Pfeifer, R., and J. Bongard. *How the Body Shapes the Way We Think: A New View of Intelligence.* Cambridge, MA: MIT Press, 2007.

This book presents an inspiring analysis of the concept of embodied intelligence in natural and artificial cognitive systems. Its aim is to demonstrate that cognition and thought are not independent of the body, but rather are tightly constrained by embodiment factors, and at the same time the body enables and enriches cognitive capabilities. The book is centered on the idea of “understanding by building,” meaning, the fact that we understand and can build intelligent agents and robots gives us a better understanding of intelligence in general. As such the book discusses many examples from robotics, biology, neuroscience, and psychology, and covers specific applications in ubiquitous computing and interface technology, in business and management for building intelligent companies, in the psychology of human memory, and in everyday robotics.

Nolfi, S., and D. Floreano. *Evolutionary Robotics: The Biology, Intelligence, and Technology of Self-Organizing Machines.* Cambridge, MA: MIT Press, 2000.

This book offers detailed discussion of the evolutionary robotics principles and of the pioneering evolutionary models and experiments by Nolfi and Floreano. It can be considered a companion of *Developmental Robotics: From Babies to Robots* because it introduces the complementary area of evolutionary robotics. *Evolutionary Robotics* comes with a free software simulator for evolutionary robotics experiments with mobile robots (gral.istc.cnr.it/evorobot) as well as the more recent evolutionary robotics simulator for the iCub humanoid (laral.istc.cnr.it/farsa).

3 Novelty, Curiosity, and Surprise

A key design principle in developmental robotics is *autonomy*, which means that the developing robot, machine, or agent is free to interact with and explore its environment. In contrast to robots whose decisions and actions are rigidly programmed in advance, or who are driven by a remote controller, autonomous robots *self-select* their actions adaptively, in response to internal states and external environment sensing (e.g., Nolfi and Parisi 1999; Schlesinger and Parisi 2001). In this chapter, we focus in particular on the autonomy of *learning*, that is, on the agent's freedom to choose *what, when*, and *how* it will learn.

A fundamental question that arises from this freedom is: what is the best strategy for exploring the environment? When confronted with a novel experience, and a variety of options for probing or examining this experience, how should the robot decide which actions or options to try first, and when should it move from one option to the next? Conventional AI approaches to this question typically treat the issue as an optimality problem (e.g., energy minimization, exploration rewards, etc.), and consequently, they often focus on analytical and learning methods that are designed to identify an optimal exploration strategy. While research in developmental robotics relies on many of the same computational tools, the way in which the problem is framed, and the theoretical perspectives that inspire and guide these models differ from conventional approaches. In particular, in this chapter we highlight the emerging area of *intrinsic motivation*, which provides robots with a form of "artificial curiosity." Thus, intrinsically motivated robots are not focused on solving a particular problem or task, but rather on the process of learning itself (e.g., Oudeyer and Kaplan 2007).

The application of intrinsic motivation (IM) as a mechanism to drive autonomous learning, not only in developmental robotics, but also more broadly within the field of machine learning, offers three important advantages over conventional learning methods (e.g., Mirolli and Baldassarre 2013; Oudeyer and Kaplan 2007). First, IM is *task-independent.* This means that the robot or artificial agent can be placed in a completely new environment—with which the model-builder may have no prior knowledge or experience—and through self-directed exploration, the robot will potentially learn not only the important features of the environment, but also the behavioral skills necessary for dealing with that environment. Second, IM promotes the hierarchical *learning and reuse* of skills. Learning is directed toward acquiring knowledge or skill or both, rather than solving a specific, predefined task. Thus the intrinsically motivated robot may acquire an ability in one context (or developmental stage) that has no immediate benefit, but which then becomes a critical building block for later, more complex skills. Finally, IM is *open ended.* Thus, learning in a particular environment is determined by the robot's level of skill or knowledge, rather than by its progress toward a predetermined, externally imposed goal. Indeed, as we will highlight, there are several IM models that illustrate this principle: as the robot achieves mastery in one area, it can efficiently shift its focus toward new features of the environment or new skills that it has not yet learned.

As a research topic within developmental robotics, the study of IM is inspired by two closely related areas of work. First, there is a wide array of theories and empirical studies, primarily within psychology, that explore how IM develops in both humans and nonhumans (e.g., Berlyne 1960; Harlow 1950; Hull 1943; Hunt 1965; Kagan 1972; Ryan and Deci 2000; White 1959). Second, there is also a considerable amount of work within neuroscience, which seeks not only to identify the neural substrates for IM, but also to explain how these biological mechanisms operate (e.g., Bromberg-Martin and Hikosaka, 2009; Horvitz, 2000; Isoda and Hikosaka 2008; Kumaran and Maguire 2007; Matsumoto *et al.* 2007; Redgrave and Gurney 2006).

In contrast to other research areas in developmental robotics (e.g., motor-skill development or language acquisition), the study of IM in robots and artificial agents is still at a comparatively early stage. As a result, there are a few key differences between how this chapter is organized and the themes that appear throughout the rest of the volume. First, there is not yet a clear correspondence between the major studies and experimental paradigms used to study infants and children, and robotics models of IM. In particular, much of the research to date within developmental robotics on IM has predominantly focused on designing effective algorithms and architectures, while there is comparatively less work that points directly toward human development (e.g., the self-other distinction; Kaplan and Oudeyer 2007). In section 3.3.1, we therefore provide a detailed description of the class of architectures that are available for simulating IM. Second, much of the modeling work that has been conducted thus far focuses on simulation studies. Consequently, there are comparatively less data available from real-world robot platforms. Nevertheless, there is a growing trend toward using robots to study IM, and in the second half of the chapter, we highlight several examples of both simulation and real-world studies.

3.1 Intrinsic Motivation: A Conceptual Overview

As we will highlight, the concept of *IM* is heavily influenced by both data and theory from psychology. Nevertheless, and perhaps surprisingly, the use of the terms “extrinsic” and “intrinsic motivation” in developmental robotics (and more generally, machine learning) differ from their use in psychology. Thus, psychologists typically define intrinsically motivated behaviors as actions that are chosen by the organism “freely,” that is, without any external incentives or consequences, while extrinsically motivated behaviors are produced in response to external prompts or cues. By this view, a child can draw simply for fun (intrinsic) or, instead, for a reward such as money or candy (extrinsic). In contrast, we adopt the view proposed by Baldassarre (2011) that extrinsically motivated behaviors are those that directly serve the needs of basic biological functions (e.g., thirst or hunger), while intrinsically motivated behaviors have no clear goal, purpose, or biological function, and are therefore presumably performed *for their own sake.*

3.1.1 Early Influences

Early approaches to understanding intrinsic motivation were influenced by existing theories of behavior, and in particular, by drive-based, homeostatic theories. A well-known example of the homeostatic approach is Hull’s theory (1943), which proposes that all behaviors can be understood as the result of either (a) “primary” physiological drives such as hunger or thirst, or (b) “secondary” or psychological drives, which are acquired in the process of satisfying the primary drives. There are two critical components of the Hullian view. First, primary drives are innate and therefore biologically specified: they are evolved for the purpose of protecting or promoting the organism’s survival. Second, they are homeostatic: this means that, for a given physiological system, there is an ideal “set point,” and the primary drive then serves to keep the organism as close to this point as possible. For example, when an animal becomes cold, it may shiver or move toward sunlight in order to increase its temperature. In other words, homeostatic drives function to bring an animal “back into balance” or equilibrium when the environment alters or disrupts the organism’s state.

Several researchers asked whether Hull’s drive theory could be applied to behaviors like play and object exploration, especially in nonhumans. For example, Harlow (1950; Harlow, Harlow, and Meyer 1950) observed the behavior of rhesus monkeys that were presented with a mechanical puzzle illustrated in figure 3.1 (e.g., including a lever, hinge, and chain). The monkeys typically became engrossed by the puzzle and played with it extensively. Notably, their exploratory behavior was not dependent on the presentation of an external reward (e.g., food), and over repeated experiences, the monkeys became progressively more effective at solving the puzzle. Thus, the monkeys in the Harlow study not only learned to solve the puzzle, but also, more important, their attempts to manipulate and explore the puzzle also seemed to be directed toward the goal of understanding or *figuring out how it worked.*

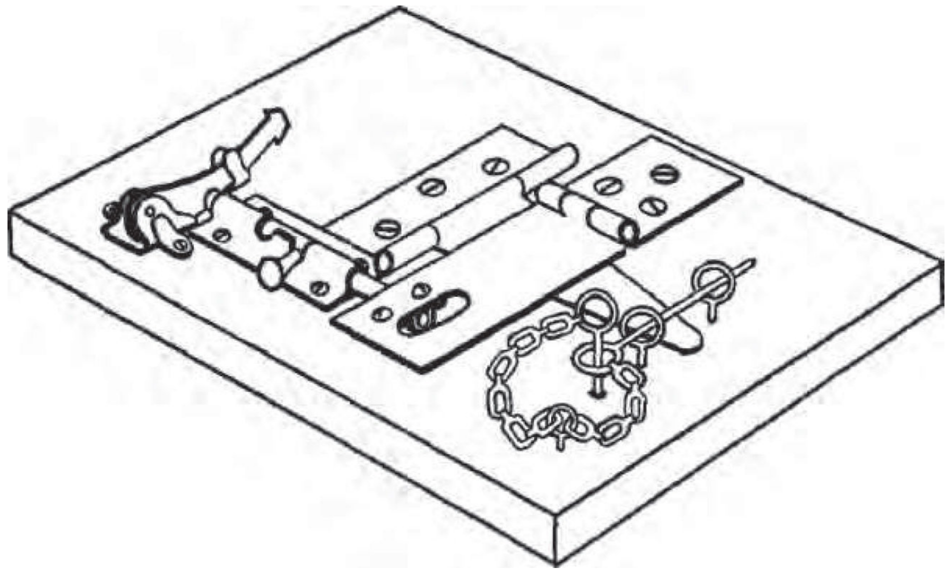


Figure 3.1

Mechanical “puzzle” studied by Harlow (1950). Public domain figure, American Psychological Association.

Other researchers observed similar instances of exploratory behavior (e.g., Butler 1953; Kish and Anonitis 1956). One way to account for these behaviors is to incorporate them within the Hullian framework, that is, as drives or instincts for “manipulation,” “exploration,” and so on (e.g., Montgomery 1954). However, as White (1959) notes, exploratory or play behaviors like those observed by Marlow are not homeostatic, and therefore differ from classical drives in two fundamental ways. First, they are not a response to an environmental perturbation or disturbance, such as deprivation of food or water. Second, performing these behaviors does not bring the organism “back” to a desired physiological state. Instead, they seem to be open ended, with no obvious goal or immediate benefit to the organism.

3.1.2 Knowledge and Competence

Subsequent approaches to IM focused on addressing the limitations of drive-based, homeostatic theories. These approaches can be divided into two broad theoretical views, the knowledge-based and the competence-based IM views (e.g., Baldassarre 2011; Mirolli and Baldassarre 2013; Oudeyer and Kaplan

2007). First, the *knowledge-based view* proposes that IM is a cognitive mechanism that enables the organism to detect novel or unexpected features, objects, or events in the environment. According to this view, IM is a product of the organism's current state of knowledge. In particular, the organism is motivated to expand its knowledge base (i.e., learn) by systematically exploring the environment, and searching for experiences that are unfamiliar or poorly understood.

Knowledge-based IM includes two variants or subclasses: novelty-based and prediction-based IMs. *Novelty-based IM* reflects the principle, proposed by several developmental theorists, that experience is organized into cognitive structures, which are used to interpret new information (e.g., Fischer 1980; Kagan 1972; Piaget 1952). Novel situations produce a mismatch or incongruity between an ongoing experience and stored knowledge, which results in an effort to resolve the discrepancy (e.g., by increasing attention to the object or situation; see "comparator theory," to follow). The novelty-based approach also suggests that there is a critical difference between situations with low, moderate, and high levels of novelty: a low level of novelty maps to a familiar experience, while highly novel experiences may not be interpretable within the organism's current knowledge base. In contrast, moderate novelty may be optimal for learning, as it is both comprehensible and unfamiliar (e.g., Berlyne 1960; Ginsburg and Opper 1988; Hunt 1965). The other variant of knowledge-based IM is *prediction-based IM*. This approach emphasizes the role of organism-environment interaction, and characterizes the organism as actively exploring the unfamiliar "edges" of its knowledge base. Prediction-based IM is consistent with the concepts of *curiosity* and *surprise*: in probing its environment, the organism implicitly predicts how objects or events will respond to its actions, and when unexpected outcomes occur, additional energy or attention is devoted to further probe the situation (e.g., Piaget 1952).

While novelty-based and prediction-based IM both generate new knowledge about the environment, there is a subtle but important difference between the two learning mechanisms. In the case of novelty-based IM, the agent is viewed as generally *passive*, as its primary tool for seeking out novel experiences is movement through space (e.g., head and eye movements). In contrast, prediction-based IM is comparatively *active*, as the agent can systematically operate on the environment and observe the outcomes of its actions (e.g., grasp, lift, or drop an object). However, this distinction is somewhat arbitrary, and it should be stressed that novelty seeking and action prediction are not mutually exclusive, and in fact can frequently co-occur.

Knowledge-based IM focuses on the properties of the environment, and how the organism gradually comes to know and understand these properties (i.e., objects and events)—and in the case of prediction-based IM, how these properties might change as a consequence of the organism’s actions. An alternative approach, the *competence-based view*, focuses instead on the organism and the particular abilities or skills it possesses. There are several theoretical motivations for competence-based IM. For example, White (1959) highlights the notion of “effectance,” which is the subjective experience that one’s actions will influence the outcome of a situation (see Bandura 1986 for a related term, “self-efficacy”). Similarly, de Charms (1968) proposes the concept he terms “personal causation.” More recently, *self-determination theory* (Deci and Ryan 1985) has elaborated on these ideas, not only by linking the concept of IM to the subjective experiences of autonomy and competence, but also by arguing that competence manifests itself as a tendency toward improvement and increasing mastery. A closely related phenomenon, described by Piaget (1952; see also Ginsburg and Opper 1988), is *functional assimilation*, which is the tendency for infants and young children to systematically practice or repeat a newly emerging skill (e.g., learning to grasp or walk). Therefore, a fundamental implication of competence-based IM is that it promotes skill development by leading the organism to seek out challenging experiences.

3.1.3 Neural Bases of IM

The ideas and approaches described thus far represent one of two fundamental influences on IM in developmental robotics, that is, the observation and analysis of behavior, coupled with psychological theory. As we noted at the start of the chapter, however, there is another research area that has provided a second fundamental influence: neuroscience. In particular, we briefly highlight here how activity in specific brain regions has been linked to each of the types of IM outlined in the previous section.

First, an important region for novelty detection is the hippocampus, which not only plays a fundamental role in supporting long-term memory, but also in the process of responding to new objects and events (e.g., Kumaran and Maguire 2007; Vinogradova 1975). In functional terms, when a novel experience is encountered, the hippocampus activates a recurrent pathway between itself and the ventral tegmental area (VTA), which uses the release of dopamine to establish new memory traces in the hippocampus. This mechanism continues to operate over repeated presentations, eventually resulting in a diminished response (i.e., habituation; see Sirois and Mareschal 2004). More generally, dopamine release in the mesolimbic pathway (including the VTA, hippocampus, amygdala, and prefrontal cortex) is associated with the detection of salient or "alerting" events (e.g., Bromberg-Martin and Hikosaka 2009; Horvitz 2000). A comprehensive theoretical account that integrates several of these areas, in addition to the hypothalamus, nucleus accumbens, and other nearby structures has been proposed by Panksepp (e.g., Wright and Panksepp 2012), who argues that activation of this network motivates "SEEKING" behaviors (i.e., curiosity, exploration, etc.).

Next, there are a number of brain regions involved in sensorimotor processing that may provide a substrate for prediction learning and the detection of unexpected objects or events. For example, the frontal eye field (FEF), which is associated with the production of voluntary eye movements, plays a critical role during visuomotor scanning are (e.g., Barborica and Ferrera 2004). Single-cell recordings from FEF cells in monkeys suggest that FEF activity is anticipatory (e.g., while tracking a target that briefly disappears). In addition, FEF activity also increases if there is a mismatch between the expected and observed location of the target when it reappears (e.g., Ferrera and Barborica 2010). Thus, neural activity in this region is not only predictive, but it also provides a "learning signal" that may modulate future sensorimotor predictions.

Finally, a brain region that has been implicated as a potential substrate for competence-based IM is the superior colliculus (SC). A recent model, proposed by Redgrave and Gurney (2006), suggests that unexpected events, such as a flashing light, activate the SC and result in a short-term (i.e., phasic) increase in dopamine release. It is important to note, however, that this pathway is not simply a "novelty detector." In particular, Redgrave and Gurney propose that a phasic dopamine increase—produced as a result of SC activation—strengthens the association between ongoing motor and sensory signals, which converge in the striatum. Thus, the SC functions as a “contingency” or “causal” detector, which not only signals when the organism’s ongoing actions produce salient or unexpected consequences, but more important, also increases the likelihood that the given action will be repeated in the corresponding context.

3.2 The Development of Intrinsic Motivation

We next turn to the question of how IM develops during infancy and early childhood. It is important to note that IM is not a distinct research topic or knowledge domain, but rather, is part of a general set of issues that cut across multiple research areas (e.g., perceptual and cognitive development). We begin by describing work that overlaps with the topic of knowledge-based IM (i.e., novelty and prediction) and then focus on competence-based IM.

3.2.1 Knowledge-Based IM in Infants: Novelty

From a behavioral perspective, the process of identifying novel objects or events in the environment can be deconstructed into two key abilities or skills. The first is *exploratory behavior*, that is, searching or scanning the environment for potential areas of interest. The second is *novelty detection*, which is identifying or recognizing that a situation is novel, and focusing attentional resources on that object or event. It is important to note that both of these phenomena can be manifested in a variety of ways. For example, exploration and novelty can be generated as a product of the child’s own behavior, such as through babbling or visual regard of the hand as it moves. Alternatively, they can also result from searching the environment. As a particular example, we focus here specifically on the phenomenon of visual exploration in young infants.

How does visual exploration develop? One way to address this question is to measure infants’ scanning patterns during free viewing of simple geometric shapes. For example, figure 3.2 presents two samples of gaze behavior from a study of visual encoding in two-and twelve-week-old infants (Bronson 1991). During the study, infants viewed an inverted-V figure while their eye movements were recorded with a camera located beneath the figure. For each infant, the initial fixation is indicated by a small dot, and subsequent gaze shifts are indicated by the links between the dots. The size of each dot indicates the relative dwell time of the fixation, with larger dots representing longer dwell times. The sample on the left (figure 3.2a, produced by a two-week-old) highlights two characteristic aspects of scanning behavior that are observed in very young infants: (1) individual fixations (the large dots) are not evenly distributed over the shape, but instead are clustered over a small area; and (2) dwell or fixation times are fairly long (e.g., several seconds). In contrast, in the scanning pattern produced by a twelve-week-old (figure 3.2b), fixations are much more brief and more evenly distributed. Other studies, looking at the same age range, report comparable findings. For example Maurer and Salapatek (1976) analyzed the gaze patterns produced one-and two-month-olds as they viewed pictures of faces. Younger infants tended to focus on a portion of the outside edge of a face, while the older infants more systematically scanned the entire face, including the eyes.

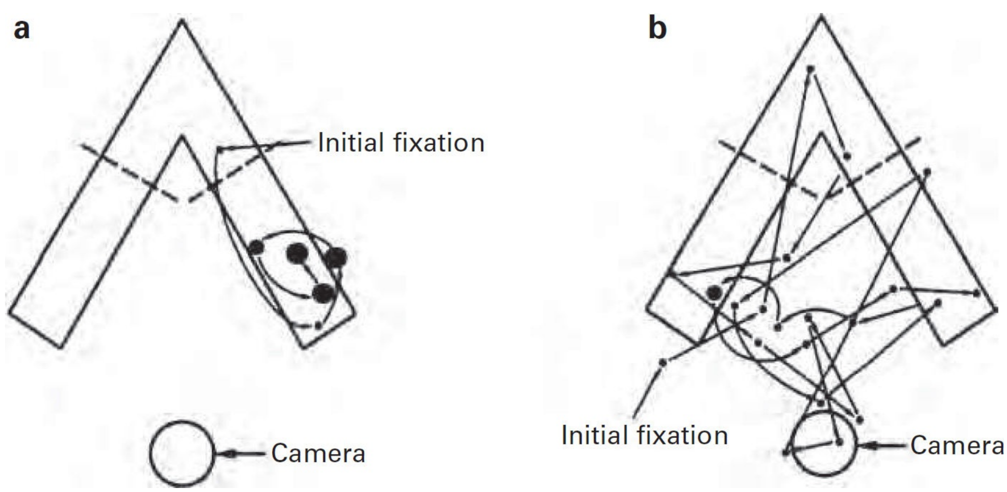


Figure 3.2

The scan pattern on the left (a) was produced by a two-week-old and has a few, long fixations clustered in one corner of the stimulus, while (b) was produced by a twelve-week-old and has many brief fixations, evenly distributed over the stimulus. From Bronson 1991. Reprinted with permission from Wiley.

One way to account for this developmental pattern is to describe it as a shift from *endogenous* to *exogenous orienting* (e.g., Colombo and Cheatham 2006;

Dannemiller 2000; Johnson 1990). Thus, during the first few weeks of postnatal life, infants' orienting behaviors are dominated by salient sensory events. Between one and two months, infants begin to develop more control over their visual exploratory behavior, and gradually acquire the ability to deploy their attention from one location to another in a more deliberate or strategic manner. We return to this issue in the next chapter, where we discuss the development of *visual selective attention.*

The second, core component of identifying novel objects or events is novelty detection. Research on this ability has focused on two questions: (1) at what age do infants begin to respond to novel objects and events, and (2) how is novelty detection manifested in their behavior? While several methods are available to investigate these questions, the dominant approach has been to narrow the scope of the problem in two specific ways. First, most studies present infants with visual images or objects, and measure the amount of time that infants spend looking at the visual stimuli (i.e., *looking time*). Second, changes in looking time—specifically, systematic increases or decreases across presentations of an image or object—are used as an index or proxy for novelty detection (e.g., Colombo and Mitchell 2009; Gilmore and Thomas 2002). The most common paradigm used to study novelty perception in infants is *habituation-dishabituation.* In chapter 4, we describe this paradigm in detail and highlight its use as a research tool for studying perceptual development (e.g., face perception). Here, in contrast, we focus on the more general question of how habituation-dishabituation provides a window into infants' cognitive processing, and specifically, how it is used to measure infants' preference for novel objects and events.

In a habituation-dishabituation study, infants are shown an object or event over a series of trials (i.e., discrete presentations of the visual stimulus), and their looking time is recorded during each trial. Infants gradually lose interest in the object or event—that is, they *habituate*—which is reflected by a decrease in their looking time across trials. At this point, infants are then presented with a visual stimulus that is similar to the one seen during habituation, but that differs along one or more critical dimensions. For example, female faces may be presented during the habituation phase, followed by male faces in the post-habituation phase. A statistically significant increase in looking time to the novel, post-habituation stimuli is then interpreted as reflecting a *novelty preference*: infants not only detect that a new object or event has been presented, but they also increase their attention toward it.

Using this paradigm, developmental researchers have asked: how does novelty preference develop during the first twelve months of infancy? Initial work on this question suggested a surprising answer. In particular, rather than showing a novelty preference, very young infants (i.e., between birth and two months) *tended to prefer familiar objects* (e.g., Hunt 1970; Wetherford and Cohen 1973). Between three and six months, this preference appears to shift toward novel objects and events, and from six to twelve months, a robust and consistent preference for novel stimuli is observed (e.g., Colombo and Cheatham 2006; Roder, Bushnell, and Sasseville 2000).

The observed shift in early infancy from familiarity preference to novelty preference can be understood by applying Sokolov's *comparator theory* (Sokolov 1963). In particular, Sokolov proposed that as infants view an object, they gradually create an internal representation (or internal "template"). The process of habituation is then interpreted as the time spent by the infant constructing an internal representation: as the internal copy comes to match the external object, looking time (i.e., visual attention) declines. When a new object is presented—which creates a mismatch between itself and the internal representation—the infant dishabituates, that is, looking time is increased as the internal representation is updated with new information.

Subsequent work on novelty perception has used comparator theory to help explain the (apparent) shift from familiarity preference to novelty preference in young infants. Specifically, comparator theory proposes that because younger infants have limited visual experience, as well as limited visual processing ability, they are less skilled at encoding objects and events, and their internal representations are less stable or complete. As a result, they tend to focus on familiar visual stimuli. According to this view, infants at all ages should show a novelty preference when the stimuli are presented in a manner that accounts for infants' processing speed and visual experience (e.g., Colombo and Cheatham 2006). Thus, novelty detection and novelty preference appear to be present in human infants as early as birth, and familiarity preference is now understood as the product of partial or incomplete visual encoding (e.g., Roder, Bushnell, and

Sasseville 2000).

3.2.2 Knowledge-Based IM in Infants: Prediction

The development of infants' ability to predict has been primarily studied by investigating their anticipatory reactions to the outcomes of simple dynamic events (e.g., a ball that rolls down a track). In this context, "prediction" is specifically defined as a sensorimotor skill, where an action is performed by the infant, such as a gaze shift or a reach, in anticipation of the event outcome.

A well-established technique for measuring predictive behavior in young infants is the *visual expectation paradigm* (VExP; see Haith, Hazan, and Goodman 1988; Haith, Wentworth, and Canfield 1993), in which infants are presented with a sequence of images at two or more locations, in a consistent pattern, while the location and timing of infants' gaze patterns to the images are recorded. In box 3.1, we provide a detailed description of the VExP, including the major developmental findings that have been revealed with this technique. It is important to note that VExP is typically used to study infants within a narrow age range—that is, between ages two and four months—which suggests that predictive or anticipatory visual activity not only is rapidly developing at this age period, but also is consistent with independent estimates of FEF maturation in human infants (e.g., Johnson 1990).

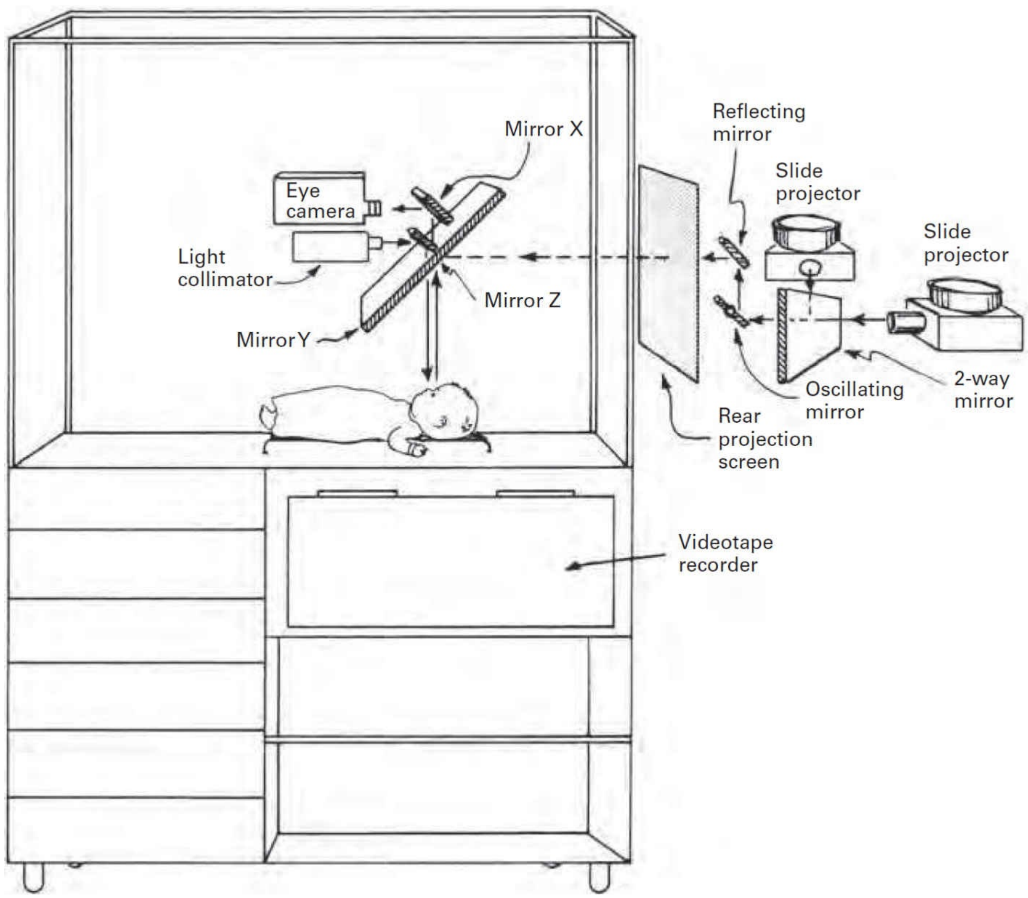
Box 3.1

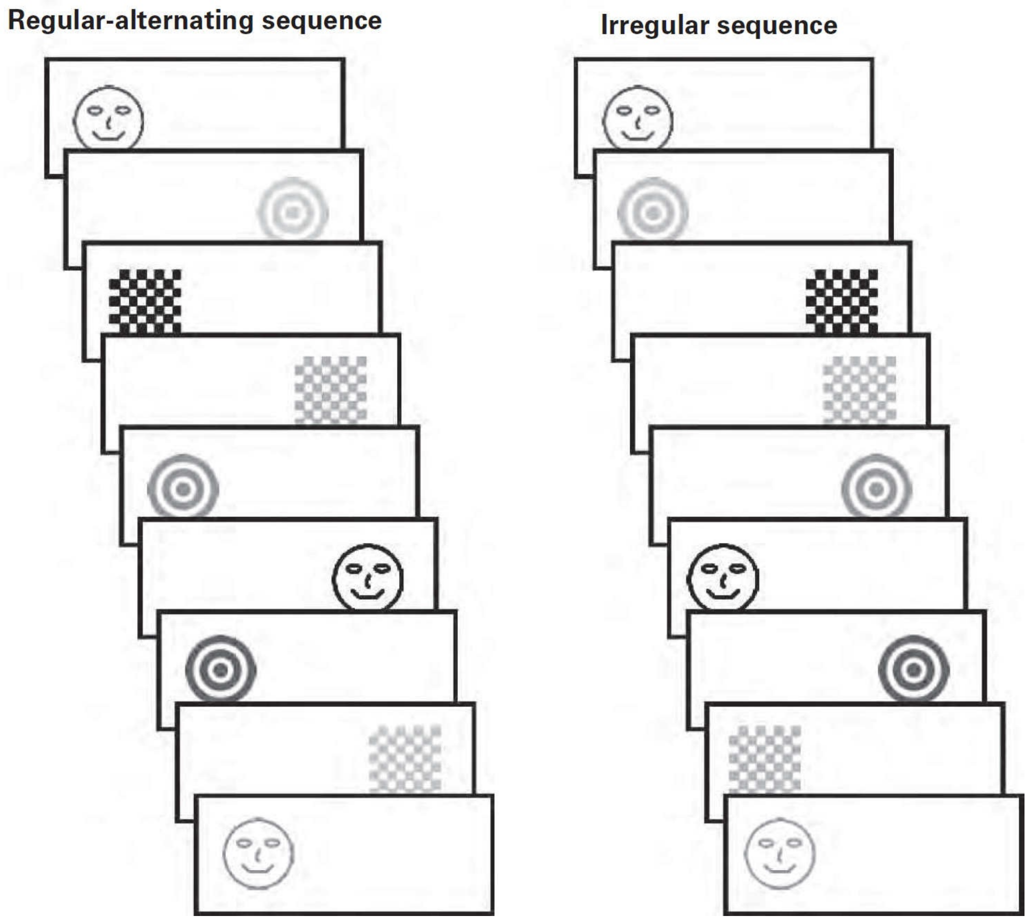
The Visual Expectation Paradigm (VExP)

One of the earliest and most basic forms of predictive behavior observed in young infants is the ability to view a sequence of events—such as images that appear on a video screen, one after another—and to anticipate the location of the events before they appear. In a groundbreaking study, Haith, Hazan, and Goodman (1988) designed the visual expectation paradigm (VExP) to examine this ability. In the VExP, infants view a series of images that appear at two or more locations, following either a regular spatial pattern (e.g., A-B-A-B-A-B) or an irregular sequence (e.g., A-B-B-A-B-A). As we highlight here, the core finding from this work is that infants as young as age two months quickly learn to predict the upcoming locations of images in the regular pattern. Subsequent work by Haith and colleagues demonstrates that young infants are not only sensitive to the spatial locations of the images, but also to the timing and content of the images as well.

Procedure

The figure below illustrates the apparatus used by Haith, Hazan, and Goodman (1988) to study infants' gaze patterns during the VExP. In the experiment, three-and-a-half-month-old infants rested on their back, while viewing a series of video images reflected through a mirror ("Mirror Y"). At the same time, a video camera ("eye camera") recorded a close-up view of one of the infant's eyes, which was illuminated with an infrared light source ("light collimator"). Test trials were divided into two sequences: a *regular-alternating sequence*, in which images alternated on the left and right sides of the screen, and an irregular sequence, in which images appeared in the two locations randomly (see figures below). All infants viewed both sequences, with the order counterbalanced across infants.





Note: Apparatus used in the VExP of Haith, Hazan, and Goodman (1988) (a), and diagrams of regular-alternating (b) and irregular image sequences (c), respectively. Figure reprinted with permission from Wiley.

Results

Haith, Hazan, and Goodman (1988) systematically analyzed infants' reaction times by computing the average difference in time between the appearance of each image, and the corresponding fixation to that location. There were two major findings. First, infants' overall reaction times were faster to the regular-alternating sequence than to the irregular sequence (i.e., 391 vs. 462 milliseconds). Second, *anticipations* were defined as eye movements to the image location within 200 milliseconds of its appearance. Using this criterion, infants were twice as likely to anticipate an image during the regular-alternating sequence than during the irregular sequence (i.e., 22 vs. 11 percent).

Subsequent Findings

In a follow-up study, Canfield and Haith (1991) extended the original findings with three-and-a-half-month-olds to infants as young as two months, by demonstrating that the younger infants also learn to anticipate two-location alternating image sequences. In contrast, a limitation at this age is that two-month-olds are unable to learn asymmetric sequences, such as A-A-B-A-A-B; however, this limitation is lifted by age three months. Several other impressive abilities appear to be in place by age three months. For example, Wentworth, Haith, and Hood (2002) found that three-month-olds not only learn three-location sequences, but they can also use the specific content of an image at one location (e.g., the center) to correctly predict the location of the next image (e.g., right vs. left). Finally, Adler *et al.* (2008) systematically varied the timing (instead of the locations) between images, and found that three-month-olds successfully learned to use the temporal interval as a predictive cue for the appearance of the upcoming image.

A more challenging example of a task that measures prediction involves tracking a ball that moves in and out of sight, as it travels behind an occluding screen. Successfully anticipating the reappearance of the ball requires two skills: first, the infant must hold the occluded object "in mind" while it is behind the screen (i.e., what Piaget calls *object permanence*), and second, they must prospectively control their eye movements by directing their gaze to the point of the ball's reappearance, before it arrives there. In chapter 4, we highlight the first component of the task, as a fundamental step in the development of object perception. Here, meanwhile, we focus on the latter skill, that is, how anticipatory or prospective gaze develops during occluded object tracking.

At age four months, infants successfully track the moving ball while it is visible (Johnson, Amso, and Slemmer 2003a). In contrast, infants at the same age are unable to track the ball once it is occluded: in particular, they do not anticipate its appearance, and only direct their gaze toward the ball after it reappears. However, when additional support is provided—for example, the width of the occluding screen is narrowed—four-month-olds produce anticipatory eye movements. Thus it appears that the basic perceptual-motor mechanism for predictive object tracking is present by age four months, but it may require perceptual support before it can be reliably produced. By age six months, infants reliably anticipate the reappearance of the ball, even when it is occluded by the wider screen.

Finally, the predictive tracking task can be made even more challenging by placing the infant next to a real track, along which the ball rolls. Again, a portion of track is occluded, so that the ball briefly passes out of sight and then reappears. In this case, predictive action can be measured in two ways at the same time: that is, by predictive eye movements in addition to predictive reaching movements. Berthier *et al.* (2001) studied how nine-month-olds performed on this task, under two tracking conditions. As figure 3.3 illustrates, in the "no wall" condition, infants watched as the ball rolled down the track, behind the screen, and out the other side. In the "wall" condition, an obstacle was placed on the track, behind the screen, which prevented the ball from reappearing after occlusion. (Note that the "wall" extended several inches higher than the screen, so that it was clearly visible to infants.)

Three major findings were reported. First, when analyzing infants' gaze behavior, Berthier *et al.* (2001) noted that nine-month-olds consistently anticipated the reappearance of the ball, only in the no-wall condition. In contrast, infants quickly learned that the wall prevented the ball from reappearing, and thus, they did not direct their gaze at the usual point of reappearance in the wall condition. Second, when analyzing infants' reaching behavior, Berthier *et al.* (ibid.) also reported that infants reliably produced more reaches during the no-wall condition than the wall condition. Infants therefore also appeared to use the presence of the wall as a cue for whether or not to reach for the ball. Third, however, as figure 3.3 illustrates, on some trials infants reached for the ball regardless of whether or not the wall was present. Interestingly, Berthier *et al.* (ibid.) found that the kinematic properties of these reaches did not vary as a function of the presence of the wall. In other words, the reaching behavior appeared to be somewhat ballistic, and once initiated, though anticipatory it was not influenced by additional visual information. In particular, they propose that these occasional reaching errors reflect a partial integration of visual and visual-motor skill, which continues to develop in the second year.

3.2.3 Competence-Based IM in Infants

As we noted earlier, competence-based IM differs from knowledge-based IM by focusing on the developing organism and the acquisition of skills, rather than on acquiring knowledge or information about the environment. An early-emerging component of competence-based IM in human infants is the discovery of *self-efficacy* (or *effectance*), that is, the recognition that one's own behavior has an effect on the objects and people around them.

One way that self-efficacy has been investigated in infants is through *behavior-based contingency perception* (or simply, contingency perception). The general design of a contingency-perception experiment is to place an infant in a situation where perceptually salient events occur (e.g., images appear on a screen, or sounds are played on a speaker), and to “link” the occurrence of the events to the infant’s ongoing behaviors. A well-known example, developed and studied by Rovee-Collier (e.g., Rovee-Collier and Sullivan 1980), is the “mobile” paradigm, in which an infant is placed in a crib, and a ribbon is used to connect the infant’s leg to a mobile hanging overhead (see figure 3.4). In behavioral terms, the mobile provides a form of *conjugate reinforcement*: it is reinforcing, because the infant quickly learns to kick the leg attached to the mobile (while the other leg is typically still), and it is a form of conjugate reinforcement because the reinforcer (presumably, sight of the mobile moving) occurs continuously and is proportional to the amount of leg movement.

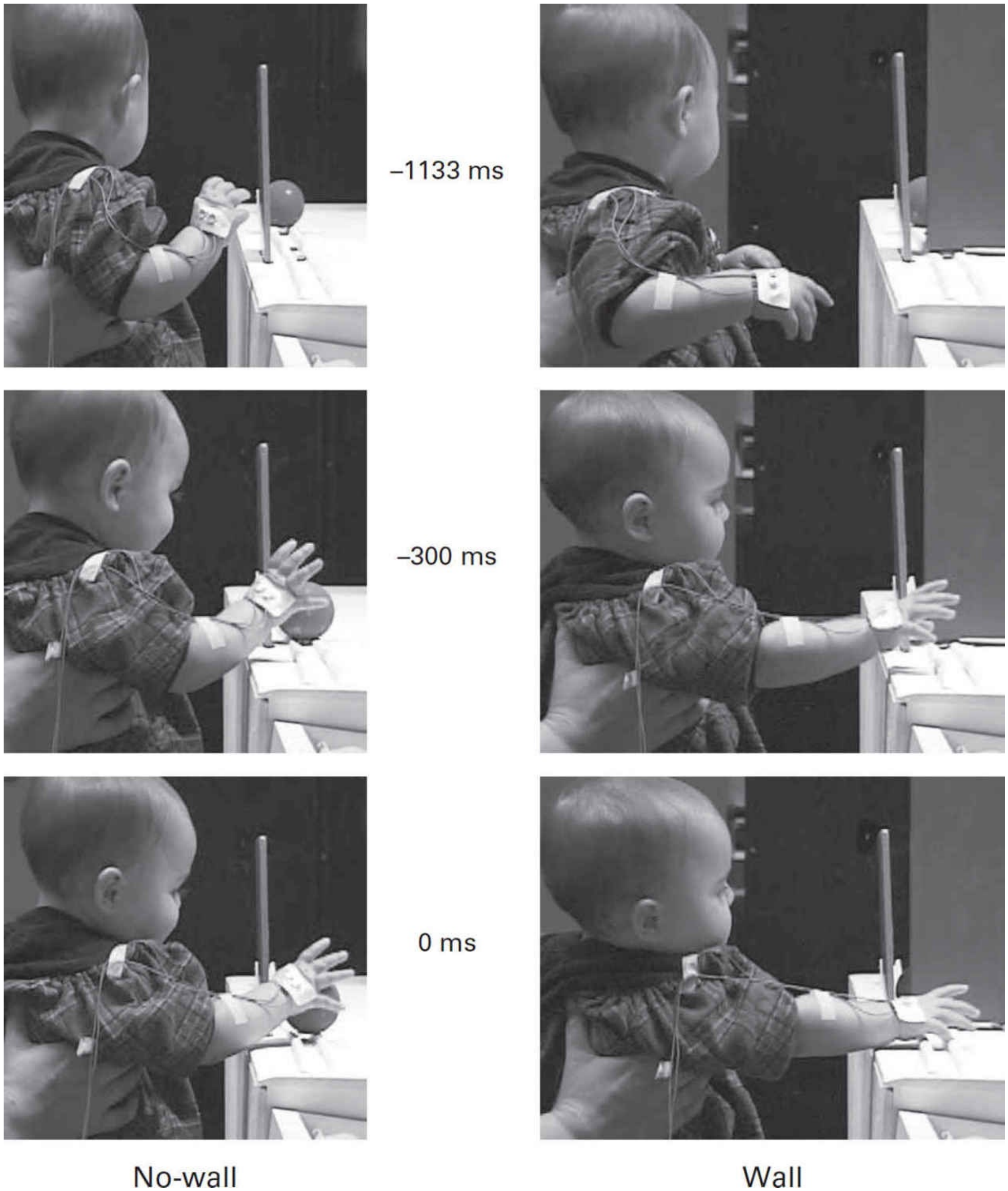


Figure 3.3

Experiment on predictive tracking task with eye and reaching predictive movements. From Berthier *et al.* 2001. Reprinted with permission from Wiley.

Figure 3.4

Rovee-Collier and Sullivan’s (1980) “mobile” paradigm, in which an infant is placed in a crib, and a ribbon is used to connect the infant’s leg to a mobile hanging overhead. Reprinted with permission from Wiley.

Over numerous studies, Rovee-Collier and colleagues have systematically investigated learning in the mobile paradigm. Interestingly, the age group that has received the most attention with this paradigm is three-month-olds. A key finding from this work is that after learning to control the mobile, three-month-olds retain a memory of the experience for several days (e.g., Rovee-Collier and Sullivan 1980). While infants typically forget after a week, their memory can be extended by as much as four weeks if they are briefly exposed to a moving mobile without actually controlling it (Rovee-Collier *et al.* 1980). An important feature of the paradigm—though one that has not been systematically studied—is that infants appear to enjoy controlling the mobile, often cooing and smiling while they kick their legs (see figure 3.4).

A related paradigm for investigating contingency perception involves presenting the infant with a video display of her legs on one video screen, while a second screen displays the legs of another infant (e.g., Bahrick and Watson 1985). In order to discriminate between the two displays (i.e., self vs. other), the infant must be able to match the proprioceptive feedback generated by moving her legs to the corresponding visual display. Two interesting questions suggested by this paradigm are: at what age do infants discriminate between the two displays, and which do they prefer? Bahrick and Watson (ibid.) first studied five-month-olds, and found that at this age infants look significantly longer at the non-self video display (i.e., the display of another infant's legs). When the experiment was repeated with three-month-olds, a bimodal distribution emerged: roughly half of the infants preferred viewing their own legs, while the other half looked longer at the non-self display. Gergely and Watson (1999) later proposed that during the first three months of life, infants focus on how their body movements create sensory consequences (what Piaget called *primary circular reactions*). This focus leads to a preference for perfect contingencies. Gergely and Watson hypothesize that after age three months, events that are perfectly contingent become aversive, causing infants to shift their preference toward events that are highly (but not perfectly) contingent, such as the social responses of caretakers (see Kaplan and Oudeyer 2007, for an IM model that captures an analogous transition). An intriguing implication of this account is that infants at risk for autism spectrum disorders (ASDs) may not make the same shift. According to Gergely and Watson, this preference for perfect contingencies in autistic children may then manifest in repetitive behaviors, self-stimulation, and an aversion to changes in the everyday environment or routine.

Finally, a somewhat different perspective on competence-based IM in infants and children is the study of *spontaneous play behavior*. Table 3.1 outlines a series of increasingly complex levels of play, which emerge over infancy and early childhood (Bjorklund and Pellegrini 2002; Smilanksy 1968).

These levels do not represent discrete stages, but rather, overlapping developmental periods during which various styles of play behavior begin to appear. The first level is *functional play* (also called sensorimotor or locomotor play), which is typically expressed as gross motor activity, such as running, climbing, digging, and other similar whole-body actions. Functional play may also involve object manipulation, such as swinging on a swing, kicking a ball, or dropping blocks. This level of play begins to appear during the first year, and continues through early childhood and becomes increasingly social. It is noteworthy that this type of play behavior (in particular, so-called rough-and-tumble play) is seen in both humans and nonhumans, and likely has an evolutionary basis (e.g., Siviy and Panksepp 2011). The second level is *constructive* (or object) *play*, which emerges during the second year and also continues to develop into early childhood. Constructive play typically involves the use of fine motor skills and the manipulation of one or more objects, with the implicit goal of building or creating. Examples include stacking blocks, arranging the pieces of a puzzle, or painting with a paintbrush.

Table 3.1

Levels of play behavior (adapted from Smilansky 1968)

Age	Type of play	Example
0–2 years	Functional or sensorimotor	Running, climbing a ladder, digging in the sand
1–4 years	Constructive	Stacking blocks, connecting pieces of a train track, drawing with a crayon
2–6 years	Pretend or symbolic	Flying in an airplane, cooking breakfast, commanding a pirate ship
6+ years	Games with rules	Kickball, four-square, checkers, hopscotch

Constructive play overlaps extensively with *pretend play*, which emerges around age two years and becomes one of the dominant forms of play during early childhood. During pretend play (also called fantasy, symbolic, or dramatic play), children use their imagination to transform their actual environment into something make-believe, such as pretending to be on a rocket or pirate ship, or imagining that they are making a meal in a real kitchen. While early forms of pretend play tend to be solitary, by age four it often becomes socio-dramatic, and not only includes elements of fantasy and pretend, but also cooperation among multiple "players" in order to coordinate and maintain the play theme. The trend toward social interaction and cooperation culminates in formalized *games with rules*, like baseball and checkers, which appear near age six, as children begin to transition into a conventional school setting.

3.3 Intrinsically Motivated Agents and Robots

We now shift to the topic of intrinsically motivated machines, artificial agents, and robots. We begin this section by first providing a conceptual overview of how IM is approached as a computational problem, and in particular, we describe a set of basic architectures for simulating knowledge-based and competence-based IM. We then survey how these architectures have been implemented in a variety of simulations, models, and real-world robotic platforms.

3.3.1 A Computational Framework for IM

Most research to date on IM within the developmental robotics approach has tended to focus on the use of reinforcement learning (RL). As Barto, Singh, and Chentanez (2004) note, RL provides a versatile framework for studying not only how the environment (i.e., "external" motivations) influences behavior, but also how internal or intrinsic factors influence behavior as well. We refer the interested reader to Sutton and Barto's (1998) comprehensive introduction to RL, and describe here the basic elements that are most relevant to modeling IM.

The core components of an RL model are an autonomous agent, an environment, a set of possible sensory states that can be experienced within the environment, and a function (i.e., policy) that maps each state to a set of possible actions. Figure 3.5a illustrates the relations between these elements: the agent senses its environment, uses the policy to select an action, and performs the selected action. The environment then provides two forms of feedback: first, it delivers a reward signal, which the agent uses to modify its policy so as to maximize future expected reward (i.e., the particular action chosen is incremented or decremented in value), and second, the sensory signal is updated. In the mobile-robot domain, the agent would be the mobile robot, the environment might be a cluttered office space, possible actions would include rotation of the robot's wheels (e.g., movement forward, backward, and turning left or right), and the sensory signal could include readings over an array of infrared sensors and the state of a "gripper" or touch sensor. Imagine in this example that the engineer would like the robot to return to its charger so that it can recharge its power supply. A simple reward function might be to give the robot a reward of 0 after each action (e.g., "step" in one of eight directions), and otherwise a 1 when it reaches the charger.

As figure 3.5a highlights, because the reward signal originates in the environment, the agent is externally motivated. In contrast, imagine instead that the reward signal occurs within the agent itself. Figure 3.5b illustrates such a scenario, which is almost identical to the previous configuration, with the exception that now the environment is limited to providing only the sensory signal, while an internal motivation system (within the agent) provides the reward signal. In this case, the agent is now internally motivated.

However, it is important not to confuse *internally* with *intrinsically* motivated behavior. In particular, when the mobile robot just described computes its own reward, it is internally motivated. Nevertheless, because its goal is to maintain a charged battery, it is also extrinsically motivated, specifically because successful behavior (i.e., reaching the charger) directly benefits the robot. On the other hand, when the robot wanders the workspace and generates an internal reward each time it succeeds, for example, at predicting which areas of the workspace have not previously been visited, it is intrinsically motivated. This is because the reward signal is not based on satisfying a homeostatic "need," but rather is based on the flow of information over time, and in particular, on the robot's current level of knowledge and experience.

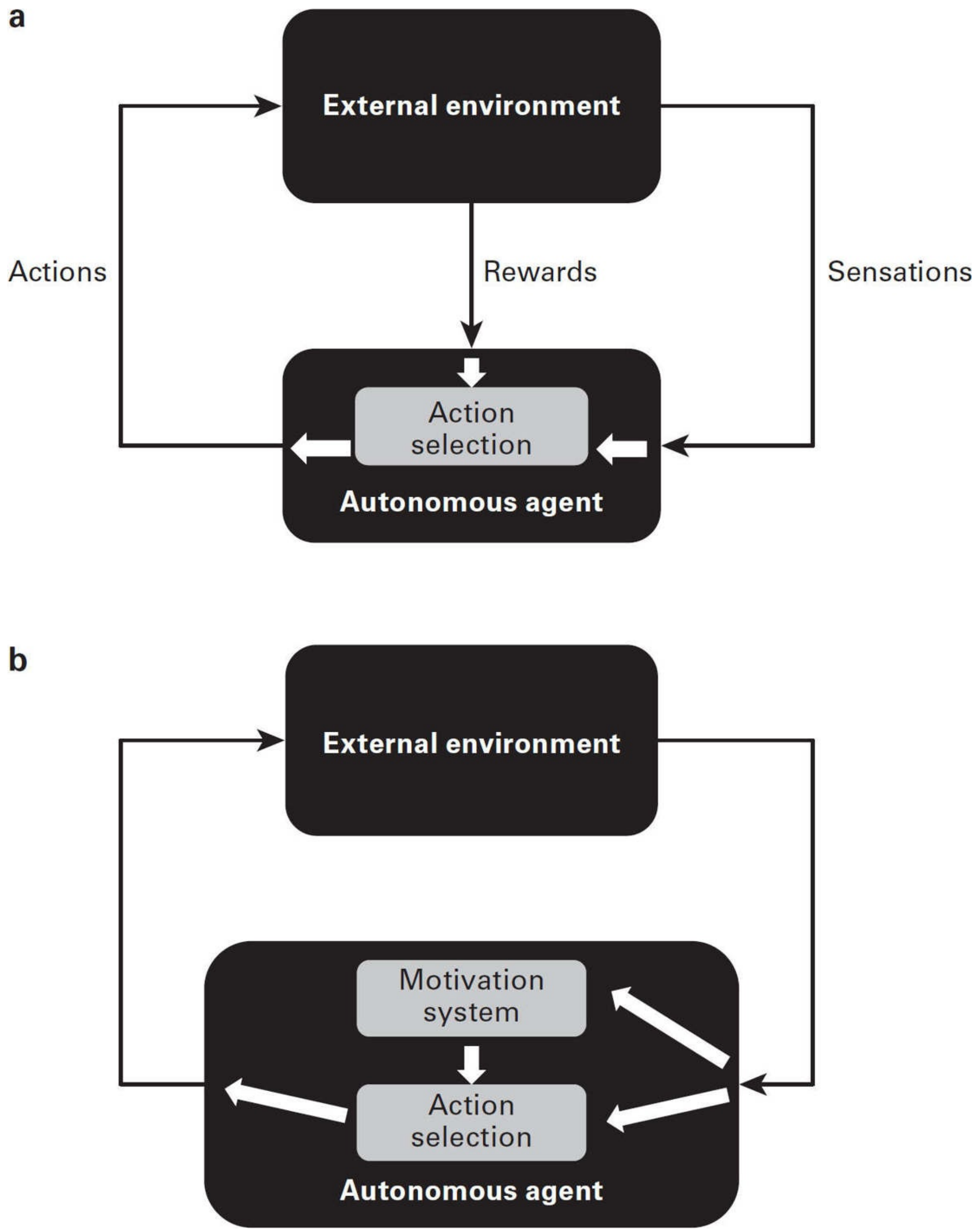


Figure 3.5

The two alternative external/internal motivation systems proposed by Oudeyer and Kaplan (2007): (a) the environment provides the reward signal and the agent is externally motivated, and (b) the agent has internal motivation system and provides its own reward signal, and the environment only provides the sensory signal. Figure courtesy of Pierre-Yves Oudeyer.

Working within this computational framework, Oudeyer and Kaplan (2007) describe a systematic taxonomy of possible architectures for simulating IM. The basic scenario captured by the taxonomy is based on a single autonomous agent that interacts with its environment over time, and which receives an intrinsically motivated reward signal after each action in addition to having its sensors updated. For simplicity and brevity, we focus here on the case where the sensory or state space is treated as discrete, and the transitions between the states after each action are deterministic. Nevertheless, it should be stressed that each of the reward functions that we describe can also be generalized and applied to continuous spaces as well as partially observable or stochastic environments, or both.

To begin, we define the event e^k as the k th sample from the set of all possible events E. Typically, e^k is assumed to be a vector of sensor readings (as described above) at a particular moment, but is otherwise general enough to accommodate the specific cognitive architecture being employed. Next, we define $r\ (e^k,t)$ as the discrete scalar reward obtained by the agent at time t as it observes or experiences event e^k. Given these basic constructs, we can then explore each of the IM learning mechanisms described thus far.

Knowledge-Based IM: Novelty

A simple and straightforward method for motivating the agent to seek out novel events is to first provide it with a function $P\ (e^k,t)$ that returns the estimated probability of an event e^k being observed at time t. One strategy is to assume that this function is initially unknown (e.g., the distribution of events is uniform; that is, all events are equally probable), and that the agent uses its experience to tune P as a model of the environment is gradually acquired. Next, given P and the constant C,

$$r\left(e^k,t\right)=C\cdot\left(1-P\left(e^k,t\right)\right) \tag{3.1}$$

results in a reward that increases proportionally as the probability of the given event decreases. When this reward function is embedded within a conventional RL problem (i.e., in which the goal is to maximize the cumulative sum of rewards), the agent should then preferentially choose actions that lead to infrequent or low-probability events. One problem with this formulation, however, is that events that are maximally novel or improbable are also maximally rewarding. As we saw earlier, this may be at odds with both the theoretical view and ample empirical data, both suggesting that *moderately novel events* are maximally interesting or rewarding. We return to this issue later.

Oudeyer and Kaplan (2007) describe reward function (3.1) as *uncertainty motivation*: the agent is intrinsically motivated to seek novel or unfamiliar events. An alternative formulation is *information-gain motivation*, in which the agent is instead rewarded for observing events that increase its knowledge. In this case, we first define $H(E, t)$ as the total entropy over all events E at time t. Thus:

$$H(E,t) = -\sum_{e^k \in E} P(e^k,t) \ln(P(e^k,t)) \tag{3.2}$$

where $H(E)$ characterizes the shape of the probability distribution $P(e^k)$. Extending this measure of information, the reward function is then defined as

$$r(e^k,t) = C \cdot (H(E,t) - H(E,t+1)) \tag{3.3}$$

that is, the agent is rewarded when consecutive events result in a decrease in entropy. In contrast to uncertainty motivation, which links IM to the absolute probabilities of events in the environment, a potential strength of information-gain motivation is that it allows IM to vary as a function of the agent's knowledge state.

Knowledge-Based IM: Prediction

Rather than learning a static world-model P, the agent can instead actively learn to predict future states. Differences between predicted or expected events and those that actually occur can then provide a basis for prediction-based IM. A key element of this formulation is the function $SM(t)$, which represents the current sensorimotor context at time t and encodes a generalized notion of *event* that includes contextual information, e.g., the robot's current camera image and IR sensor readings, the state of its motors, and so on. We use here the notation $SM(\rightarrow t)$, which incorporates not only the state information at time t, but also information from past contexts, as needed. Next, Π is a prediction function that uses $SM(\rightarrow t)$ to generate a prediction of the event $\tilde{e}^k$ estimated or expected to occur on the next timestep:

$$\Pi(SM(\rightarrow t)) = \tilde{e}^k(t+1) \tag{3.4}$$

Given the prediction function Π, the prediction error $E_r\ (t)$ is then defined as

$$E_r\,(t) = \left\| \tilde{e}^k\,(t+1) - e^k\,(t+1) \right\| \tag{3.5}$$

that is, as the difference between the expected and observed events at time $t + 1$. Finally, a particularly compact reward function defines the reward r as the product of a constant C and the prediction error E_r at time t:

$$r\,(SM\,(\rightarrow t)) = C \cdot E_r\,(t) \tag{3.6}$$

Interestingly, Oudeyer and Kaplan (2007) refer to reward function (3.6) as *predictive-novelty motivation.* In this case, the agent is rewarded for seeking out events that it predicts "badly," that is, where prediction errors are greatest. Note, however, that like uncertainty motivation, this formulation also suffers from the fact that reward increases monotonically with novelty. One way to address this limitation is by assuming a "threshold" of moderate novelty $E_r^{ó}$ that maps to maximal reward, and around which all other prediction errors are less rewarding:

$$r\,(SM\,(\rightarrow t)) = C_1 \cdot e^{-C_2 \cdot \left\| E_r\,(t) - E_r^{\sigma} \right\|^2} \tag{3.7}$$

An alternative to (3.6) proposed by Schmidhuber (1991) is to reward improvements between consecutive predictions $E_r\ (t)$ and $E'_r\ (t)$:

$$r\,(SM\,(\rightarrow t)) = E_r\,(t) - E'_r(t) \tag{3.8}$$

where

$$E'_r\,(t) = \left\| \Pi'\,(SM\,(\rightarrow t)) - e^k\,(t+1) \right\| \tag{3.9}$$

Thus (8) compares two predictions made with respect to time t. The first prediction $E_r\ (t)$ is made before $e^k\ (t + 1)$ is observed, while the second $E'_r\ (t)$ is made after the observation and the prediction function has been updated to Π′ and becomes the new prediction model.

Competence-Based IM

As we noted earlier, a unique feature of competence-based IM is its focus on skills, rather than on environmental states or knowledge of the environment. As a consequence, computational approaches to modeling competence-based IM also differ from those used to simulate knowledge-based IM. An important component of this approach is the notion of a goal g_k, which is one of several k

goals or options. A related concept is that goal-directed behaviors occur in discrete episodes, which have a finite duration t_g (i.e., the budget of time allotted to achieve goal *g*), and may include as a low-level building block various methods for learning forward and inverse models and planning strategies to use them (e.g., see Baranes and Oudeyer 2013, for discussion of such hierarchical exploration and learning architectures). Finally, the function l_a computes the difference between the expected goal and the observed result:

$$l_a(g_k, t_g) = \left\| \widetilde{g_k(t_g)} - g_k(t_g) \right\| \tag{3.10}$$

where l_a denotes the level of (mis)achievement of the intended goal. Given these components, a reward function can be designed that favors large differences between attempted and achieved goals:

$$r(SM(\rightarrow t), g_k, t_g) = C \cdot l_a(g_k, t_g) \tag{3.11}$$

Oudeyer and Kaplan (2007) give reward function (3.11) the amusing description of *maximizing-incompetence motivation.* Indeed, such a function rewards the agent for selecting goals that are well beyond its skill level (and then failing miserably to accomplish them!).

To address this problem, a strategy similar to the one employed in reward functions (3.3) or (3.8) can be used, in which consecutive attempts are compared. Oudeyer and Kaplan (2007) refer to this as *maximizing-competence progress*, as it rewards the agent for subsequent goal-directed behaviors that improve over previous attempts:

$$r(SM(\rightarrow t), g_k, t_g) = C \cdot (l_a(g_k, t_g - \Theta) - l_a(g_k, t_g)) \tag{3.12}$$

where $t_g - \Theta$ indexes the previous episode in which g_k was attempted.

3.3.2 Knowledge-Based IM: Novelty

The set of architectures in section 3.3.1 represents an idealized abstraction of IM at the computational level. In particular, it is important to note that they have not yet been systematically evaluated or compared. Nevertheless, in recent years several researchers have begun to implement these and other related architectures, in both simulation and on real-world robot platforms. We briefly highlight here recent work from each of the classes of IM, beginning with novelty-based IM.

As we noted in section 3.2.1, novelty-seeking behavior can be divided into exploration and novelty detection. A model that integrates both of these components is proposed by Vieira-Neto and Nehmzow (2007), who investigate visual exploration and habituation in a mobile robot. First, the robot explores its environment by implementing a basic obstacle-avoidance strategy. As it wanders the environment, the robot acquires a salience map of the visual input. Next, highly salient locations on the map are selected for additional visual analysis. Specifically, each of these regions is processed through a visual novelty filter that takes as input the color values in the corresponding region and projects them onto a self-organizing map (SOM) of features. A habituation mechanism is implemented in the model by gradually lowering the connection weights of nodes in the SOM that are continuously active.

Figure 3.6a presents a snapshot of the robot's input as it begins to explore the environment: the numbered patches correspond to the salient locations (with 0 marking the most salient location) and the circles around each location represent the output of the novelty filter (a circle identifies locations with novelty levels that exceed a threshold). As the plot on the right illustrates, the output of the novelty filter is initially large, but slowly falls over time. By the fifth pass through the environment, the robot has become familiar with the sides and floor of the arena, and the output of the novelty filter is consistently low.

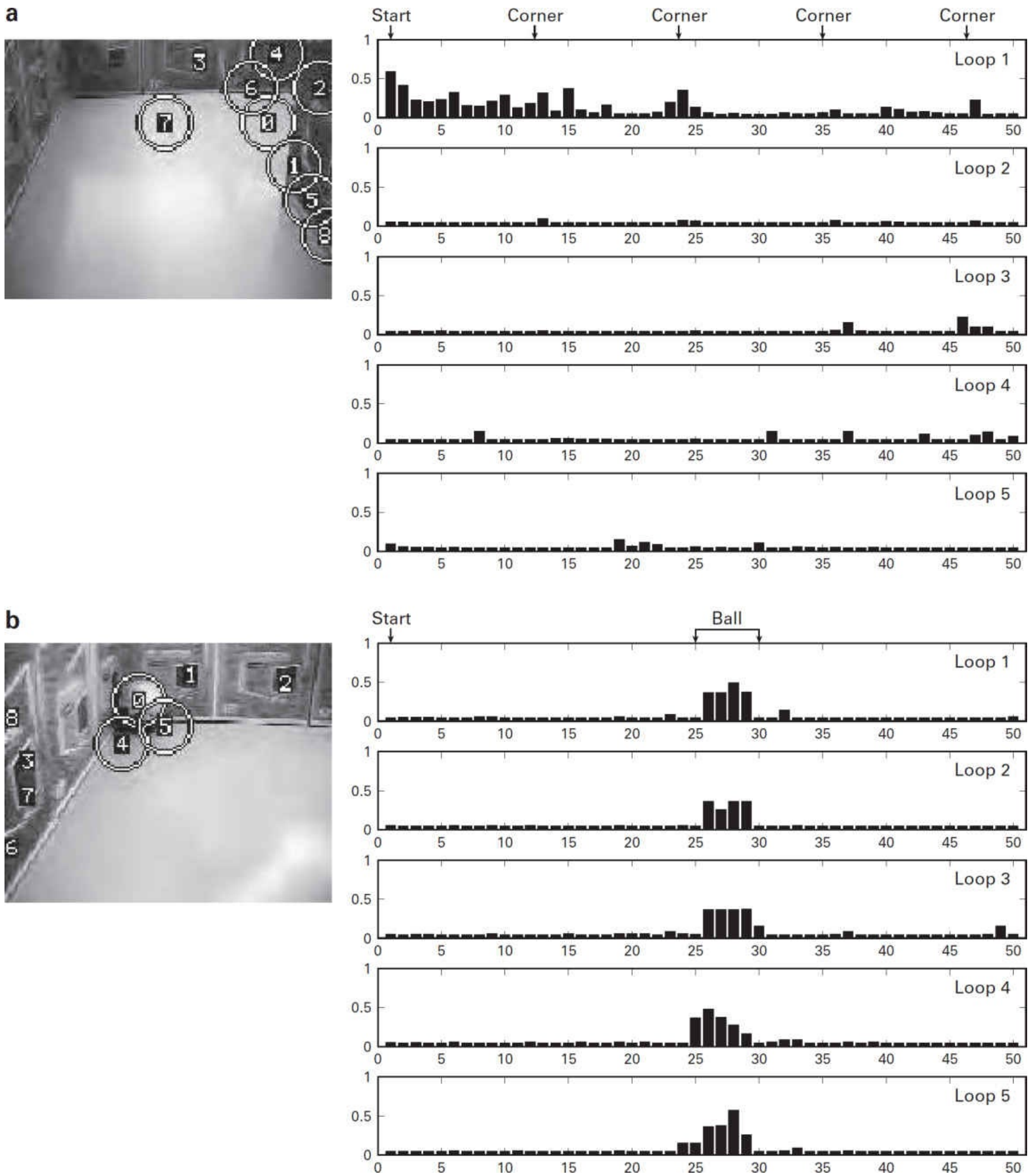


Figure 3.6

Results from Vieira-Neto and Nehmzow (2007) experiment on visual exploration and habituation in a mobile robot. Snapshot of the robot's input as it begins to explore the environment (a). Robot's response to a new object (b). Reprinted with permission from Springer.

Figure 3.6b illustrates how the robot responds when a new object—a red ball in the second corner—is introduced into the environment. When the robot reaches the red ball, three maxima in the salience map occur at the ball's location (i.e., labels 0, 4, and 5), which results in further processing of this location by the novelty filter. Consequently, the output of the novelty filter abruptly increases. Note that in this implementation, the habituation mechanism is deactivated during the novelty phase, so that the novelty of the ball can be estimated over several encounters (i.e., Loops 2–5). Although the model is not explicitly designed to capture the process of visual exploration and learning in a human infant or child, it not only provides a parsimonious explanation for how a basic behavioral mechanism such as obstacle avoidance can drive visual exploration, but also demonstrates how novel objects or features in the environment can be detected and selected for further visual processing.

A related approach is proposed by Huang and Weng (2002), who investigate novelty and habituation in the SAIL (Self-organizing, Autonomous, Incremental Learner) mobile-robot platform (see figure 3.7a). In contrast to the Vieira-Neto and Nehmzow (2007) model, which uses visual salience and color histograms to determine novelty, the Huang and Weng model defines novelty as the difference between expected and observed sensory states. In addition, the model combines sensory signals across several modalities (i.e., visual, auditory, and tactile). Another important feature of the Huang and Weng model is that it implements novelty detection and habituation within an RL framework. In particular, the model includes both intrinsic and extrinsic reinforcement signals: the intrinsic training signal is provided by sensory novelty, while the external signal is provided by a teacher who occasionally rewards or punishes the robot by pushing either the "good" or "bad" buttons on the robot.

Figure 3.7b illustrates the model's cognitive architecture. Sensory input is propagated into the IHDR (incremental hierarchical decision regression) tree, which categorizes the current sensory state, in addition to updating the model's estimate of the current sensory context (which is stored as a context prototype). The model then uses the combined context + state representation to select an action, which is evaluated by the value system. Next, the Q-learning algorithm is used to update the context prototypes, which combine sensory data, actions, and Q-values.

$$r(t) = \alpha p(t) + \beta r(t) + (1 - \alpha - \beta) n(t) \tag{3.13}$$

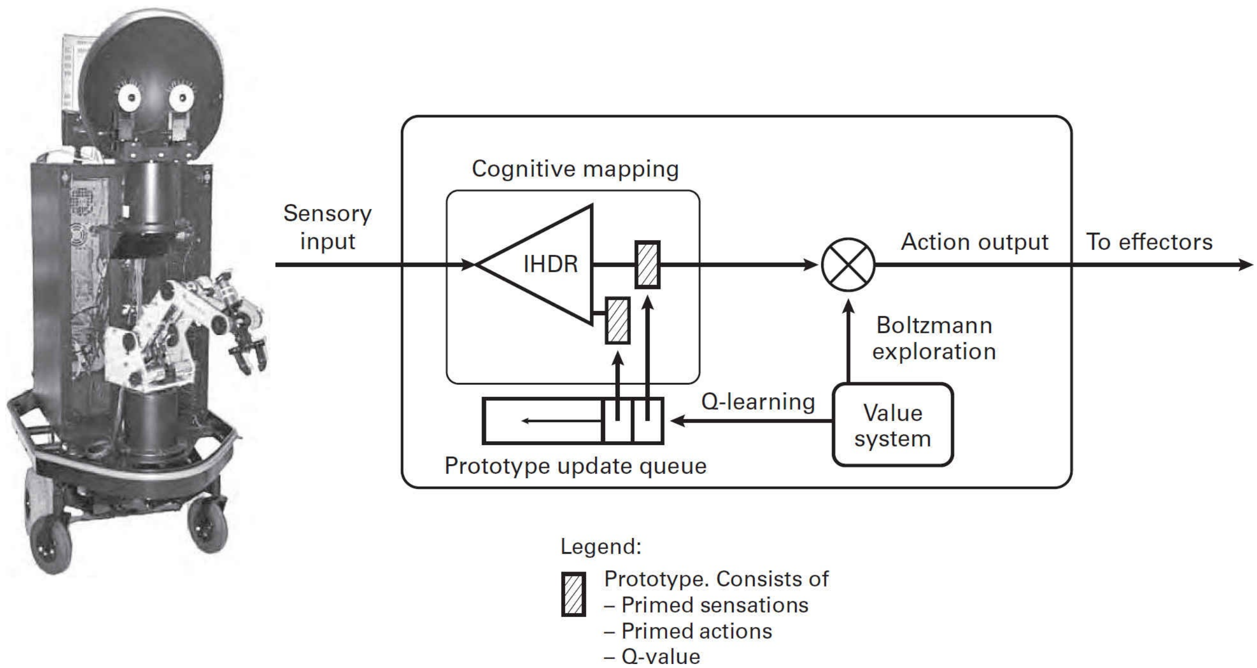


Figure 3.7

The SAIL robot (a) and the model's cognitive architecture (b) (Huang and Weng 2002). Courtesy of John Weng.

Equation (3.13) presents the reward function implemented in the Huang and Weng model. Reward on each timestep is the sum of three components: punishment *p* and positive reinforcement *r*, which are generated by the teacher, and novelty *n*, which is generated by the robot intrinsically. Note that the values α and β are adjustable parameters that weight the relative contributions of each of the three reward signals. In addition, Huang and Weng assume that punishment has a stronger effect on behavior than reinforcement, and that each of the two external reward signals is greater than the intrinsic reward (i.e., $\alpha > \beta > 1 - \alpha - \beta$).

Habituation in the model is an emergent feature: because novelty is determined relative to the robot's experience, initially all sensory inputs are novel, and as a result, the robot indiscriminately explores its environment. After several minutes, however, the discrepancy between expected and observed sensory inputs begins to decrease, and as a result, the robot orients selectively toward visual stimuli that have been infrequently experienced or are visually complex (e.g., a Mickey Mouse toy). Thus, the robot gradually habituates to well-learned objects, and strategically selects actions that will lead to novel sensory input. In addition, Huang and Weng also show that this orienting response toward novel stimuli can be selectively shaped or overridden by the feedback provided by the teacher.

Hiolle and Cañamero (2008) investigate a related model, in which a Sony AIBO robot visually explores its environment in the presence of its caretaker. An interesting twist in the Hiolle and Cañamero model is that exploration is explicitly driven by an arousal mechanism, which can be modulated not only by looking at the caretaker, but also by when the caretaker touches the robot. Like the Huang and Weng model, the robot in the Hiolle and Cañamero study learns an internal model of its environment (represented by a Kohonen self-organizing map). During visual exploration, the robot compares visual input with its internal representation, and its looking behavior is guided by a three-choice decision rule: (1) for low levels of novelty, the robot turns its head away from the current direction, (2) for moderate levels of novelty the robot remains still (and continues to encode its current experience), and (3) for high levels of novelty, the robot makes a barking sound and searches for the caretaker. In the latter case, sight of the caretaker lowers arousal a moderate amount, while touch by the caretaker lowers the arousal level significantly.

During training, Hiolle and Cañamero compare the performance of the robot in two learning contexts. In the high-care context, the caretaker is continually present and actively soothes the robot when it expresses distress. In the low-care context, meanwhile, the caretaker is only sporadically present and does not actively respond to the robot. Two key findings emerge from this comparison. First, in both contexts, the robot learns to adapt its visual exploratory behavior as a function of the availability of the caretaker. Thus, in the high-care context, when under high arousal the robot frequently barks and searches for the caretaker. In contrast, in the low-care context, the robot instead learns to shift its focus away from visual experiences that are highly novel and therefore produce distress. Second, the robot also develops a more robust internal model of its environment in the high-care context, resulting in lower average long-term levels of novelty. Taken together, these findings not only highlight the role of the caretaker during visual exploration, but more important, they also illustrate the relation between novelty seeking and arousal modulation and social interaction.

Finally, a fourth approach is proposed by Marshall, Blank, and Meeden (2004), who also define novelty as a function of expected and observed sensory inputs. Indeed, the Marshall, Blank, and Meeden model explicitly incorporates both novelty-based and prediction-based computations. In particular, they simulate a stationary robot that is situated in the center of circular arena and watches a second robot that travels from one side of the arena to the other. As the stationary robot observes its environment and views the moving robot, it generates a prediction of the upcoming visual input. This anticipated input is then compared with the observed input, and used to derive a prediction error. Similar to equation (3.8), novelty is then defined as the change in prediction error over two consecutive timesteps. Two key findings emerge from the Marshall, Blank, and Meeden model. First, in the process of orienting toward visual stimuli that are highly novel, the stationary robot learns to track the motion of the moving robot "for free" (i.e., without any explicit extrinsic reward). Second, and perhaps more important, after achieving high accuracy in learning to track the moving robot, the stationary robot gradually spends less time orienting toward it. Thus, as in the Huang and Weng model, a habituation mechanism emerges as a consequence of learning to detect novel events.

3.3.3 Knowledge-Based IM: Prediction

As the previous example illustrates, there is some overlap between novelty-based and prediction-based models of IM. Thus, while we focus in this section on prediction-based models, it is important to note that these models not only share a number of features with the novelty-based approach, but in some cases, they also combine elements of prediction and novelty within the same computational framework.

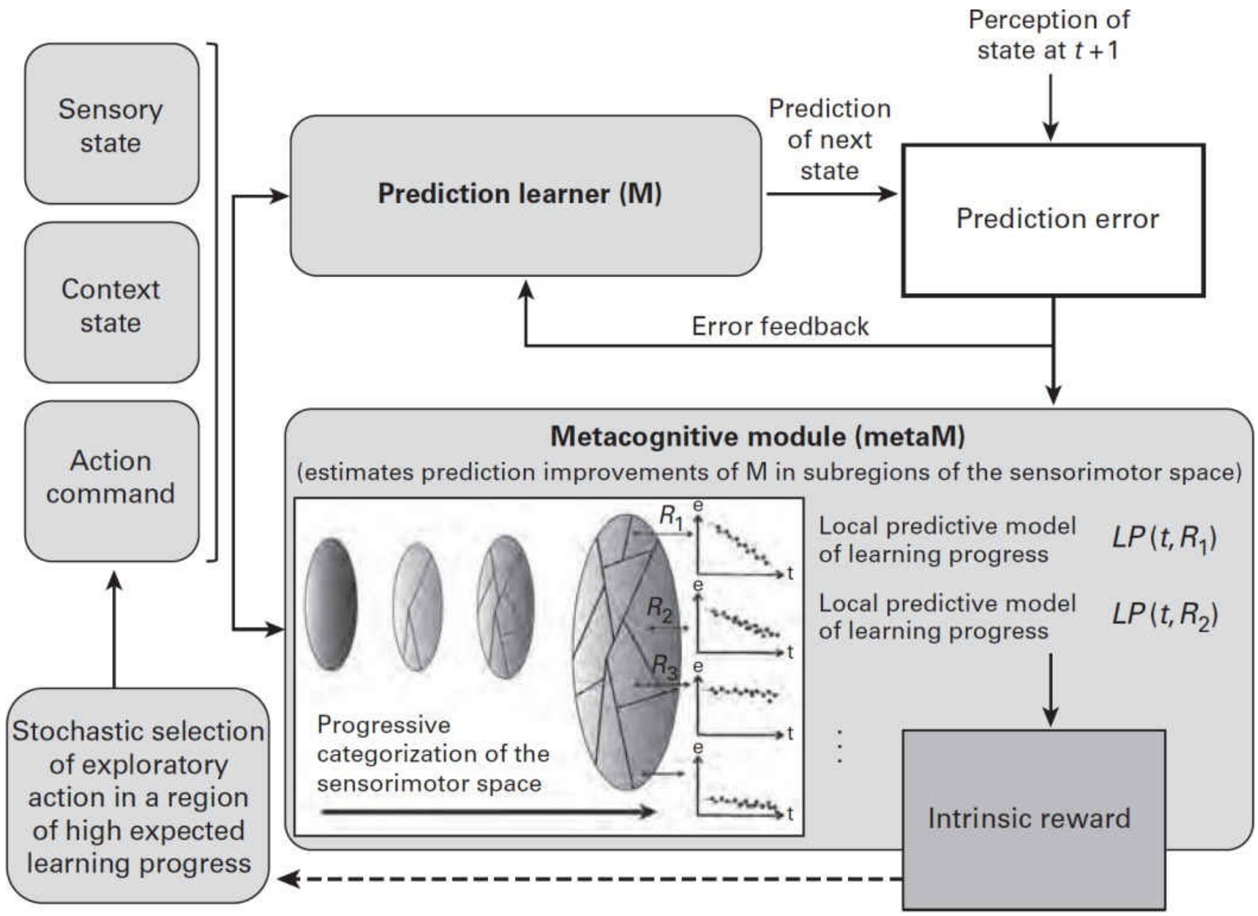
An ambitious and intriguing model of prediction-based IM is proposed by Schmidhuber (1991, 2013), who argues that the cognitive mechanisms that underlie IM are responsible for a diverse range of behaviors, including not only novelty seeking, exploration, and curiosity, but also problem solving, artistic and musical expression (or more generally, aesthetic experience), humor, and scientific discovery. Schmidhuber's "Formal Theory of Creativity" is comprised of four major components:

1. *A world model.* The purpose of the world model is to encompass and represent the totality of the agent's experience. In effect, the model encodes the full history of the agent, including the actions taken and the sensory states observed. At the functional level, the world model can be viewed as a *predictor* that compresses raw data into a compact form, by detecting patterns or regularities in experience.
2. *A learning algorithm.* Over time, the world model improves in its ability to compress the agent's history of experience. This improvement is the result of a learning algorithm that identifies novel sensory data or events, which when encoded, increase the compression rate of the data stored in the world model.
3. *Intrinsic reward.* Improvements in the world model (i.e., increased compression) provide a valuable learning signal. In particular, Schmidhuber proposes that novelty or surprise can be defined as the magnitude of improvement in the world model. Thus, each time the learning algorithm detects an experience that increases compression of the model, the action that produced the experience is rewarded.
4. *Controller.* The final component is the controller, which learns on the basis of feedback from the intrinsic reward signal to select actions that produce novel experiences. The controller therefore functions as an exploratory mechanism that generates new data for the world model, and in particular, is intrinsically motivated to produce experiences that increase the predictive power of the world model.

An important feature of Schmidhuber's theory, which distinguishes it from other prediction-based models, is that rather than generating an IM reward signal on the basis of the prediction error itself, the reward is based instead on changes in the prediction error over time, that is, on *learning progress* (see section 3.1.1). For discrete-time models, learning progress can be measured as the difference in consecutive prediction errors (see equation 3.8). First, given the current state and planned action, the world model generates a prediction of the next state, which is then observed and used to compute the initial prediction error. The world model is updated on the basis of this error, and then, using the original state and action, a subsequent prediction is generated by the updated model. A prediction error is again calculated, and this error is subtracted from the initial one. A positive change in the prediction error over consecutive predictions corresponds to learning improvement, and generates an IM signal that increases the value of the action selected by the controller. In psychological terms, this action is rewarded because it leads to an improvement in the predictor. Alternatively, negative or null changes in prediction error lead to a decrease in the value associated with the corresponding action.

Oudeyer and his collaborators have employed a related approach in a series of computational architectures, beginning with Intelligent Adaptive Curiosity (IAC; Oudeyer, Kaplan, and Hafner 2007; Oudeyer *et al.* 2005; Gottlieb *et al.* 2013). These architectures were specifically designed to study how the IM system could be scaled to allow efficient life-long autonomous learning and development in real robots with continuous highdimensional robotic sensorimotor spaces. In particular, the IAC architecture and its implications were studied in a series of experiments, called the *Playground Experiments* (Oudeyer and Kaplan 2006; Oudeyer, Kaplan, and Hafner 2007). Figure 3.8a illustrates the cognitive architecture employed by the IAC. Similar to the Schmidhuber model, prediction learning plays a central role in the IAC architecture. In particular, there are two specific modules in the model that predict future states. First, the "Prediction learner" M is a machine that learns a forward model. The forward model receives as input the current sensory state, context, and action, and generates a prediction of the sensory consequences of the planned action. An error feedback signal is provided on the difference between predicted and observed consequences, and allows M to update the forward model. Second, the "Metacognitive module" metaM receives the same input as M, but instead of generating a prediction of the sensory consequences, metaM learns a metamodel that allows it to predict how much the errors of the lower-level forward model will decrease in local regions of the sensorimotor space, in other words, modeling learning progress locally. A related challenge for this approach is the task of partitioning this sensorimotor space into a set of well-defined regions (Lee *et al.* 2009; Oudeyer, Kaplan, and Hafner 2007).

In order to evaluate the IAC architecture in a physical implementation, the Playground Experiments were developed (Oudeyer and Kaplan 2006; Oudeyer, Kaplan, and Hafner 2007). During the experiment, a Sony AIBO robot is placed on an infant play mat and presented with a set of nearby objects, as well as an “adult” robot caretaker (see figure 3.8b). The robot is equipped with four kinds of motor primitives with parameters denoted by several continuous numbers and which can be combined, thus forming an infinite set of possible actions: (1) turning the head in various directions; (2) opening and closing the mouth while crouching with varying strength and timing; (3) rocking the leg with various angles and speed; (4) vocalizing with various pitches and lengths. Similarly, several kinds of sensory primitives allow the robot to detect visual movement, salient visual properties, proprioceptive touch in the mouth, and pitch and length of perceived sounds. For the robot, these motor and sensory primitives initially are black boxes and it has no knowledge about their semantics, effects or relations. The IAC architecture is then used to drive the robot’s exploration and learning purely by curiosity, that is, by the exploration of its own learning progress. The nearby objects include an elephant (which can be bitten or “grasped” by the mouth), a hanging toy (which can be “bashed” or pushed with the leg) and an adult robot “caretaker” preprogrammed to imitate the learning robot when the latter looks at the adult while vocalizing at the same time.


Sensory state
Context state
Action command
Perception of state at t + 1
Prediction of next state
Prediction learner (M)
Prediction error
Error feedback
Metacognitive module (metaM)
(estimates prediction improvements of M in subregions of the sensorimotor space)
Local predictive model of learning progress
LP(t, R1)
Local predictive model of learning progress
LP(t, R2)
Progressive categorization of the sensorimotor space
Intrinsic reward
Stochastic selection of exploratory action in a region of high expected learning progress

a

b

Figure 3.8

The modeling architecture (a) and the robot platform used in the Playground Experiments (b) (Gottlieb *et al.* 2013). Figure courtesy of Pierre-Yves Oudeyer; reprinted with permission from Elsevier.

A key finding from the Playground Experiments is the self-organization of structured developmental trajectories, where the robot explores objects and actions in a progressively more complex stage-like manner, while acquiring autonomously diverse affordances and skills that can be reused later on. As a result of a series of runs of such experiments, the following developmental sequence is typically observed:

1. The robot achieves unorganized body babbling.
2. After learning a first rough model and metamodel, the robot stops combining motor primitives, exploring them one by one, but rather explores each primitive in a random manner.
3. The robot begins to experiment with actions toward areas of its environment where the external observer knows there are objects (the robot is not provided with a representation of the concept of *object*), but in a nonaffordant manner (e.g., it vocalizes at the nonresponding elephant or bashes the adult robot, which is too far away to be touched).
4. The robot explores affordance experiments: it focuses on grasping movements with the elephant, then shifts to bashing movements with the hanging toy, and finally shifts to exploring vocalizations to imitate the adult robot.

Two important aspects of this sequence should be noted. First, it shows how an IM system can drive a robot to learn autonomously a variety of affordances and skills (see Baranes and Oudeyer 2009 for the reusability for control) for which no engineer provided in advance any specific reward functions. Second, the observed process spontaneously generates three properties of infant development so far mostly unexplained: (1) qualitatively different and more complex behaviors and capabilities appear along with time (i.e., stage-like development); (2) a wide range of developmental trajectories emerge, with both shared and unique temporal patterns; and (3) communication and social interaction emerge autonomously (i.e., without explicit direction from the model builder).

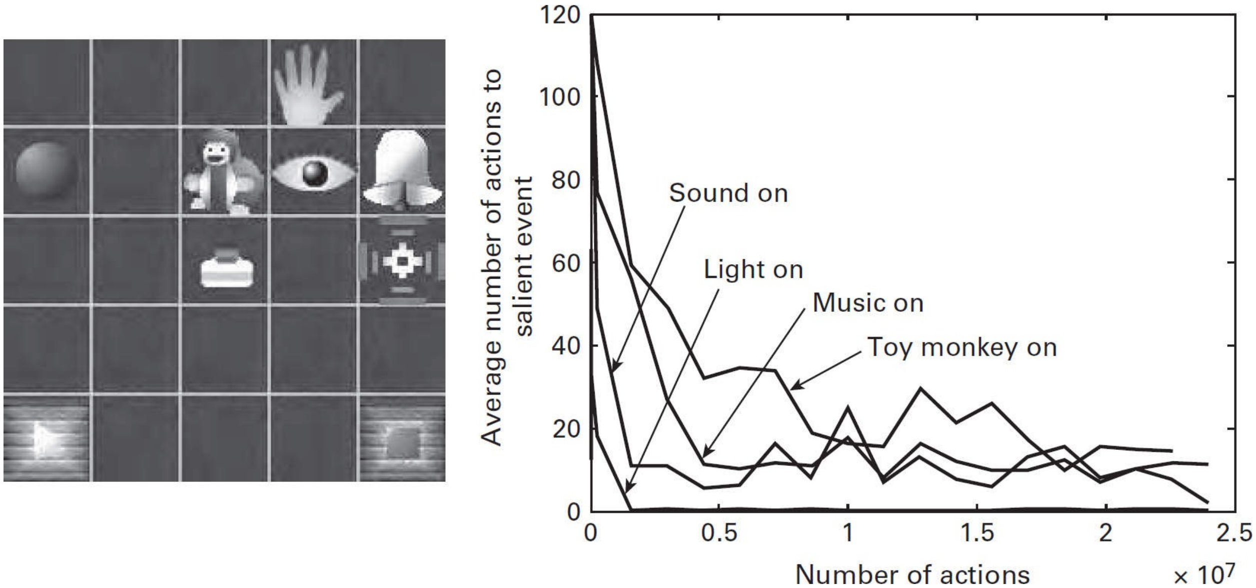


Figure 3.9

The toy-world environment (a) and pattern of skill learning (b) in Barto, Singh, and Chentanez 2004. Figure courtesy of Andy Barto.

Barto, Singh, and Chentanez (2004) propose a third model that investigates prediction-based IM. An important feature of the Barto, Singh, and Chentanez model is that it employs the *options framework*, which includes both *primitive actions* that occur once per timestep, as well as *options*, which are composed of multiple primitive actions and occur on a longer (variable) timescale. Figure 3.9 illustrates the task domain for the model: a 5 × 5 grid, in which the agent can move its hand or eye, and also mark locations with the t-shaped (crosshair) icon. Each object in the grid produces a salient response when manipulated by hand. For example, one of the blocks plays music when touched, while touching the other block turns the music off. Some objects, however, only respond when an appropriate sequence of actions is performed. The bell, for instance, rings when the ball is rolled toward it. Thus, some objects can be explored by producing a primitive action, while others only respond when the correct option is performed.

The reward signal for intrinsic motivation in the model is linked to the outcomes of the options. In particular, when an option is selected, the model predicts the outcome of the final action in the option. Intrinsic reward is then proportional to the magnitude of the prediction error. During early learning, the agent occasionally “unintentionally” triggers a salient event, which produces an unexpected outcome and motivates the agent to then focus on reproducing the event. As prediction errors decline reward also diminishes, and thus the agent shifts its attention to other objects in the task space. Like Oudeyer’s IAC model, the Barto, Singh, and Chentanez (2004) model also acquires a set of stable actions in a regular order: it first learns to produce simple events, such as turning on the light, which then become component skills that are integrated into options that produce more complex events (e.g., turning the monkey on, which requires a sequence of fourteen primitive actions!).

3.3.4 Competence-Based IM

The modeling work described thus far focuses on what the robot or autonomous agent learns about its environment, either by seeking out novel or unfamiliar experiences, or by predicting how its actions will transform its ongoing stream of sensory data. In this section we highlight models that emphasize the competence-based approach, in which the exploration and learning process is focused on *discovering what the robot can do.*

While robotics researchers have not yet attempted to simulate most of the developmental phenomena that we described in section 3.2, an important topic that has the potential to link the two disciplines is *contingency perception.* Recall that contingency perception begins to develop during early infancy, and is manifested in the infant’s ability to detect the influence that their actions have on events in the environment. As we noted in section 3.1.3, a neural mechanism that may help account for this capacity is proposed by Redgrave and Gurney (2006), who suggest that behaviors which produce novel or unexpected sensory events are followed by a burst of dopamine from superior colliculus cells. Baldassarre (2011; Mirolli and Baldassarre 2013) proposes that these phasic bursts may serve as a learning signal that supports two related functions. First, the bursts provide a “contingency signal” that binds or links the organism’s actions with the concurrent sensory consequences. Second, they provide an intrinsic reinforcement signal that rewards the corresponding action.

In order to evaluate the proposal, Fiore *et al.* (2008) implemented the model in a simulated robot rat that is placed in a box with two levers and a light (see figure 3.10a). The rat has a number of built-in behaviors that enable it to explore its environment, including pushing the levers and avoiding contact with walls. In this environment, pressing lever 1 causes the light to turn on for two seconds, while pressing lever 2 has no effect. Figure 3.10b illustrates a diagram of the modeling architecture that determines the robot's responses to the two levers: visual input is projected through an associative layer to the basal ganglia, which then project to the motor cortex. Transient light produces activity in the superior colliculus, which results in a dopamine (see DA in figure 3.10b) signal that is combined with an efferent copy of the motor signal and modulates the strength of the connections between the associative cortex and basal ganglia. Fiore *et al.* (2008) show that within twenty-five minutes of simulated time in the environment, the robot rat acquires a bias toward pressing lever 1 roughly four times as often as lever 2. Thus, their model not only demonstrates the feasibility of the Redgrave and Gurney learning mechanism, but it also provides a behavior-based implementation on a simulated-robot platform.

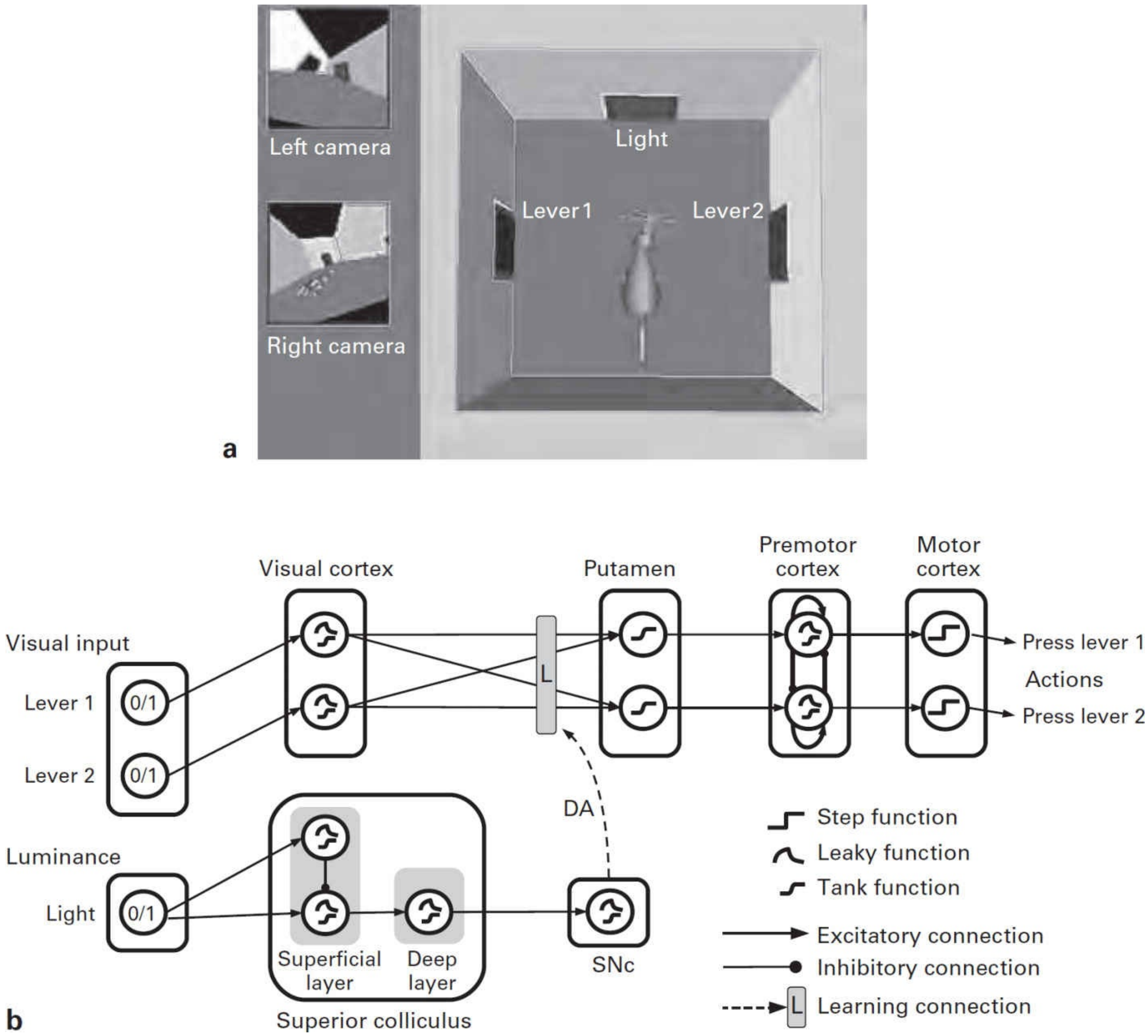


Figure 3.10

The simulated robot rat (a) and modeling architecture (b) used by Fiore *et al.* (2008) to investigate contingency detection and intrinsic motivation. Figure courtesy of Gianluca Baldassarre.

While the Fiore *et al.* model highlights the role of perceptually salient events from a neurophysiological perspective, a more general question concerns how a given neural signal gains the ability to function as an intrinsic reward. Schembri, Mirolli, and Baldassarre (2007) investigate this question by simulating a population of mobile robots that learn to solve a spatial navigation task. There are two important features of the model. First, the lifespan of each robot is divided into a childhood phase and an adult phase; during childhood, the robot wanders through and explores its environment, while during adulthood it is evaluated on its ability to reach a designated target. The reward signal is intrinsically generated during childhood and extrinsically generated during adulthood. Second, the population of robots evolves over multiple generations. In particular, the robots that are most successful at reaching the target are selected to produce the next generation (variation is introduced with a mutation operator during reproduction).

Using the actor-critic architecture, Schembri, Mirolli, and Baldassarre (2007) ask whether evolution can produce an internal critic that effectively evaluates and motivates the robot's exploratory behavior during childhood. In other words, can an IM system evolve, and if so, will it result in improved performance on the navigation task during adulthood? The simulation results provide strong support for this idea. Not only do adults easily learn to solve the navigation task, but also the IM system rapidly emerges during evolution and leads to a pattern of exploratory behavior in young robots that facilitates learning in adults. The model suggests two important implications for competence-based IM. First, it illustrates how intrinsically motivated behaviors or skills—which may have no immediate benefit or value to the organism—can be exploited at a later stage of development. Second, it also shows how evolution can help establish the capacity for intrinsically motivated learning that has a measurable, though indirect, impact on long-term fitness.

Another important question raised by competence-based IM models is how they perform compared to other approaches, and in particular, relative to knowledge-based IM models. Merrick (2010) addresses this question by proposing a general neural network architecture that can accommodate both approaches. Figure 3.11a illustrates the version of the network used to model competence-based IM. First, sensory input from a Lego "crab" robot (see figure 3.11b) projects to the *observation layer*, which classifies the input. Next, the *observation layer* projects to the *error layer*, in which each of the observation values are weighted by a corresponding error weight. The activation values from this layer then project to the *action* or reinforcement learning layer, which produces a set of potential actions. Alternatively, the *error layer* can be replaced with a set of novelty units, which are used to estimate the novelty for each observation, or interest units, which are modified novelty units that respond maximally to moderate novelty. In each case, the corresponding network controls the legs of the robot; the reinforcement learning rule used to train the network varies as a function of the model's respective IM motivation system. In particular, the competence-based IM is rewarded for selecting actions that are associated with high learning errors (i.e., TD or temporal-difference errors).

Merrick (2010) compared the performance of four versions of the model: novelty, interest, and competence, and as a baseline, a model that selects actions at random. One important measure of learning is the frequency with which the model repeats a behavior cycle, such as lifting a leg, lowering the leg, and then lifting it again. Figure 3.11c presents the mean frequency of consecutive repetitions, across all behavior cycles. As figure 3.11c illustrates, repetitions were significantly more frequent in the competence model. In addition, Merrick (ibid.) found that the duration of these behavior cycles was significantly longer in the competence model as well. On the one hand, this pattern of findings is somewhat expected, given that the competence model is specifically designed to focus on the process of skill-development and improvement. On the other hand, however, it is important to note that the pattern also demonstrates a key developmental principle highlighted by Piaget, that is, *functional assimilation*, which we noted earlier in the chapter is the tendency for infants and young children to practice or repeat an emerging skill.

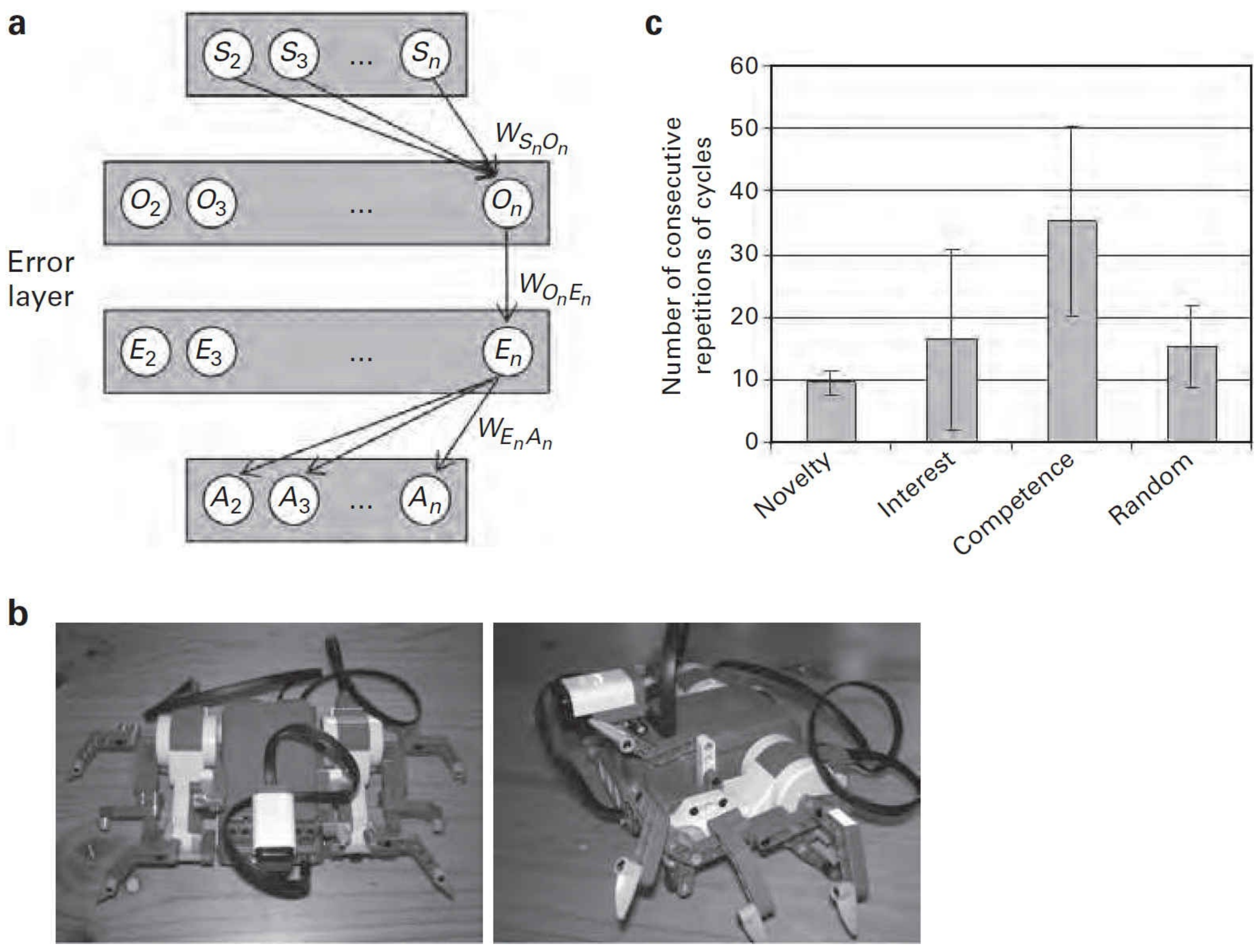


Figure 3.11

The neural architecture (a) and robot "crab" platform (b) used by Merrick (2010) to compare competence-based and knowledge-based IM. The number of consecutive behavior cycles produced by the different models is presented in (c). Figure courtesy of Kathryn Merrick. Reprinted with permission from IEEE.

3.4 Conclusions

Intrinsic motivation is a relatively new area of research in developmental robotics. In contrast, the idea of an intrinsically motivated infant or child has deep roots in the history of psychology, including connections with the concepts of curiosity, exploration, surprise, and the drive to understand. Harlow's work with rhesus monkeys suggests an important question: while traditional drives satisfy a biological need like hunger, what need is satisfied by solving a puzzle or exploring a novel object? In response to drive-based theories of intrinsic motivation, a more elaborate view has been proposed in recent years, including (1) knowledge-based IM, which can be subdivided into novelty-and prediction-based IM; and (2) competence-based IM. Each of these variants can also be linked to functional properties of the mammalian brain, including regions specialized for detecting novelty, for predicting upcoming events, and for detecting contingencies between self-produced actions and environmental consequences.

In addition, there is also extensive behavioral evidence for novelty-based, prediction-based, and competence-based IM in infants and young children. First, infants’ visual activity represents an early form of exploration, in which visual attention is biased toward objects and events that are relatively unfamiliar. Second, by age two months infants generate actions that are directed toward future events, such as shifting their gaze to a location where an object is about to appear. Over the next several months, more sophisticated forms of predictive or future-oriented behaviors emerge, such as anticipatory reaching. Third, also as early as age two months, infants quickly detect objects and events in their environment that respond contingently to their actions. Indeed, infants show a strong attentional bias toward contingent events, which suggests that perceived control of the environment is a highly salient stimulus.

A major focus in developmental robotics has been to establish a taxonomy of architectures for modeling IM at the computational level. Significant progress toward this goal is offered by Oudeyer and Kaplan (2007), who present a systematic framework for organizing a wide array of architectures within the two classes of knowledge-and competence-based IM.

While there are not yet any IM models that are designed to capture a particular infant behavior or stage of development, there are a number that fit well within the novelty-, prediction-, and competence-based approaches. First, several researchers have proposed novelty-based strategies for motivating exploration in mobile robots. A common theme across these models is the use of a habituation mechanism, which computes novelty as the difference between the current state and a memory trace of recent experiences. Within this family of models, there a number of unique features, such as combining novelty with: (1) visual salience, (2) an external reinforcement signal, (3) a social cue from a caretaker, or (4) sensory prediction.

Second, there are also several models that focus on prediction as a core learning mechanism. A significant contribution to the prediction-based approach is offered by Schmidhuber (1991), who proposes an ambitious and encompassing theoretical framework in which prediction (and compression of knowledge) plays a central role. In addition, work by Oudeyer, Kaplan, and Hafner (2007) on the AIBO platform illustrates a key consequence of prediction-based IM: by linking IM to learning progress, the robot shifts its attention and actions from one region of the environment to another in a progressive and systematic manner. A related approach is proposed by Barto, Singh, and Chentanez (2004), who describe a toy-world model of prediction-based IM in which the agent's actions become hierarchically organized as a result of learning to predict the consequences of its actions.

Finally, competence-based models of IM have also received some support. A noteworthy model is proposed by Fiore *et al.* (2008), who investigate Redgrave and Gurney's (2006) theory of contingency detection and dopamine release in the superior colliculus. In particular, Fiore *et al.* demonstrate that the theory can be successfully implemented in a simulated rat, which learns that one of two levers in its environment controls a light. Merrick (2010) offers another valuable contribution by systematically comparing a variety of IM architectures that control the movement of a robot crab. A key finding from this work is that competence-based IM produces a developmentally relevant pattern, that is, repetition of a newly learned behavior.

We conclude by noting that because modeling of IM in robots and artificial agents is a relatively new area of research, there are a number of important and interesting behaviors that have not yet been simulated, and therefore deserve further study. These include not only experimental paradigms like VExP and habituation-dishabituation experiments, but also phenomena such as pretend play and intrinsically motivated problem solving. Indeed, a potential long-term goal may be to design a robot that is capable of engaging in a wide range of intrinsically-motivated behaviors, such as painting and drawing, musical composition, daydreaming, and so on.

Additional Reading

Baldassarre, G., and M. Mirolli, eds. *Intrinsically Motivated Learning in Natural and Artificial System*s. Berlin: Springer-Verlag, 2013.

Baldassarre and Mirolli's edited volume presents a wide variety of approaches to understanding intrinsic motivation, including not only neurophysiology and behavior in real organisms, but also computational models and robotics experiments. An important feature of the book is a focus on both theory and empirical data, as well as a comprehensive discussion of the open challenges for researchers who investigate intrinsic motivation. It represents the state of the art in this area and will continue to be an influential work as new ideas and approaches emerge.

Berlyne, D. E. *Conflict, Arousal, and Curiosity*. New York: McGraw-Hill, 1960.

Berlyne's text—now more than fifty years old—is an essential read for students of intrinsic motivation. A key feature of his book is a chapter that analyzes the strengths and limitations of drive-reduction theory, which ultimately provides a foundation for an alternative approach that highlights the adaptive roles of curiosity and learning. In other chapters he focuses on additional issues that are central to developmental robotics, including novelty, uncertainty, and exploration. Another valuable feature is Berlyne's use of data from animal-behavior experiments, which helps bridge the gap between artificial systems and humans.

Ryan, R. M., and E. L. Deci. "Self-Determination Theory and the Role of Basic Psychological Needs in Personality and the Organization of Behavior." In *Handbook of Personality: Theory and Research*, 3rd ed., ed. O. P. John, R. W. Robins, and L. A. Pervin, 654–678. New York: Guilford Press, 2008.

Though written primarily for the psychology community, Ryan and Deci's chapter provides a detailed introduction to self-determination theory (SDT), which emphasizes the role of autonomy and competence in human experience. Their approach also addresses a fundamental dimension of experience that is often overlooked or neglected by behavioral researchers, that is, the qualitative, personal, or subjective aspect. Understanding the nature of subjective experience, and in particular, the developmental significance of self-efficacy, may provide valuable insights for the study of intrinsic motivation in robots and other artificial systems.

5 Motor-Skill Acquisition

For human infants, mastering two basic sets of motor skills—manipulation (e.g., reaching and grasping) and locomotion (e.g., crawling and walking)—provides an essential foundation for many of the behaviors and abilities that develop during the first two years of postnatal life. In addition, for parents, the emergence of these core motor skills is dramatic and rapid: for example, at age three months, their child learns to roll over, at six months she is sitting up, by eight months she has started to crawl, and on her first birthday, she takes her first steps. As we discussed in chapter 3, these developmental milestones appear to be intrinsically motivated, that is, rather than serving some immediate need or goal, they appear to be driven by the desire to improve the skill itself (e.g., Baldassarre 2011; von Hofsten 2007). While infants may benefit from observing their parents or siblings, family members typically provide no direct instruction, feedback, or assistance to the infant during motor-skill acquisition. And yet, these skills consistently develop in most infants on a predictable schedule (e.g., Gesell 1945).

In this chapter, we survey the core motor skills that infants develop in the first two years, and contrast this developmental pattern with the data obtained from models and robotics experiments that simulate learning of the same skills. In particular we note, as we illustrated in chapter 2, that recent advances in the design and construction of child-sized robots allow developmental robotics researchers to study the rich spectrum of physical behaviors that infants and children produce. Thus, robot platforms provide a unique and valuable tool for investigating motor-skill acquisition: because they are designed to mimic the size and shape of human children, and in some cases also capture physical processes at the skeletal and muscle levels, the study of humanoid robots like iCub, NAO, and CB^2 may reveal fundamental principles underlying the emergence of these skills in both natural and artificial organisms.

It is important to note that developmental robotics not only differs from conventional robotics in terms of the size and strength of the robot platforms, but also in terms of the modeling philosophy itself. Thus, a traditional approach often found in “adult” humanoid robotics is to first estimate the robot’s current position (using vision, joint-angle sensors, etc.), and then to compute the necessary change in joint angles and joint torques or forces that will produce the desired movement or end position, or both. In other words, this approach focuses on solving the *inverse-kinematic* and *inverse-dynamic problems* (e.g., Hollerbach 1990). In contrast, as we will highlight, an alternative strategy employed in developmental robotics is instead to learn a mapping between spatial locations and joint positions and joint forces through the production of a wide range of exploratory movements. The key difference here is that the developmental approach typically focuses on *learning* of motor skill by trial and error, rather than by computing a desired movement trajectory in advance.

As an example of the kind of research question that developmental robotics is well suited to address, consider the following developmental pattern. The production of smooth, skilled reaching movements is a long-term achievement that takes human children two to three years to master (e.g., Konczak and Dichgans 1997). Along the way, infants often pass through a period of development in which their movements are comparatively jerky and appear somewhat reflex-like (e.g., von Hofsten and Rönnqvist 1993; McGraw 1945; Thelen and Ulrich 1991). Shortly after birth, for instance, neonates generate spontaneous hand and arm movements that are visually elicited (e.g., Ennouri and Bloch 1996; von Hofsten 1982). While these “prereaching” movements are directed toward nearby objects, infants rarely make contact with the target. Over the next two months, prereaches decline in frequency. At age three months, a more robust and organized set of reaching behaviors begins to emerge, which includes several important and new properties (e.g., the hand or grasp preshape, corrective movements, etc.; Berthier 2011; von Hofsten 1984). A similar pattern is also observed during the development of walking: very young infants produce a highly stereotyped stepping behavior (i.e., the stepping reflex), which disappears by age three months, but can be elicited in older infants by placing them in water or supporting them on a treadmill (e.g., Thelen and Ulrich 1991). Like the development of reaching, infants begin to crawl and subsequently walk a few months after the reflex-like stepping behavior has disappeared.

To date, there are no computational models that account for this U-shaped developmental pattern. However, an important concept that plays a critical role in many models of motor-skill acquisition, and that may help explain the U-shaped pattern, is the phenomenon of *motor babbling* (e.g., Bullock, Grossberg, and Guenther 1993; Caligiore *et al.* 2008; Kuperstein 1991). Analogous to preverbal babbling in human infants, motor babbling is a more general phenomenon, in which infants learn to control their bodies by actively generating a wide variety of movements in a trial-and-error fashion. Thus, the precocious or early movements that infants produce (such as prereaches) may also be understood as a form of motor babbling. What remains unexplained, however, is why these movements diminish and later reemerge in a more mature form. One possible explanation is that the "decline" phase represents the transition from ballistic, stereotyped movements to visually guided action, which requires integrating multiple sensory inputs (e.g., vision and proprioception; Savastano and Nolfi 2012; Schlesinger, Parisi, and Langer 2000).

In the next section, we describe the major milestones observed in infants during the development of manipulation and locomotion. In particular, we highlight four fundamental skills: reaching, grasping, crawling, and walking. We focus on these skills for two reasons. First, not only are they essential survival skills for the species, but they also have profound influence on both perceptual and cognitive development (e.g., Kermoian and Campos 1988). Second, manipulation and locomotion are also comparatively well-studied skills within robotics, and in particular, from the developmental robotics perspective (e.g., Asada *et al.* 2009; Shadmehr and Wise 2004). After reviewing the pattern of human development, therefore, the remainder of the chapter surveys the array of models that have been proposed for simulating motor-skill acquisition, and the major findings provided by this work.

5.1 Motor-Skill Acquisition in Human Infants

In chapter 4, we noted Greenough and Black's (1999) concept of *experience-expectant* development, that is, a pattern of development in which a skill or ability reliably and consistently emerges across all members of the species. This pattern contrasts with *experience-dependent* development, in which a particular skill or ability only emerges under a set of very specific conditions. Both of these developmental patterns are observed during motor-skill acquisition in human infants. On the experience-expectant side are behaviors such as reaching and walking, which are—barring developmental pathology or pathological rearing conditions—universal skills that all children acquire, regardless of cultural-historical context, geographical region, native language, and so on. Other early skills that fall in the same category are oculomotor control, trunk and neck control, and nursing. In contrast, experience-dependent skills typically develop at a later age, and require explicit instruction, such as swimming, playing musical instruments (e.g., violin or piano), and drawing. These skills also vary widely across cultural, historical, and geographical contexts.

In this section, we focus on the development of experience-expectant abilities, and in particular, on four motor skills that emerge in infancy: reaching, grasping, crawling, and walking.

5.1.1 Manipulation: Reaching

To help provide a context for our discussion of the development of reaching, table 5.1 summarizes the major milestones in reaching and grasping that occur during the first two years. As we noted in the introduction, the earliest example of reaching behavior is observed in newborn infants, who produce brief forward extensions of their hand toward nearby objects (e.g., Bower, Broughton, and Moore 1970; Ennouri and Bloch 1996; Trevarthen 1975; von Hofsten 1984). Figure 5.1 illustrates the apparatus used by von Hofsten (1984) to study the development of prereaching movements in young infants. Von Hofsten (ibid.) reported an increase in object-oriented forward extensions of the infant's hand between birth and two months. The behavior then appears to decline between seven and ten weeks; interestingly, as prereaches become less frequent, infants spend increasingly more time fixating the target object. Between ten and thirteen weeks, reaching movements become more frequent again, this time co-occurring with fixations of the object. In addition, at this age the tendency to open the hand during the *transport phase* (i.e., movement of the hand toward the target) also increases (e.g., Field 1977; von Hofsten 1984; White, Castle, and Held 1964). Taken together, these findings support the idea that early prereaches are spontaneous, synergistic movements, which become temporarily suppressed as intentional, visually guided reaching begins to emerge between three and four months.

Table 5.1

Timescale and major milestones for reaching and grasping development in human infants (adapted from Gerber, Wilks, and Erdie-Lalena 2010)

Age (months)	Competence
0–2 months	Grasp reflex Prereaching appears and increases in frequency
2–3 months	Prereaching declines in frequency
3–4 months	Onset of reaching Hands held predominately open
4–6 months	Hand preshape emerges Palmar/power grasp
6–8 months	Radial-palmar grasp Scissors grasp Hand preshape predominates
8–12 months	Radial-digital grasp Pincer/precision grasp Online reach corrections
12–24 months	Adult-like reaching kinematics Prospective (prereach) arm control

The U-shaped pattern of reaching development from birth to age three months not only implicates the role of vision as a major influence, but also raises an important and interesting question: do infants learn to control the movement of their hands by visually guiding them toward the target (e.g., Bushnell 1985; Clifton *et al.* 1993; McCarty *et al.* 2001a)? Clifton *et al.* (1993) addressed this question by following a group of infants longitudinally between ages six and twenty-five weeks, and found that the onset of reaching for objects in an illuminated room, versus objects that glowed (or made a sound) in the dark, did not differ statistically. In both cases, the average age of the first successful reach was twelve weeks in both conditions, and the average age of the first successful grasp followed at fifteen weeks. These data suggest, at least at the onset of reaching, that localization of the target and proprioceptive input from the hand and arm are sufficiently well coordinated. It remains an open question, however, if this coordination is achieved in the weeks prior to reach onset through visual feedback of the hand.

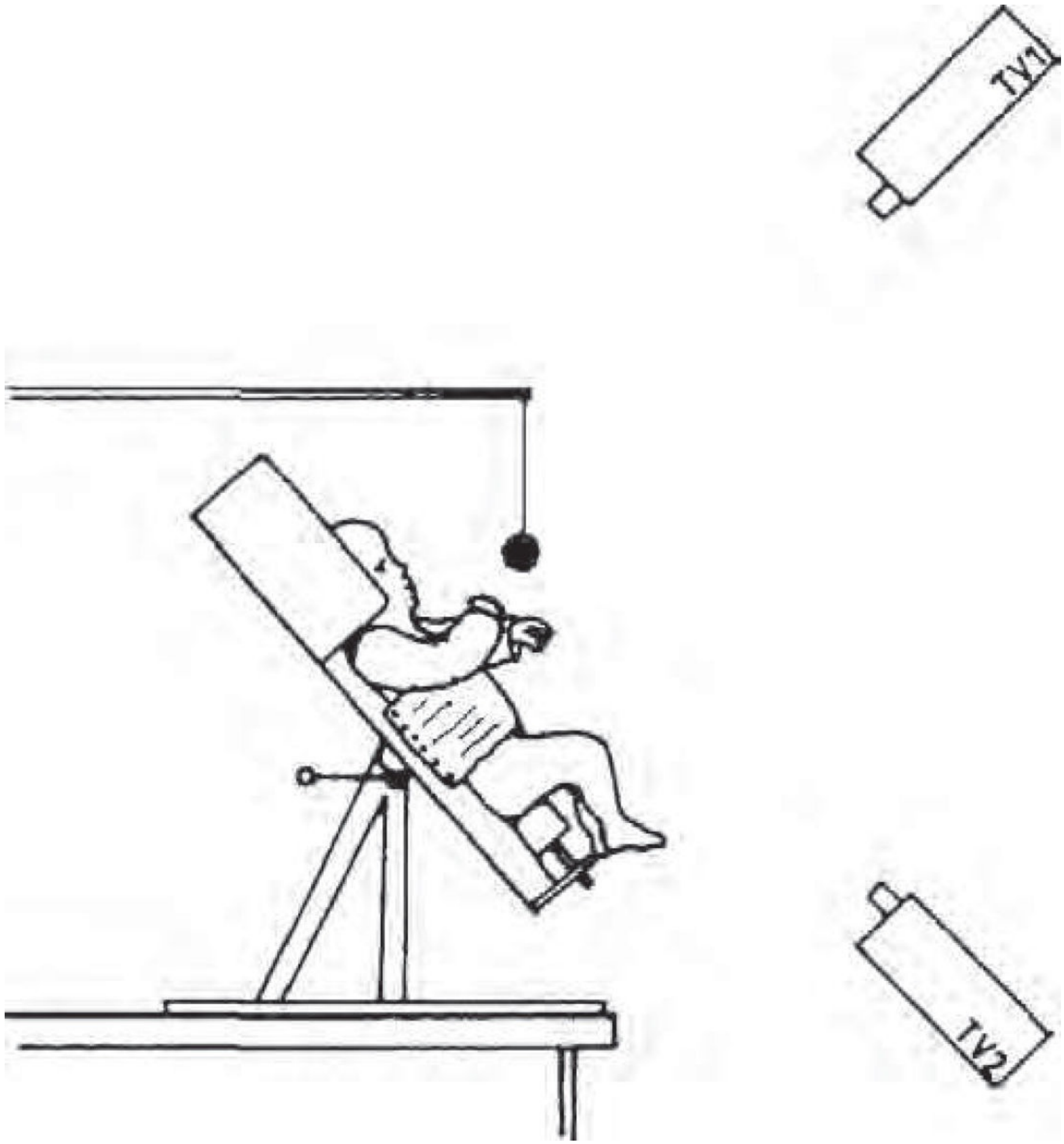


Figure 5.1

Experimental setup used by von Hofsten (1984) to study prereaching in young infants. Copyright © 1984 by the American Psychological Association. Reproduced with permission.

After the onset of reaching around age four months, there are several subsequent improvements. For example, between ages four and twelve months, infants become more effective at using visual information from the target to update their reaching movements. When presented with targets that appear to abruptly change location during a reach, five-month-olds typically reach toward the original target location, while nine-month-olds adjust their trajectories mid-reach (Ashmead *et al.* 1993). In addition, guidance of the hand toward the target is not only updated online using vision of the target, but also with stored information about the target location. For example, as early as age five months, infants will continue to reach for an object even if it is darkened during mid-reach (McCarty and Ashmead 1999). Infants at this age can also learn to adapt their reaching movements while wearing displacing prisms, which shift the apparent target location (e.g., McDonnell and Abraham 1979).

In addition, there are a number of changes in the kinematic properties of infants' reaching movements that continue to occur after the onset of reaching. One important feature is that infants' reaches become progressively straighter and smoother with age (e.g., Berthier and Keen 2005). This pattern is due in part to the fact that infants begin reaching by holding the elbow relatively fixed, while rotating the shoulder, which results in comparatively rounded or curved reaching trajectories (e.g., Berthier 1996). During the second year, infants begin to coordinate elbow and shoulder rotation (e.g., Konczak and Dichgans 1997). Another feature is that infants' hand-speed profiles become more adult-like; in particular, the peak movement speed shifts "backward" in time, closer to the onset of the reach (e.g., Berthier and Keen 2005). This shift reflects a tendency toward producing one large, rapid initial movement, followed by a subsequent series of smaller, slower corrective movements as the hand nears the target.

5.1.2 Manipulation: Grasping

While there is a three-or four-month gap between the earliest form of reaching (i.e., prereaching in neonates) and the onset of voluntary grasping, the two behaviors overlap considerably, not only in real time but also in their respective developmental periods. Thus, soon after the onset of visually controlled reaching movements, the palmar grasp also emerges and begins to develop. We highlight here two important patterns that occur during the development of grasping.

First, infants' grasping behaviors follow a consistent and predictable developmental pattern between ages six and twelve months (see figure 5.2;

Erhardt 1994; Gerber, Wilks, and Erdie-Lalena 2010). The earliest voluntary grasp is the *palmar grasp* (or *power grasp*), in which infants approach an object with an open hand, and once contact is made with the palm, enclose the object with their fingers. The palmar grasp then transitions into the *scissors grasp* at eight months, where the four fingers form a unit that opposes the thumb. At age nine months, only two fingers (the index and middle fingers) oppose the thumb, creating the *radial-digital grasp.* This is followed at ten months by an early form of the *pincer grasp* (or *precision grasp*), characterized by use of the thumb and index finger; by age twelve months, infants have mastered this technique, and can now use the *mature pincer grasp* to pick up small objects, such as pieces of food.

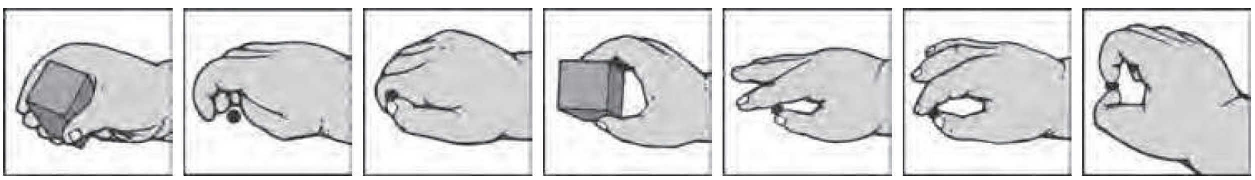


Figure 5.2

Development of grasping between six and twelve months (Erhardt 1994).

In addition to the role of grasping as a fine-motor skill, its development also reflects a second important function: planning and prospective action. In chapter 3, we touched on this issue in our discussion of prediction-based intrinsic motivation, as well as in chapter 4, where we described the development of the perception of affordances. In the context of grasping, this issue has been explored by investigating the development of *hand* (or *grasp*) *preshaping.* The hand preshape is an orienting of the hands and fingers during the transport phase (i.e., movement of arm and hand toward the target), as a function of the size, shape, and position of the target object.

The emergence of the hand preshape lags several weeks behind the onset of reaching: until approximately age four months, infants typically reach with their hand in a stereotyped, open configuration, regardless of the size and shape of the target object (e.g., Witherington 2005). The earliest form of preshaping is orienting of the hand to match the orientation of the target, which begins to emerge at age four and a half months (e.g., horizontally vs. vertically oriented rods; von Hofsten and Fazel-Zandy 1984; Lockman, Ashmead, and Bushnell 1984). Orienting of the hand to match the target object orientation continues to improve over the next several months. For example, by nine months infants will correctly orient their hand, given a preview of the target but no visual information once the reach is initiated (e.g., McCarty *et al.* 2001a).

A second, more complex dimension of hand preshape is correctly positioning the fingers prior to contacting the object. Newell *et al.* (1989) investigated this skill by comparing the grasps of infants between ages four and eight months as they reached toward a small cube and three differently sized cups. Interestingly, infants at all ages distinguished between the objects by generating size-and shape-specific grasp configurations (e.g., small cube versus large cup). However, the timing of the hand shape varied with age: in particular, the youngest infants relied almost exclusively on the strategy of shaping the hand *after* making contact with the object. With age, infants progressively increased the frequency of shaping their hand *prior* to contact. McCarty, Clifton, and Collard (1999) report a similar developmental pattern in infants aged nine to nineteen months, on a more complex task that involves grasping objects with handles (e.g., a spoon with applesauce) oriented in different directions. We describe this study in detail in box 5.1.

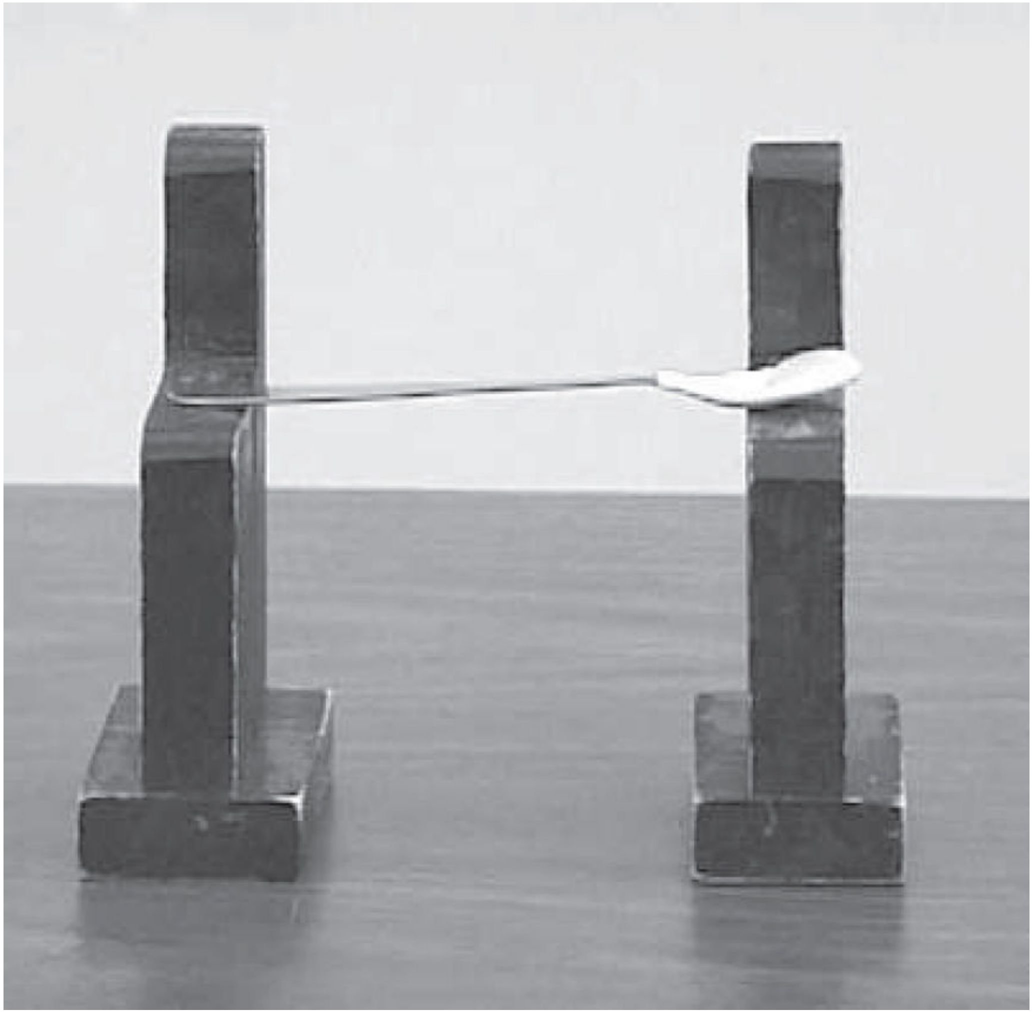
5.1.3 Locomotion: Crawling

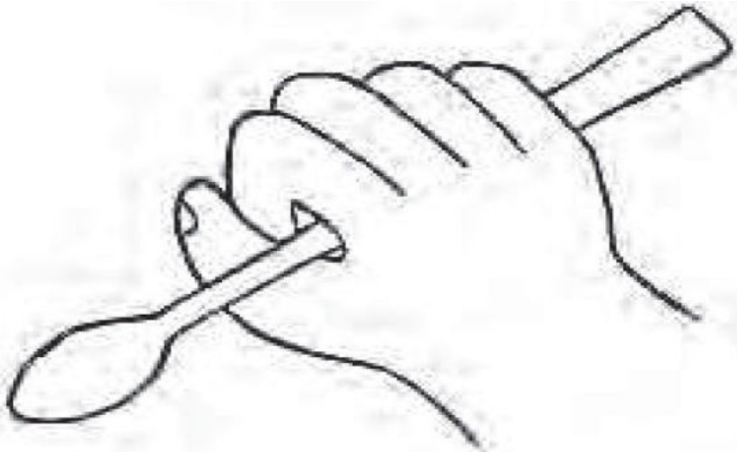
Table 5.2 presents the major stages in the development of crawling and walking. While infants do not begin to locomote independently until approximately age six or seven months (i.e., “creeping”), there are several prior achievements that precede the development of crawling that help make it possible. For example, infants typically begin to roll over on their side at three months, from front to back at four months, and from back to front at five months (Gerber, Wilks, and Erdie-Lalena 2010). Most infants can also sit without support at six months. These developments in trunk control indicate not only significant gains in gross motor skill, but also increased strength in the same muscle groups that are used during locomotion.

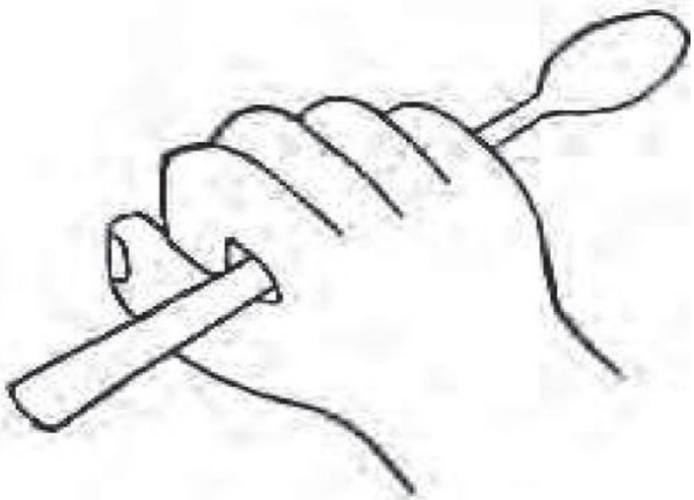
Box 5.1

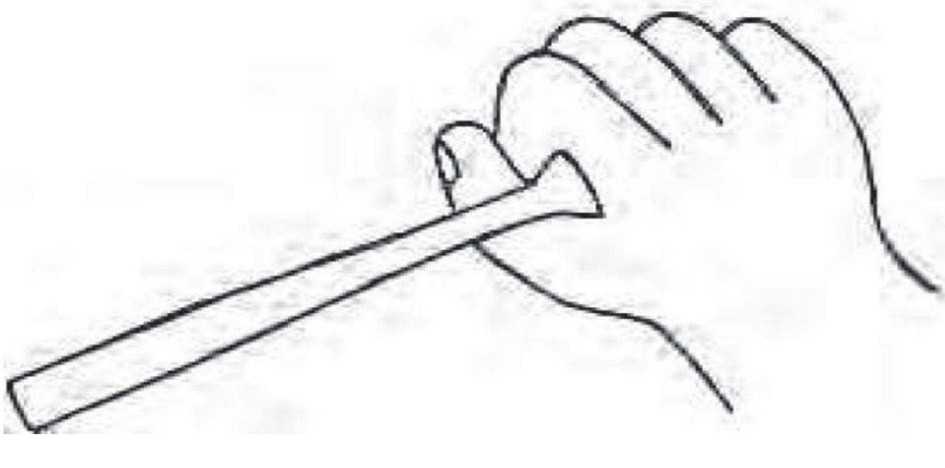
Overview

McCarty, Clifton, and Collard (1999) describe an elegant and simple method for studying planning and prospective action in infants: a spoon is loaded with applesauce, and placed in front of the child, on a wooden stand (see figure below). On some trials, the spoon is oriented with the handle on the left, while on other trials the handle is on the right. As a grasping task, the spoon can be gripped in three ways: (1) the handle can be grasped with the ipsilateral hand (i.e., the one on the same side as the handle), producing a radial grip; (2) the handle can be grasped with the contralateral hand, producing an ulnar grip; or (3) the hand on the same side as the goal can grasp the “bowl” of the spoon directly, producing a goal-end grip (see top, middle, and lower hand-spoon diagrams, respectively). The radial grip is the most efficient, allowing the goal-end to be directly transported to the mouth. In contrast, the ulnar grip requires either transfer of the handle to the opposite hand before transport to the mouth, or an awkward orientation of the grasping hand and arm before eating. McCarty, Clifton, and Collard (ibid.) suggest that if infants want to retrieve the applesauce as efficiently as possible, they should (1) show a bias toward producing a radial grip, and therefore, (2) prospectively select the ipsilateral hand prior to reaching for the spoon.









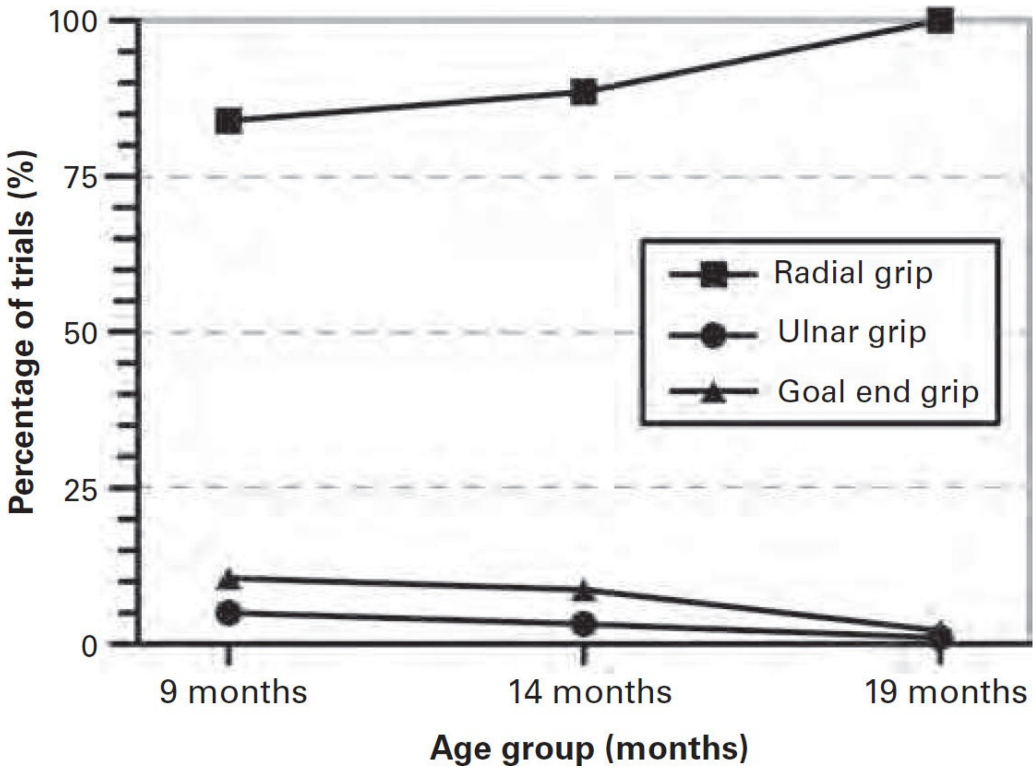
Procedure

Infants at ages nine, fourteen, and nineteen months participated in the study. Prior to the applesauce task, each infant's hand preference was assessed by placing a series of toys at midline, and noting which hand was used to grasp each object. Infants were then presented with a series of test trials, including first a set of toys mounted on handles (e.g., a rattle) and then the applesauce-loaded spoon. The orientation of the handle was alternated across trials.

Results

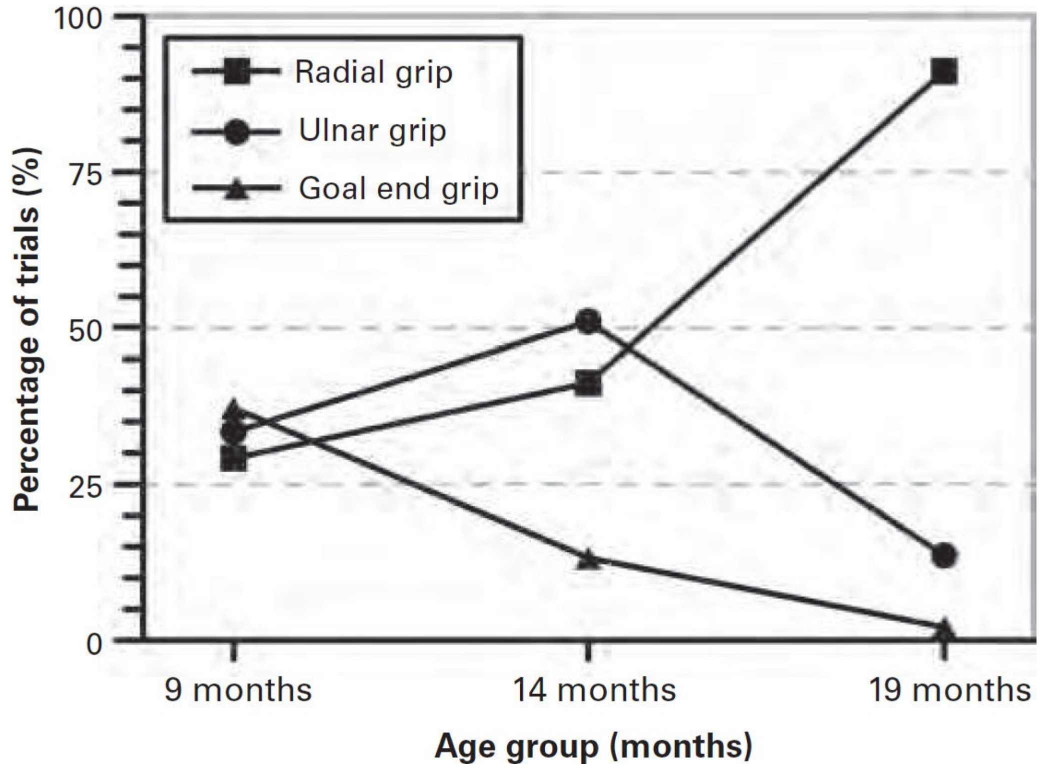
The pattern of results across the two handle conditions (i.e., toys vs. applesauce) was comparable. We present here the findings from the applesauce condition. After each infant's hand preference was determined, the test trials were divided into two categories: *easy trials* are those in which the handle of the spoon was on the same side as the infant's dominant hand, while *difficult trials* are those in which the handle of the spoon was on the opposite side. The line chart below presents the proportion of radial, ulnar, and goal-end grips for the three age groups, during easy and difficult trials, respectively (upper and lower plots). On easy trials, the proportion of radial grips was significantly higher for older infants; thus, even when the handle was oriented in a direction that facilitated the radial grip, younger infants produced it less often than older infants. On the difficult trials, a similar pattern emerged. However, as the lower plot illustrates, nine-month-olds were equally likely to use all three grips when the handle was on the opposite side of their dominant hand. The tendency to produce a radial grip on difficult trials (i.e., with the nondominant hand) increased with age, reaching almost 90 percent by age nineteen months.

Easy Trials



In a follow-up study, McCarty, Clifton, and Collard (2001b) used a similar paradigm to study how infants grasped (and subsequently used) tools with handles, such as a hairbrush, and how prospective grasping behavior varied as a function of whether the goal action was directed toward the self or toward an external goal. As in their previous study, McCarty and colleagues (ibid.) found that radial grips increased in frequency with age. In addition, they also found across all ages that radial grips were more likely in the context of a self-directed action than an externally directed action.

Difficult Trials



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In the month prior to the onset of crawling, infants often produce a number of behaviors that fall into the category of "precrawling," including alternating between prone and sitting positions, rocking on the hands and knees, and pivoting or rotating in the prone position (e.g., Adolph, Vereijken, and Denny 1998; Goldfield 1989; Vereijken and Adolph 1999). Adolph, Vereijken, and Denny (1998) also identified a precursor form of crawling at age seven months that they described as "belly crawling" or creeping, in which the infant remains prone on his stomach and pushes with his legs. While experience with belly crawling did not influence the average onset age of hands-and-knees crawling, Adolph, Vereijken, and Denny (ibid.) also reported that at onset, belly-crawlers were more efficient at hands-and-knees crawling, and also more consistent in "diagonal" alternation of the limbs (e.g., coordinated movement of the left leg and right arm).

Table 5.2

Major stages of locomotion development during the first year (adapted from Vereijken and Adolph 1999)

Age (months)	Stages of locomotion development
0–6 months	Immobility
7 months	Belly crawling (“creeping”)
8 months	Hands-and-knees crawling
9 months	Sideways cruising
10 months	Frontward cruising
12 months	Independent walking

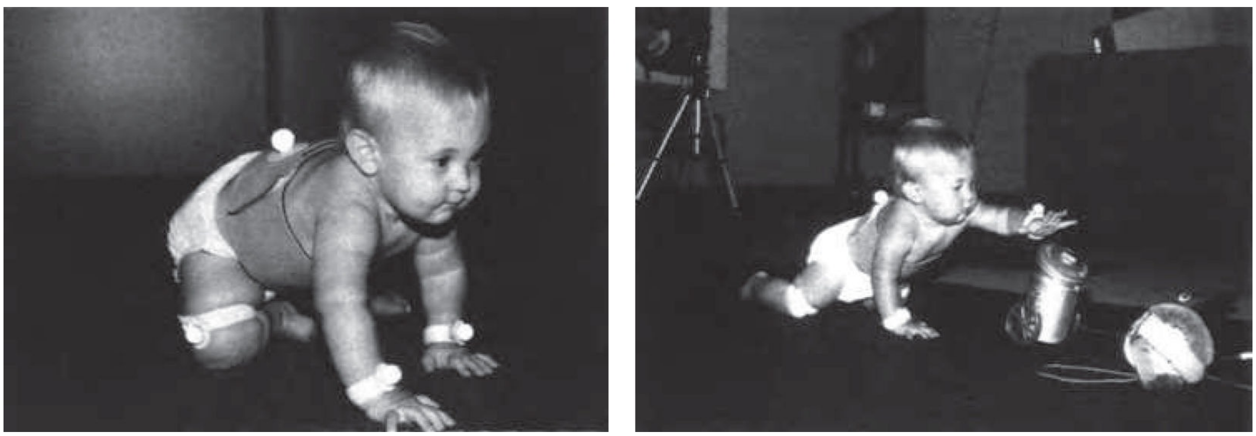


Figure 5.3

An infant participant demonstrating hands-and-knees crawling in the Freedland and Bertenthal (1994) study.

Figure 5.3 illustrates an example of hands-and-knees crawling in a young infant. The emergence of the diagonal pattern during the development of hands-and-knees crawling, around age eight months, is important for several reasons. First, it reflects a relatively skilled level of timing and coordination of the arms and legs (e.g., Freedland and Bertenthal 1994). Second, it also affords the infant a flexible strategy for locomotion while also maintaining balance, especially in contrast to other crawling patterns, such as ipsilateral limb movements (e.g., Freedland and Bertenthal 1994). Finally, the diagonal crawling pattern is important because it illustrates *asymmetry*: in particular, theorists such as Gesell (1946) proposed that infants move from one stage of motor skill development to the next by “overcoming” or “breaking” the symmetric organization imposed by the biomechanical system. Support for this claim, in the context of learning to reach and crawl, is provided by Goldfield (1989), who found that the emergence of a hand preference in infants—as assessed by a reaching task—was highly associated with the onset of crawling.

5.1.4 Locomotion: Walking

As we noted at start of the chapter, both reaching and walking initially appear as reflex-like behaviors in newborn infants. In the case of walking, neonates produce a stepping reflex that is elicited by supporting the infant in an upright position, and then placing the infant’s feet on a horizontal surface (e.g., Bril and Breniere 1992; Zelazo, Zelazo, and Kolb 1972). With this contextual support, young infants produce a well-organized pattern of alternating stepping movements with their legs. By age three months, however, this response no longer occurs.

What role, if any, does this early stepping behavior play in the process of learning to walk? One proposal is that the “loss” of the stepping reflex is due to the maturational shift of neural control from the spinal cord and brain stem, to the cortex (e.g., McGraw 1941). In other words, learning to walk involves suppressing or inhibiting the stepping reflex, while gradually developing voluntary control over the same muscle groups. However, in a series of studies, Thelen (1986; Thelen, Ulrich, and Niles 1987; Thelen and Ulrich 1991) found that between ages two and nine months, even when infants do not generate stepping movements on a stationary surface, they continue to produce the stepping pattern when placed on a moving treadmill. In addition, at this age treadmill stepping is not purely reflex-like, but instead relatively flexible and well-coordinated. For example, when the treadmill is divided into two parallel belts, each moving at different speeds, seven-month-olds maintain a regular gait by modulating the timing of the stepping movements with each leg (Thelen, Ulrich, and Niles 1987). Taken together, these results are consistent with the idea that neonatal leg movements are the result of a *central pattern generator* (CPG) at the spinal cord level, which is responsible for the basic coordination and timing of the leg movements, and that it is not suppressed, but instead gradually integrated with several other emerging abilities, including voluntary control of the legs and postural control of the trunk and upper body (Thelen and Ulrich 1991). As we will highlight, CPGs play a central role in developmental robotic studies as a neural mechanism that supports crawling and walking.

Thelen and Ulrich (1991) propose, thus, that the early stepping pattern does not disappear, but instead continues to develop and improve (e.g., during supine kicking of the legs), though it is not expressed as supported or independent walking until other necessary skills are in place. In particular, a rate-limiting factor (i.e., control parameter) that may constrain the emergence of independent walking is postural control (e.g., Bril and Breniere 1992; Clark and Phillips 1993; Thelen 1986), which begins to develop shortly after birth and follows a cephalocaudal (i.e., top-to-bottom) developmental pattern through the first year. From zero to three months, infants are first able to lift their heads (while prone on their stomach), then their head and chest, and finally, their upper body while using their arms for support (Johnson and Blasco 1997). Between three and six months, as we noted earlier, infants then learn to roll over, and maintain a seated, upright posture. Between six and nine months, infants are able to transition from the prone to seated position on their own, and they can also pull themselves up to a standing position. At age ten months they are competent at cruising (i.e., supported walking), while at eleven months they can stand alone without support. Finally, near their first birthday, most infants take their first steps and begin to develop independent walking.

While postural control (especially strength and balance) helps make the first steps possible, early walking behavior is far from adult-like (e.g., Bril and Breniere 1992; Clark and Phillips 1993; Vereijken and Adolph 1999). There are two important changes that occur during the second year. First, infants increasingly synchronize and coordinate the movement of their arms and legs. For example, at the onset of walking, rotations of the upper and lower leg segments (i.e., thigh and shank) are loosely coupled, and the phase relation between the two is irregular; within three months of walking, however, thigh and shank rotations are highly correlated and the phase relation resembles the pattern produced by adults (Clark and Phillips 1993). Similarly, early walkers extend and lift their arms, which helps create “ballast” but also precludes use of the arms during the swing phase. With experience, however, skilled walkers lower their arms, and swing them in phase with leg and hip rotation (Thelen and Ulrich

1991).

Infants also explore other forms of interlimb coordination as they learn to crawl, cruise, and walk. An interesting example is bouncing, which develops near the emergence of crawling but differs by recruiting a simultaneous (rather than alternating) pattern of leg movements. Goldfield, Kay, and Warren (1993) investigated the development of this skill by placing infants in a spring-mounted harness (i.e., the “Jolly Jumper”), and conducting a kinematic analysis of infants’ bouncing behavior. Testing sessions were repeated over six consecutive weeks. Goldfield, Kay, and Warren (ibid.) hypothesized three phases of learning: (1) an initial phase focused on exploring the relation between kicking movements and bouncing (i.e., “assembly”), (2) a second phase, focused on “tuning” the timing and force of the component behaviors, and (3) a final phase, in which an optimal bouncing pattern emerges. They defined optimality as a stable pattern of bouncing, at or near the resonant period of the spring-mass system, with low variability in the period and high amplitude. Kinematic analyses provided clear support for each of the learning phases. In particular, a stable pattern emerged near age eight months, in which infants timed their kicking movements to coincide with the lowest point in the oscillation.

In addition to coordination within and between limbs, a second important dimension of walking that emerges during the second year is the ability to dynamically maintain balance while moving. Thus, early walkers tend to rely on a “stiff leg” strategy, which helps preserve upright posture, but fails to recruit available degrees of freedom (DOFs) in the legs and hips (e.g., Clark and Phillips 1993). With experience, however, older infants learn to “relax” these joints and incorporate their rotation into the stepping movement (e.g., Vereijen and Adolph 1999). Note that this is the same qualitative pattern that is observed in infants during the development of reaching, as early movements are characterized as stiff and rigid, while subsequent movements are smoother, more fluid, and recruit a higher number of joint DOFs. Indeed, the strategy of freezing and then freeing DOFs also plays a central role in motor-skill models, which we will highlight (e.g., Berthouze and Lungarella 2004; Lee, Meng, and Chao 2007; Schlesinger, Parisi, and Langer 2000). As a result of this developmental pattern, there are several improvements in walking that emerge during the second year, including (1) longer steps, (2) reduced distance between the feet during steps, (3) pointing the feet more forward, and (4) straighter paths while walking (e.g., Bril and Breniere 1992; Vereijken and Adolph 1999).

5.2 Reaching Robots

We describe here two classes of developmental robotics models of reaching. In the first set are *developmentally inspired* models, which exploit known properties and principles of motor-skill acquisition in human infants. In the second set, meanwhile, are models which are not only inspired by reaching development in human infants, but also seek to reproduce the developmental pattern in an artificial agent or robot.

A fundamental goal of developmentally inspired models of reaching is to implement a cognitive architecture, learning algorithm, or physical design that borrows key features (e.g., physical, neurophysiological, etc.) from human infants, and to demonstrate that these features constrain or simplify the problem of learning to reach in a fundamental way (e.g., Kuperstein 1988, 1991; Schlesinger, Parisi, and Langer 2000; Sporns and Edelman 1993; Vos and Scheepstra 1993). In addition, these models also help reveal and identify the underlying neural mechanisms that shape motor development. For example, Schlesinger, Parisi, and Langer (2000) highlight Bernstein's *DOF problem* (Bernstein 1967), that is, the fact that biomechanical systems have a large and redundant number of DOFs, including joints, muscles, neurons, and so on, which from a control perspective means there are an unlimited number of ways to produce a given movement trajectory. Schlesinger, Parisi, and Langer (2000) investigate this issue by using a genetic algorithm (GA) as a proxy for trial-and-error search (i.e., "hill climbing") in a population of artificial neural networks, which controls the movements of a one-DOF eye and a three-DOF arm. As we noted in the previous section, one strategy for solving the DOF problem at the joint level is to lock or "freeze" redundant joints, which reduces the dimensionality of the resulting joint space that must be explored. Schlesinger, Parisi, and Langer (ibid.) demonstrate that the freezing strategy need not be programmed into the model, but that it can in fact emerge "for free" as a result of the learning process: in particular, the model quickly learns to freeze the shoulder joint, and to reach by rotating the body axis and elbow joint.

A related problem involves learning a function that associates visual input of the target object with a motor program that moves the endpoint to the target location. An early and influential approach to this problem is Kuperstein's INFANT model (1988, 1991), which was implemented with a dual-camera vision system and a multijoint arm. INFANT divides the process of coordinating vision and movement into two phases. During the first phase, the arm is driven to a series of random postures, while the hand grasps an object. At the end of each posture, the vision system records the resulting view of the grasped object. A multilayer neural network is then trained to produce the motor signal that corresponds to the given visual input; in particular, the prior (randomly generated) motor signal is used as the teaching pattern, against which the computed motor signal is compared. As we noted at the beginning of the chapter, this training strategy—in which the simulated infant generates its own training data through random movement—illustrates the phenomenon of *motor babbling*. During the second phase, visual input of the target at a new location is presented to the neural controller, which then drives the arm to the learned posture and results in reaching to the target location. More recently, Caligiore *et al.* (2008) have proposed a related approach that also bootstraps motor babbling, but in this case to solve a more difficult reaching problem (i.e., reaching around obstacles). A key feature of the Caligiore model is the use of CPGs, which contribute to the production of cyclic movements that, together with motor babbling, help solve the problem of obstacle avoidance during reaching.

Two potential criticisms of INFANT are that, first, an extended period of visuomotor training is required before the model begins to reach, and second, it benefits from a feedback rule that explicitly corrects movement errors. More recent approaches have been proposed to address these issues (e.g., Berthier 1996; Berthier, Rosenstein, and Barto 2005; Sporns and Edelman 1993). For example, Berthier (1996) proposed a reinforcement-learning (RL) model that simulates movement of the infant's hand in a 2D plane. In a subsequent version (Berthier, Rosenstein, and Barto 2005), the model was updated to include dynamic force control of the arm, as well as a 3D workspace. In particular, the muscles controlling rotation of the shoulder and elbow joints are modeled as linear springs. Rather than a supervised learning signal, the model is provided with a scalar reward signal (i.e., estimated time to the target), which does not explicitly specify how the arm should be moved. The model therefore learns by exploratory movements, which are generated through the addition of Gaussian noise to the output motor signal.

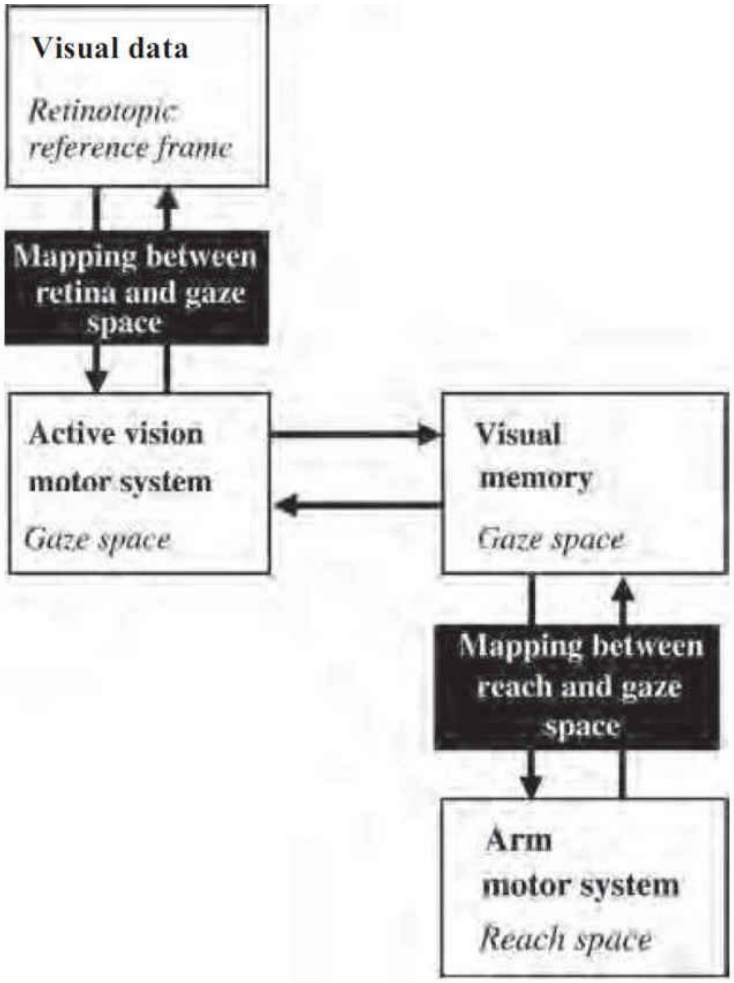
The Berthier model produces a number of important findings. First, the model captures the *speed-accuracy trade-off*: movements to smaller targets have longer durations than those to larger targets. Second, performance varies as a function of the magnitude of the Gaussian noise added to the movement signal. Interestingly, and perhaps counterintuitively, the model performs more accurately for *larger levels of noise*, than for smaller levels. Berthier, Rosenstein, and Barto (2005) interpret this result as supporting the idea that incorporating stochasticity into the motor signal promotes the exploratory process, and facilitates learning. Finally, the model also reproduces several important kinematic features of infants' reaches, including (1) the number of reaching "submovements," (2) the shape of the speed profile, and (3) the tendency for the largest speed peak to occur early in the movement (i.e., near reach onset; see Berthier and Keen 2005).

The models described thus far succeed in demonstrating that a core set of developmentally inspired principles are sufficient for learning to reach. There are a number of additional models that extend these findings by implementing the model within a physical robot, which develops the ability to reach in a manner that is analogous to the experience of human infants. An example of this approach is described by Lee and colleagues (e.g., Hulse *et al.* 2010; Law *et al.* 2011), who focus on the problem of coordinating visual input and arm postures and movements within a common spatial reference frame. Figure 5.4a illustrates the general architecture proposed to solve this problem. Visual data are acquired through a dual-camera input, which is then mapped from a retinotopic coordinate system to an active-vision gaze system (see figure 5.4b). At the same time, a second map coordinates sensory data from the arm with the gaze-space system. Thus, the gaze-space system not only provides a common reference frame for visual and proprioceptive (i.e., arm position) data, but also offers the means for either modality to direct the movement of the other, that is, to shift gaze toward the arm endpoint position, or alternatively, to move the arm toward the current gaze position.

An important feature of the model is the mechanism used to generate training data. In contrast to the strategies described earlier (e.g., motor babbling and Gaussian noise), the Lee model leverages *visual exploratory behavior* (i.e., scanning and search) as a source of visual activity, which not only serves to drive learning of the retina-gaze space mapping, but also provides a motivation for producing and improving reaching movements (i.e., reaching toward fixated objects). A series of analyses illustrates that the model quickly learns to coordinate vision and arm movements, and also to recalibrate the visuomotor mapping when one of the sensory inputs is shifted in space (e.g., the camera head is translated thirty centimeters; Hulse, McBride, and Lee 2010). The ability of the model to rapidly adjust to a shift in the camera position is particularly noteworthy, and may help explain how infants adapt their reaches while wearing displacing prisms (McDonnell and Abraham 1979).

Like the Lee model, Metta, Sandini, and Konczak (1999) propose a learning strategy that also relies on gaze position: once gaze is directed toward a visual target and the target is "foveated," the position of the eyes provides a proprioceptive cue that can be used to specify the location of the target in gaze space. The primary task of the Metta model, then, is to learn the mapping that coordinates the position of the eyes with movement of the arm to the fixated location. To accomplish this, the model relies on the *asymmetric tonic neck reflex* (ATNR). Sometimes referred to as the "fencer's pose," the ATNR is a synergistic movement of the infants' head and arm: when a young infant turns his or her head to the side, the arm on the corresponding side is raised and straightened. The Metta model exploits this mechanism in a four-DOF robotic platform, by directing gaze to the hand once it enters the visual field (i.e., "hand regard"). Thus, when the hand is fixated, the model quickly learns to calibrate the sensory maps that link eye and arm positions. Indeed, Metta, Sandini, and Konczak (ibid.) demonstrate that after roughly five minutes of experience with hand-eye movement, the robot is able to accurately move its arm to a visually fixated location. A limitation of this method, however, is that the model does not reach accurately to locations that are infrequently (or never) "visited" by the hand. Natale *et al.* (2007; see also Nori *et al.* 2007) addressed this problem, while also extending the robot platform to a twenty-two-DOF humanoid upper torso, by employing a motor babbling strategy that drives the hand to a wider range of locations. After calibrating the hand-eye map, the robot is then able to reach to both familiar and novel locations.

a



Visual data
Retinotopic reference frame
Mapping between retina and gaze space
Active vision motor system
Gaze space
Visual memory
Gaze space
Mapping between reach and gaze space
Arm motor system
Reach space

b

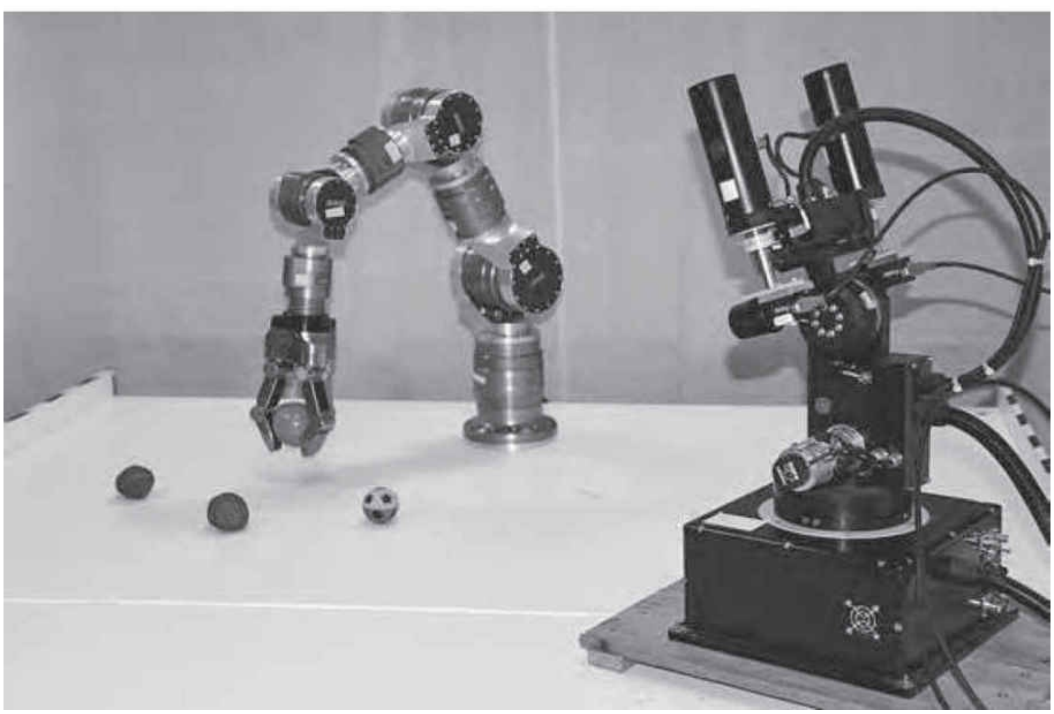


Figure 5.4

Diagram of the Hulse *et al.* (2010) architecture (a), and the active-vision and robot arm system (b). Reprinted with permission from IEEE.

As we noted at the beginning of the chapter, the iCub robot is an ideal platform for simulating the development of reaching in infants (e.g., Metta *et al.* 2010; see figure 5.5a). Indeed, a number of researchers have begun to use the platform as a tool for studying motor-skill learning, and in particular, to design and test models of reaching. However, not all of this work fits within the developmental robotics perspective; some studies, for example, are intended to address more general questions that span cognitive/humanoid robotics and machine learning, such as computational strategies for dynamic motion control (e.g., Mohan *et al.* 2009; Pattacini *et al.* 2010; Reinhart and Steil 2009).

An example of recent work on the iCub that explicitly adopts the developmental robotic perspective is the model proposed by Savastano and Nolfi (2012), who simulate the development of reaching in a fourteen-DOF simulation of the iCub. As figure 5.5a illustrates, the iCub is trained and tested in a manner that corresponds to the method used by von Hofsten (1984; see figure 1), in which the infant is supported in an upright position while a nearby object is presented within reach. Like Schlesinger, Parisi, and Langer (2000), the Savastano model uses a GA to train the connection weights in a neural network that controls body, head, and arm movements (figure 5.5b; solid lines denote pretrained, fixed connections, in other words, orienting and grasping "reflexes," while dashed lines indicate modifiable connections). Two unique features of the model are (1) that it is initially trained with low-acuity visual input, which gradually improves over time; and (2) a secondary pathway (i.e., "internal" neurons)—representing cortical control of movement—remains inactive until the midpoint of training. Several major results are reported. First, while the model is designed to generate prereaching movements, as visual acuity improves, the percentage of these movements declines, replicating the developmental pattern reported by von Hofsten (1984) and others. Second, with experience, reaches also become progressively straighter (e.g., Berthier and Keen 2006). Finally, and perhaps most interesting, if the limitations on acuity and the secondary pathway are lifted at the start of training, overall reaching performance is lower in the model. This provides further support for the idea that early constraints on motor-skill development can facilitate long-term performance levels (e.g., Schlesinger, Parisi and Langer 2000).

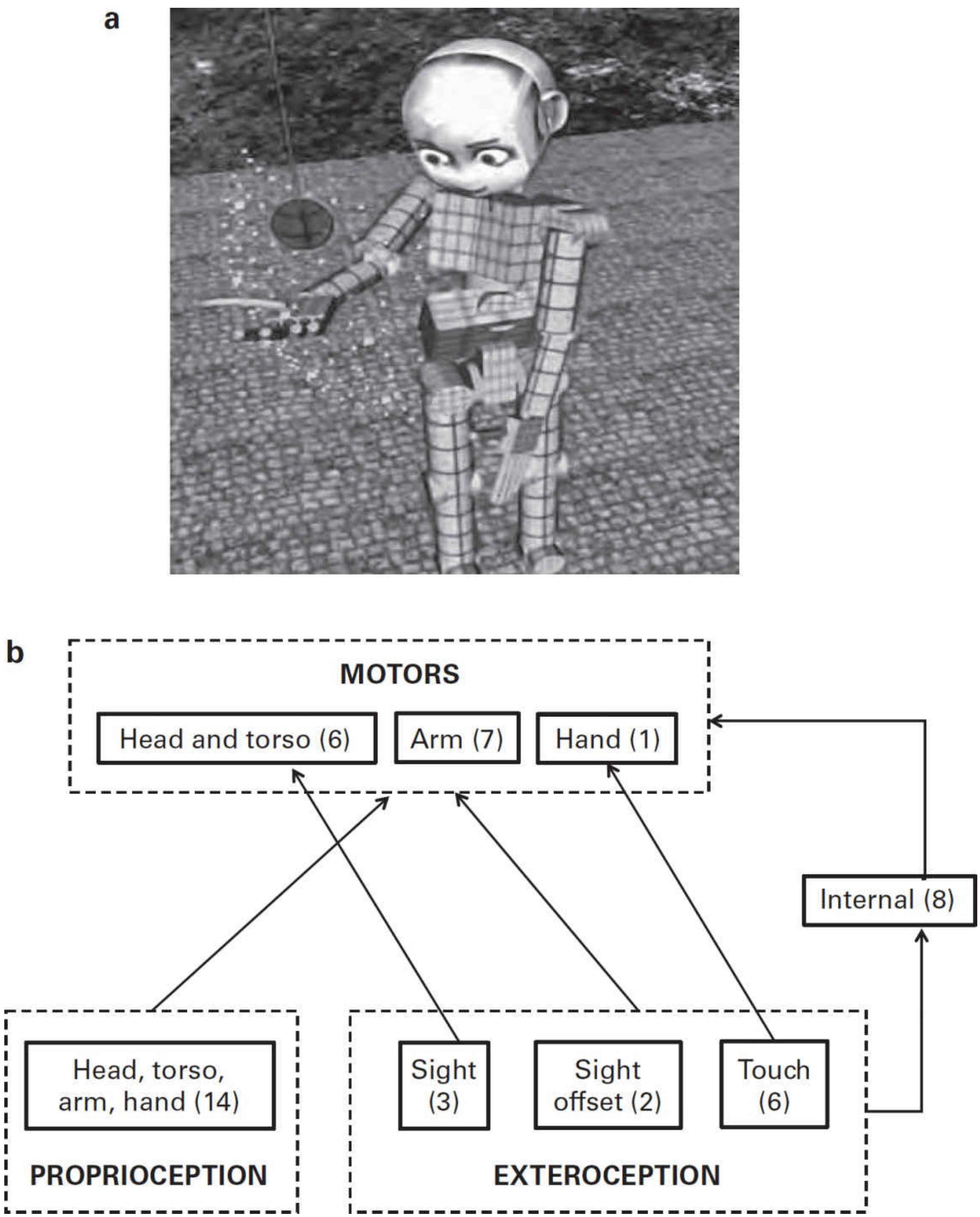

a
b
MOTORS
Head and torso (6)
Arm (7)
Hand (1)
Internal (8)
Head, torso, arm, hand (14)
PROPRIOCEPTION
Sight (3)
Sight offset (2)
Touch (6)
EXTEROCEPTION

Figure 5.5

The iCub robot simulator (a) and the neurorobotic controller (b) investigated by Savastano and Nolfi (2012). Figures courtesy of Stefano Nolfi.

5.3 Grasping Robots

As we noted in section 5.1.2, reaching and grasping are skills that overlap in both developmental and real time. In addition, grasping can also be characterized as “reaching with the fingers” to specific locations on the target object (e.g., Smeets and Brenner 1999). It is therefore not surprising that some of the same ideas used to study reaching are also exploited in models of grasping. An example of this is the model proposed by Caligiore *et al.* (2008) that we noted in the previous section, which examines the utility of motor babbling as a developmental mechanism for learning to reach around obstacles. In a similar vein, Caligiore *et al.* (ibid.) propose that motor babbling can also provide a bootstrap for learning to grasp. In particular, they use the iCub simulator to study a dynamic reaching model robot, which develops the ability to grasp in the following way: (1) either a small or large object is placed in the iCub’s hand; (2) the preprogrammed grasping reflex causes the hand to perform an “involuntary” palmar grasp (see figure 5.2); (3) a motor-babbling module drives the arm to a random posture; and once the posture is achieved, (4) the iCub fixates the object. As figure 5.6a illustrates, position and shape information from the target are propagated through two parallel networks, which associate the corresponding sensory inputs with proprioceptive inputs from the arm and hand (i.e., arm posture and grasp configurations, respectively). Through Hebbian learning, the model is then able to drive the arm to the seen location of an object, and “re-establish” the grasp configuration. Figure 5.6b illustrates the performance of the model after training; the ends of the reaching movements are presented for the small (left) and large (right) objects, placed at twelve locations in the workspace. Thin lines represent successful reaches, while thick lines represent successful reaches and grasps. Caligiore *et al.* (2008) note that the overall grasp success of the model is relatively low (2.8 percent and 11.1 percent for the small and large objects, respectively), which is due in part to the comparatively basic mechanisms used to drive learning. Nevertheless, the fact that the model is more successful at grasping the large object is consistent with the developmental pattern that the power grasp (i.e., voluntary palmar grasp) emerges before the precision grasp (Erhardt 1994).

A related approach is proposed by Natale, Metta, and Sandini (2005a), who use the Babybot platform to study reaching and grasping (see figure 5.7a). Comparable to the strategy used by Natale *et al.* (2007), the Babybot first learns to fixate its hand, which is driven to a range of locations through motor babbling. Once a variety of arm postures are associated with gaze positions, the Babybot then learns to grasp seen objects. Figure 5.7b illustrates the process: (1) an object is placed in Babybot's hand, and a preprogrammed palmar grasp is executed (images 1–2); (2) the object is brought to the center of the visual field (image 3); (3) the object is returned to the workspace, and the Babybot uses a preprogrammed object-recognition module to search for it (images 4–6); and (4) once localized, the previously acquired reaching behavior is used to guide the hand toward the object and grasp it (images 7–9). While the grasping behavior described by Natale, Metta, and Sandini (2005a) is not systematically evaluated —and like Caligiore *et al.* (2008), the skill represents a relatively early stage of grasping development—the model makes an important contribution by illustrating how the components that are exploited or developed while learning to reach (e.g., motor babbling, visual search, etc.) also provide a foundation for learning to grasp.

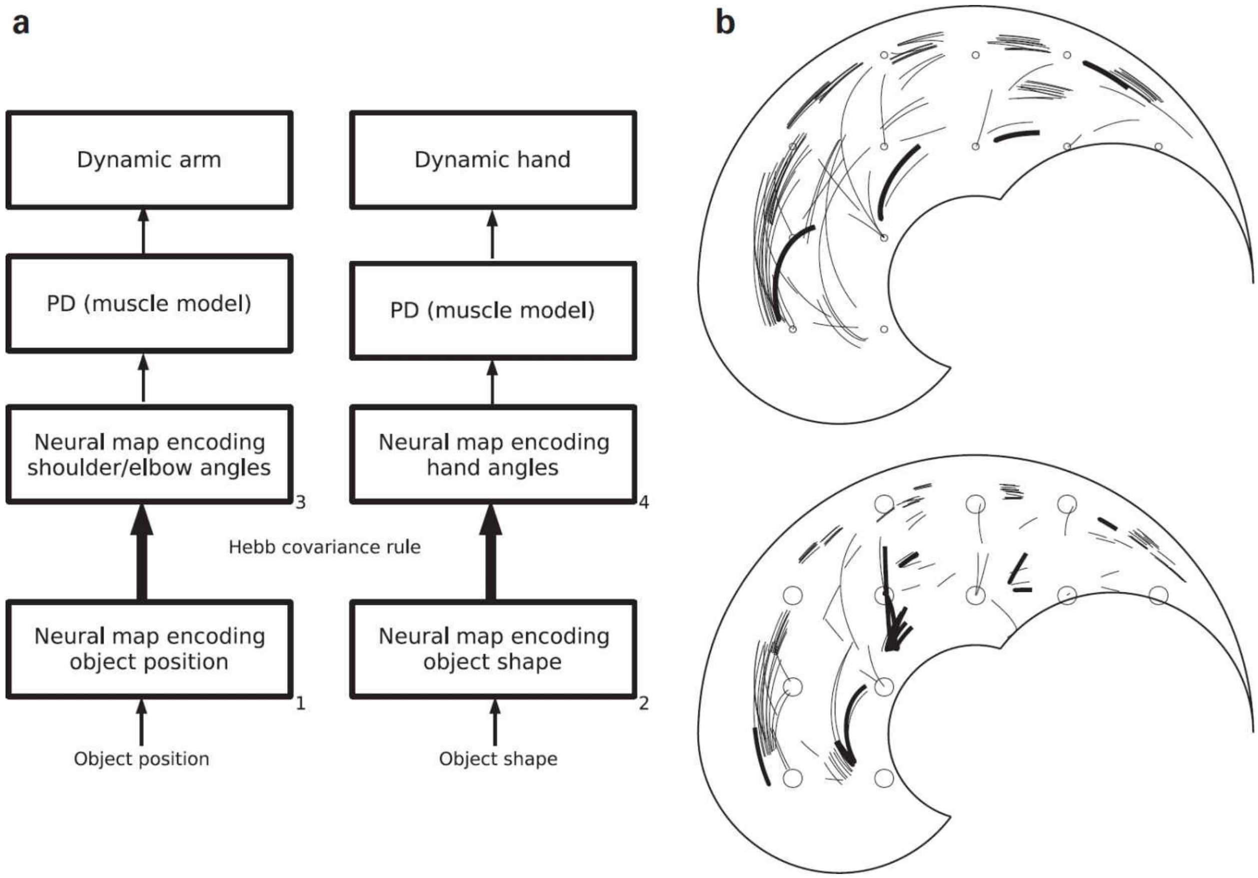
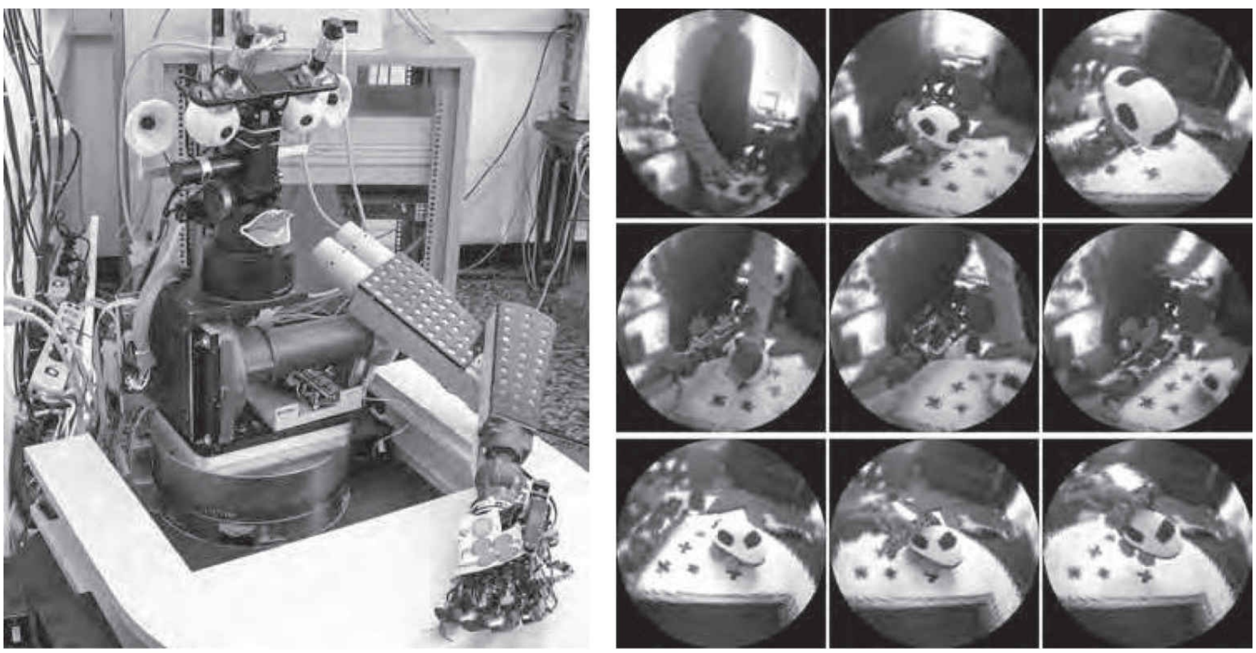


Figure 5.6

Diagram of the model architecture investigated by Caligiore *et al.* (2008) (a), and grasping performance of the model (left = small object, right = large object) (b). Figures courtesy of Daniele Caligiore.

While the Caligiore and Natale models capture the early emergence of grasping behavior, Oztop, Bradley, and Arbib (2004) describe a model that develops a comparatively large repertoire of grasp configurations. Figure 5.8a illustrates the seventeen-DOF arm/hand platform, as well as examples of both power grips (top panel) and precision grips (middle and bottom panels) that are produced by the model after training. During training, the model is presented with input information specifying the location and orientation of the target object, which propagates to a layer that activates a corresponding arm and hand configuration; this layer then drives movement of the arm and hand toward the object, resulting in a reach and grasp. A reinforcement-learning (RL) algorithm then updates connections in the model between the input, arm/hand configuration, and movement layers. Figure 5.8b presents the results of an experiment that replicates Lockman, Ashmead, and Bushnell (1984), in which five-and nine-month-olds reached for an oriented cylinder. The first panel presents the data from the human study, which found that during the reaching movement, nine-month-olds (dotted line) were more successful at orienting their hand correctly toward the vertical dowel than five-month-olds (solid line). Oztop, Bradley, and Arbib (2004) hypothesized that young infants were less successful due to poor use of the visual information provided by the object. They then simulated five-month-olds by providing the model with only target location information, while nine-month-olds were simulated by providing both location and orientation information. In figure 5.8b, the second panel presents the simulation data, which corresponded to the pattern observed in human infants and provided support for Oztop, Bradley, and Arbib's (ibid.) hypothesis.



a b

Figure 5.7

The Babybot robot designed by Natale, Metta, and Sandini (2005). View of a grasping sequence (a) recorded from the Babybot's left camera (b). Figures courtesy of Lorenzo Natale.

As we described in box 5.1, a relatively advanced form of grasping behavior involves reaching for an object that is then manipulated, such as an applesauce-loaded spoon. In box 5.2, we present the Wheeler, Fagg, and Grupen (2002) version of the “applesauce task,” in which a humanoid robot learns to reach for, grasp, and place a tool-like object in a container.

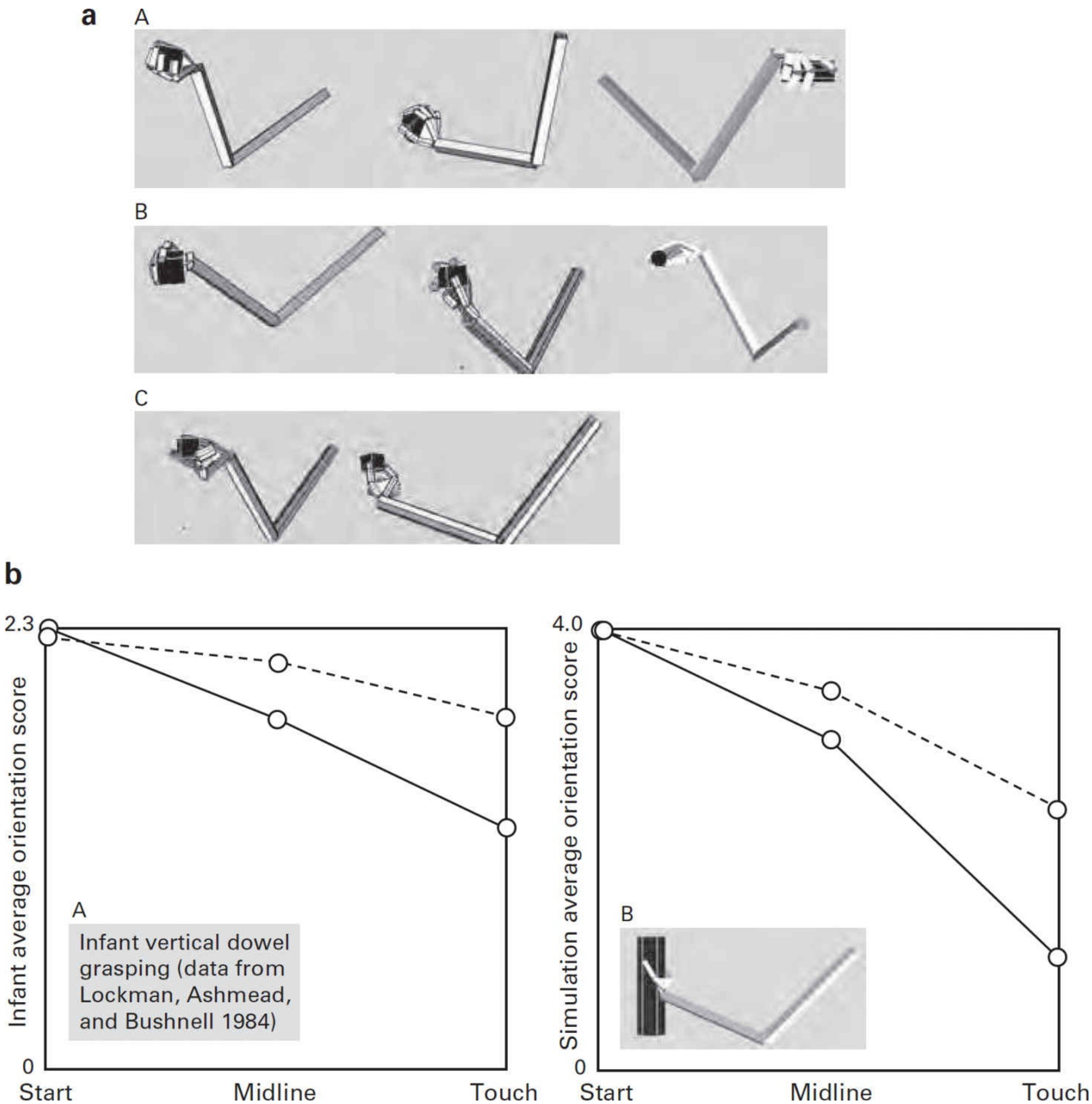


Figure 5.8

Diagram of the model architecture investigated by Oztop, Bradley, and Arbib (2004) (a), and grasping performance of the model (left = small object, right = large object) (b). Reprinted with permission from Springer.

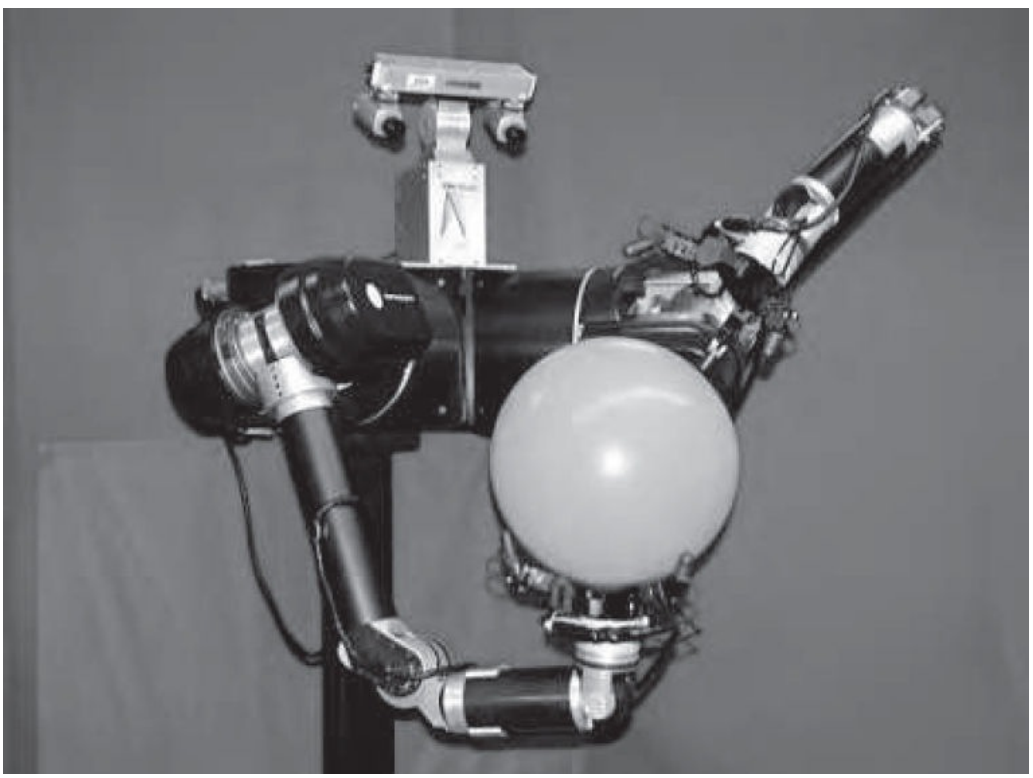
Box 5.2

Prospective Grasp Control: The “Pick-and-Place” Robot

Overview

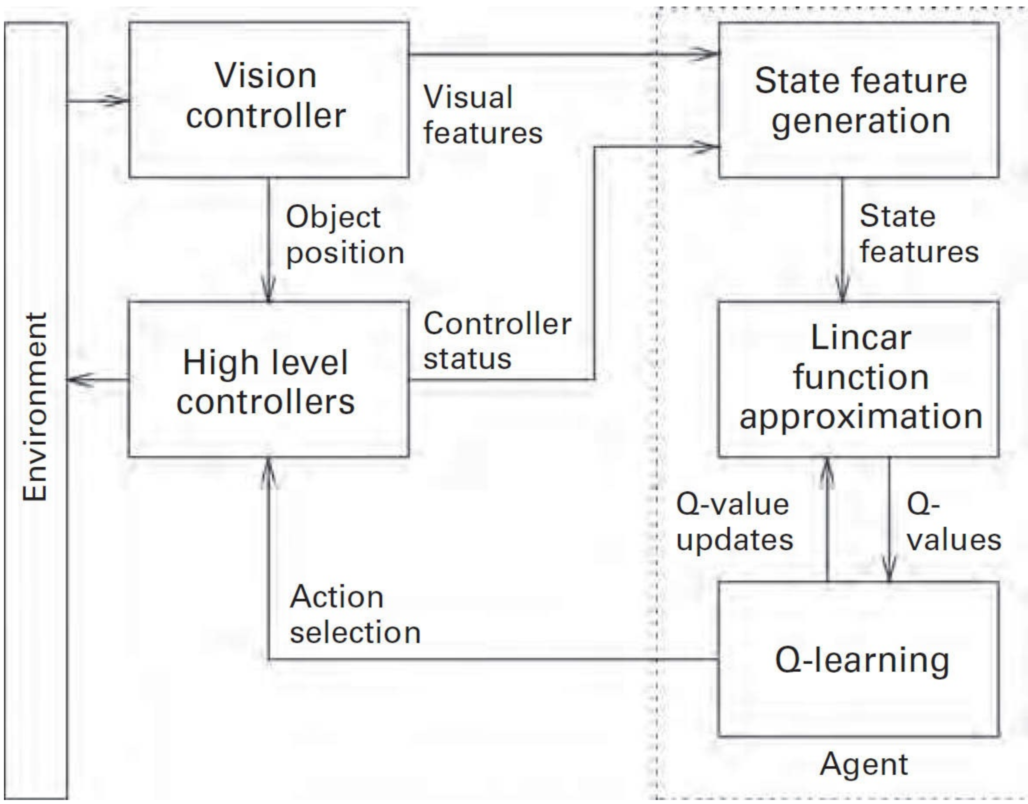
The McCarty, Clifton, and Collard (1999) "applesauce" study not only highlights how reaching and grasping can be used to index the development of planning and prospective action, but it also demonstrates how this capacity develops during infancy. There are a number of important questions raised by this work, including: what is the developmental mechanism that promotes the shift toward flexible use of the grasping hand? What kinds of experiences are part of this shift, and how does the development of a hand preference influence the process?

In order to address these questions, Wheeler, Fagg, and Grupen (2002) designed an upper-torso robot with two arms and a binocular vision system ("Dexter," figure below). Analogous to the applesauce study, Dexter is presented with a pick-and-place task in which an object (mounted to a handle) must be grasped and placed in a receptacle. Like the spoon, the object can be grasped at either end; only grasping the handle, however, permits insertion in the receptacle. With this paradigm, Wheeler, Fagg, and Grupen (ibid.) investigated whether learning by trial and error would produce a learning trajectory that mirrored the developmental pattern in infants. In addition, they also systematically manipulated a side bias in Dexter, in order to study the effects of hand preference.



Procedure

The figure below illustrates the cognitive architecture designed and studied by Wheeler, Fagg, and Grupen (2002). A set of high level controllers are built in, which select from six basic actions: (1/2) grasp with left or right hand, respectively, (3/4) swap from left to right hand, or vice versa, (5/6) insert the object held in the left or right hand, respectively, into the receptacle. A precoded feature generator encodes Dexter's current state, which is used to generate an action. Exploration is achieved through occasional selection of random actions (i.e., ε-greedy). Successful insertion of the object in the receptacle results in a reward of 1, while failed trials result in a 0. In order to simulate the development of a hand preference, Dexter was first pretrained for 400 trials with the object oriented in the same direction. For the remaining 600 trials, the object was then oriented randomly across trials.

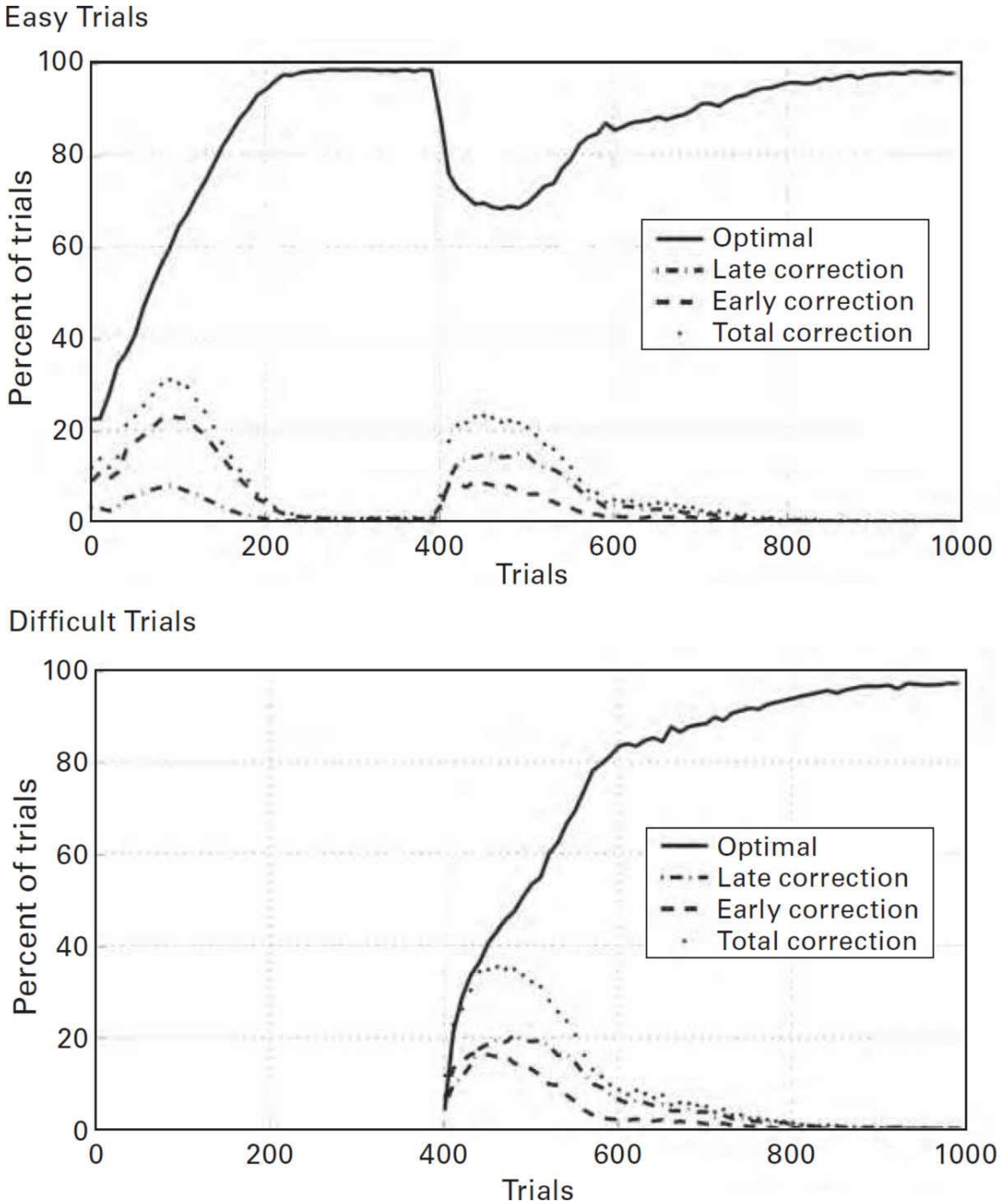


Results

As in the infant study, easy and difficult trials were analyzed separately. Easy trials were those in which the object was oriented in the same direction as pretraining trials, while difficult trials were in the opposite direction. The solid curve in the chart below presents the proportion of optimal trials, that is, in which Dexter grasped the handle with the arm that was on the same side as the handle. The upper panel illustrates that Dexter reached near-optimal performance during the pretraining phase, but when orientation of the object varied across trials (starting at 400 trials), performance rapidly dropped, before slowly approaching optimality again.

Interestingly, this finding mirrors the result observed with infants that even when the spoon is oriented in the direction that favors the dominant hand, infants occasionally reach with the nondominant hand, which is a suboptimal solution. In the case of the Wheeler, Fagg, and Grupen

(2002) model, this behavior is the result of the exploration policy, which enables Dexter to learn how to respond to difficult trials, by reaching with the nondominant hand. As the figure below illustrates, total corrections (i.e., the analog of ulnar and goal-end grips) initially increases for both easy and difficult trials (upper and lower figures, respectively), but then gradually declines as Dexter learns to use the handle orientation as a visual cue for selecting the appropriate arm to use.



5.4 Crawling Robots

As we noted in section 5.1.4, CPGs play a fundamental role in both the theories and computational models of locomotion (e.g., Arena 2000; Ijspeert 2008; Wu *et al.* 2009). Indeed, all of the models that we describe in this section leverage the CPG mechanism as a core element. As an example, figure 5.9a illustrates the CPG model of locomotion proposed by Kuniyoshi and Sangawa (2006). Their model represents the CGP as a neuron in the medulla (within the brainstem) that generates an oscillatory signal; its output stimulates the activity of muscle spindles, which produce body movements. At the same time, spinal afferent signals (S0) travel to the primary somatosensory area (S1), which produces activity in the primary motor area (M1). The sensorimotor loop is closed by connections from M1 back to the CPG, which allow patterned activity from M1 to modulate the output of the CPG. Figure 5.9b is a snapshot of a simulated infant with 19 joint segments and 198 muscles that is controlled by a pair of circuits like the one illustrated in figure 5.9a (i.e., one circuit for the left and right hemispheres/body sides). Two important results emerge from the model. First, the simulated infant often produces "disorganized" movements, which may provide an adaptive exploratory function (i.e., spontaneous motor babbling). Second, coherent, synergistic movements also occur: for example, at the start of the illustrated sequence, the infant rolls from face up to face down. In addition, after rolling over, the infant generates a crawling-like behavior. It is important to note that these coordinated behaviors are not preprogrammed, but are instead the result of linkages and synchronous oscillations between the CPGs that briefly occur.

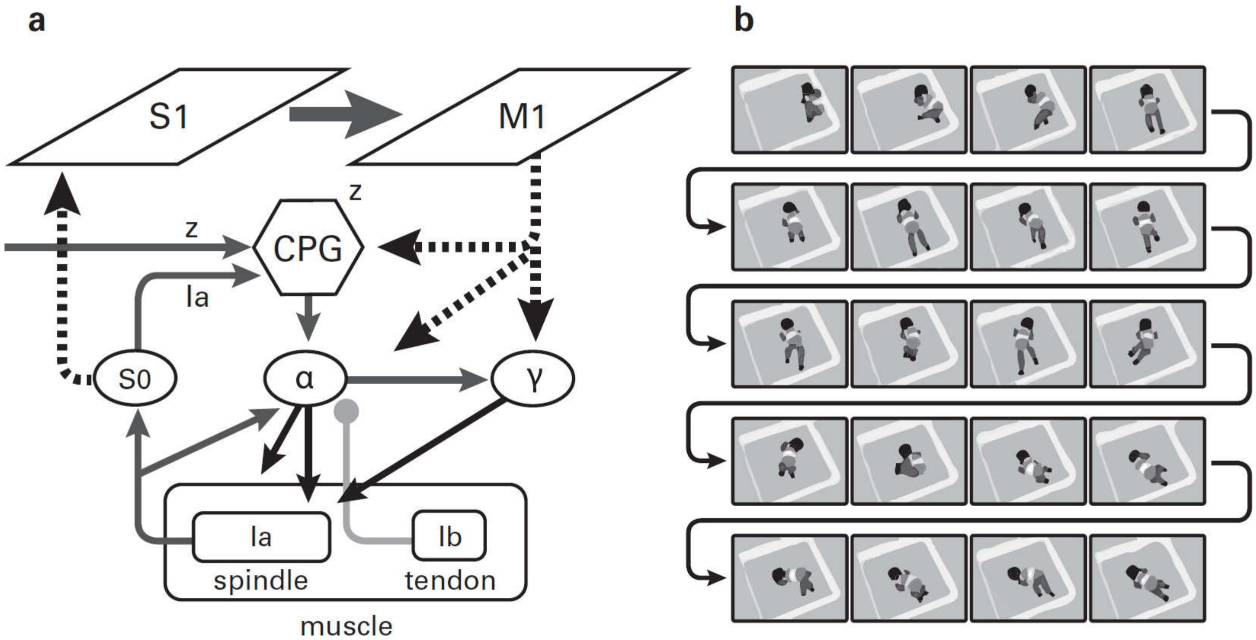


Figure 5.9

Diagram of the CPG-circuit proposed by Kuniyoshi and Sangawa (2006) (a), and crawling behavior of the simulated infant (b). Figures courtesy of Professor Yasuo Kuniyoshi, University of Tokyo. Reprinted with permission from Springer.

While the model proposed by Righetti and Ijspeert (2006a, 2006b) also focuses on CPGs, they employ a unique approach by first gathering kinematic data from human infants, which they use to inform and constrain their model. In particular, a motion capture system is used to identify and record the positions of infants' limbs and joints while crawling. A key finding from these kinematic analyses is that skilled infant crawlers produce a "trot-like" gait, in which the diagonally opposed leg and arm move in phase, while moving a half period out of phase with the opposite pair of limbs (i.e., confirming the diagonal-alternation pattern we described in section 5.1.3). However, a key difference between the trot-like gait of infant crawlers and a classic trot is that infants spend 70 percent of the movement cycle in the stance phase. In order to capture this temporal asymmetry in the stance and swing phases, Righetti and Ijspeert (2006a) model the CPGs as spring-like oscillatory systems that switch between two stiffness parameters as a function of the phase (i.e., direction of oscillation). Figure 5.10a presents a comparison of the trajectories of the shoulder and hip joints (i.e., arm and leg, respectively) of the infants (solid line) and the corresponding oscillations produced by the model (dashed line). In addition, Righetti and Ijspeert (ibid.) also evaluate the model by using it to control the crawling behavior of a simulated iCub robot. As figure 5.10b illustrates, the crawling pattern produced by the robot (figure 5.10b, lower panel) corresponds to the gait pattern produced by a human infant (figure 5.10b, upper panel). Subsequent work on the iCub platform has provided a number of important advances, including the ability to combine periodic crawling movement with shorter, ballistic actions, such as reach-like hand movements (e.g., Degallier, Righetti, and Ijspeert 2007; Degallier *et al.* 2008).

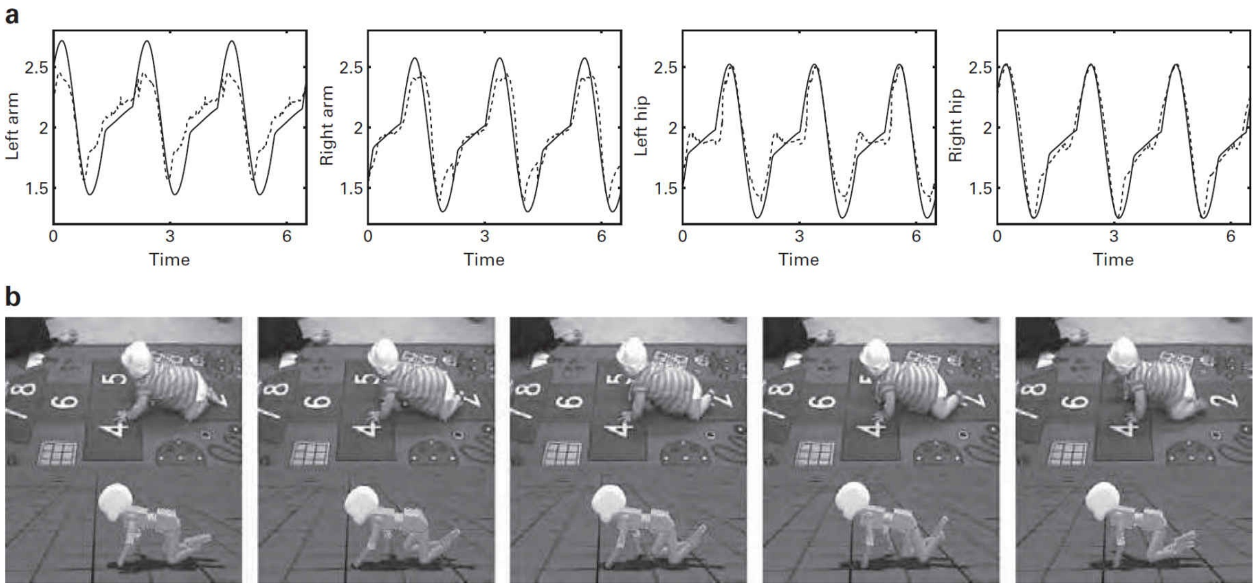


Figure 5.10

Observed shoulder and hip trajectories in a crawling human infant (solid line) and the corresponding trajectories produced by Righetti and Ijspeert's (2006) crawling model (dashed line) (a), and crawling examples in a human infant and the simulated iCub robot (b). Figures courtesy of Ludovic Righetti.

In addition to work on the iCub, another humanoid robot platform that has been used to study crawling development is the NAO (see chapter 2). Li *et al.* (Li *et al.* 2011; Li, Lowe, and Ziemke 2013) raise an important challenge: they argue that a successful model of locomotion should be general and robust enough that it can be "ported" from one platform to another with minimal modification. In order to test this proposal, they implement the CPG architecture designed by Righetti for the iCub platform (e.g., Righetti and Ijspeert 2006a) on the NAO. However, as Li *et al.* (2011) note, a key difference between the two platforms is that NAO has larger feet. In order to address this issue, the legs are spread wider apart (than in the iCub) to assist with forward movement. Figure 5.11a illustrates the four-cell CPG architecture, which includes inhibitory connections between limb pairs and excitatory connections across "diagonal" limbs (e.g., right arm and left leg); the inhibitory connections enforce a half-period phase shift between limbs, while the excitatory connections produce in-phase movements of the corresponding limbs. As expected, crawling successfully generalizes to the NAO platform. Figure 5.11b provides an illustration of crawling behavior on the NAO robot, which resembles the pattern produced by iCub (see figure 5.10b). In order to provide further support for the idea that the same underlying CPG mechanism can produce multiple forms of locomotion, Li, Lowe, and Ziemke (2013) have recently extended their model with a six-cell CPG architecture that produces an early form of upright, bipedal walking behavior.

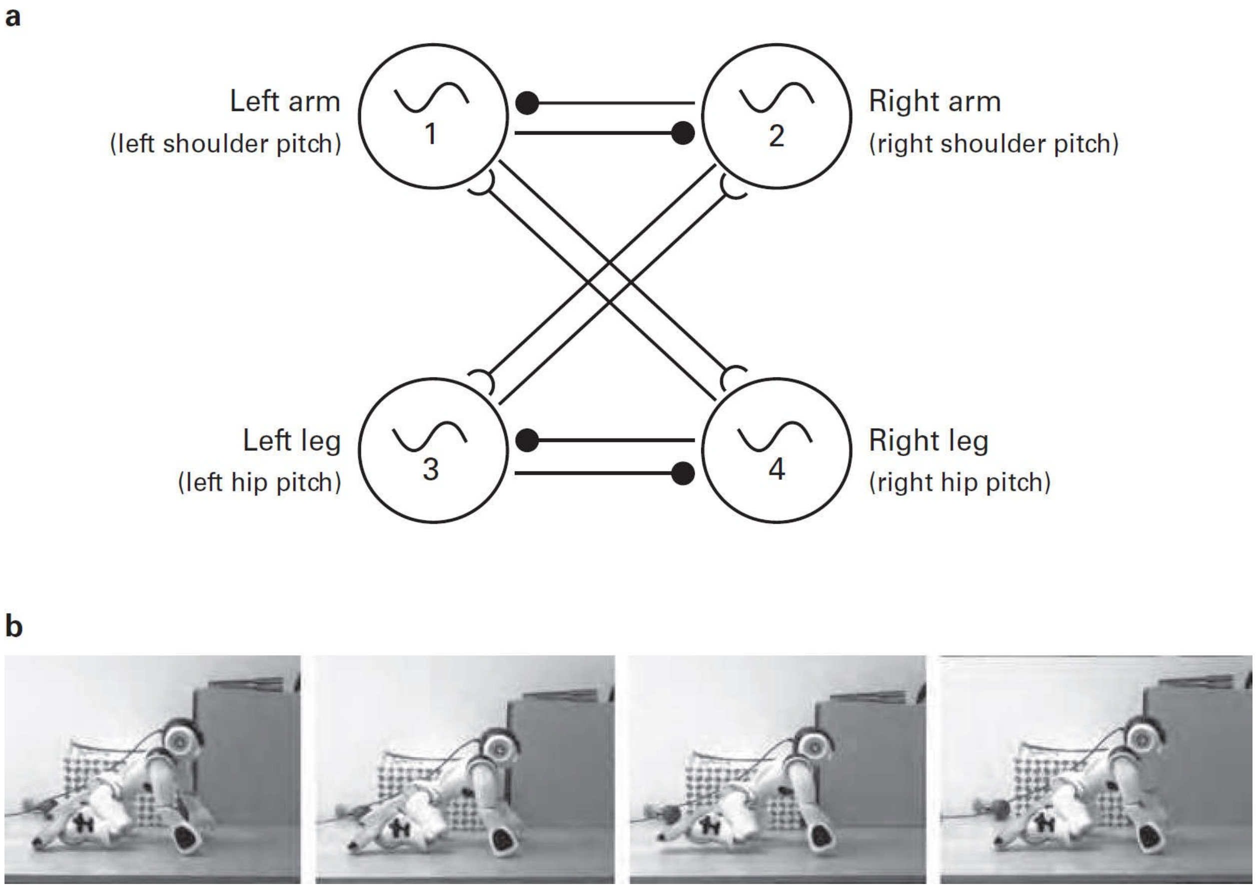


Figure 5.11

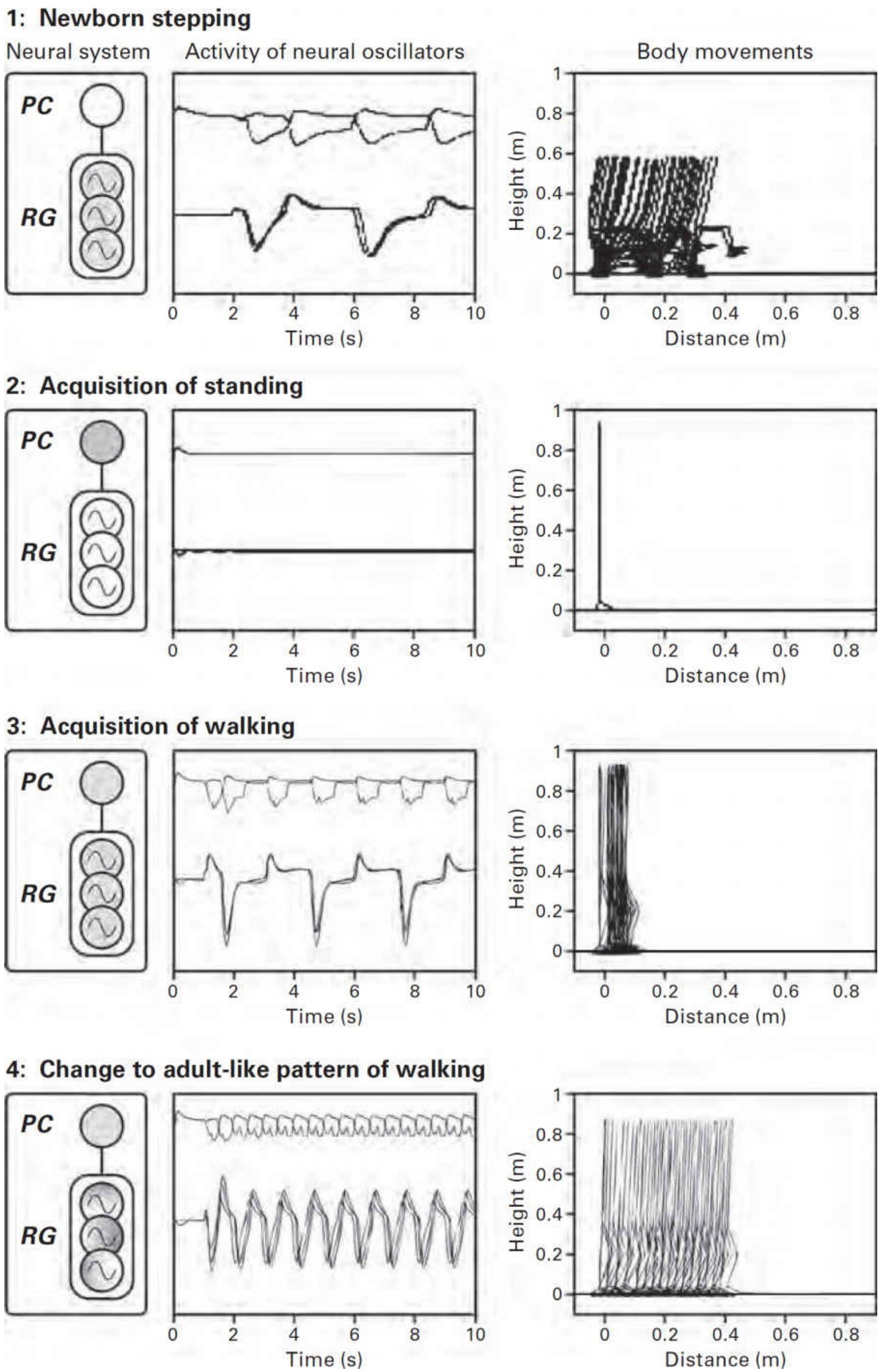
CPG architecture employed by Li *et al.* (Li *et al.* 2011; Li, Lowe, and Ziemke 2013) to produce crawling (a), and an illustration of crawling behavior on the NAO robot platform (b). Figures courtesy of Li Cai.

5.4 Walking Robots

While developmental robotics researchers have not yet captured the complete transition from crawling to independent walking, there are several models of walking that have provided insight into how this process occurs. As we noted earlier in the chapter, one mechanism that may play a crucial role is successive changes in the joint or neuromuscular DOFs that are utilized during body movement. In particular, Taga (2006) proposes a CPG model in which various components of the system are systematically fixed or released (i.e., freezing and freeing of DOFs). Figure 5.12 illustrates the model: PC represents the posture-control system, and RG is the rhythm generator, which produces periodic signals. In neonates, the PC system is nonfunctional, while the oscillators in the RG are linked via excitatory connections. At this stage, the system produces reflex-like stepping movements when the simulated infant is supported in an upright position. Subsequent developments (e.g., standing, independent walking, etc.) are accounted for in the model through a process of tuning excitatory and inhibitory connections within the RG and between the RG and PC.

Lu *et al.* (2012) describe a model that focuses specifically on supported walking. In particular, a wheeled platform is designed for the iCub robot, which provides both upper-body trunk support and balance. An interesting constraint imposed by the “walker” is that because it is rigidly attached to the iCub, the robot cannot move in the vertical dimension. In other words, while walking, iCub must find a movement strategy that keeps the waist and upper body at a fixed height from the ground. The solution proposed to solve this problem is the “bent-leg” gait, in which iCub keeps both of its knees bent while stepping. A series of tests of the bent-leg gait in the iCub simulator compared a range of heights for the walker, resulting in a stable solution where the maximum bend in iCub’s legs is approximately 45 degrees. Lu *et al.* (ibid.) conclude by demonstrating that the solution acquired in simulation successfully transfers to the real robot platform.

Hase and Yamazaki (1998) take a similar approach, but also implement a unique feature: rather than representing the supporting forces as a rigid body that holds the infant at a fixed height, they instead model support as a set of tuneable forces. Figure 5.13a presents a diagram of the simulated infant, which has the physical properties (i.e., size and muscle capacity) of a twelve-month-old. As the figure illustrates, supporting forces are modeled as spring-damper systems that operate on the shoulder and hip joints and that apply upward force to the corresponding joint when it falls below a height threshold (i.e., the restoring force is graded). Movement of the model is controlled by a CPG architecture, and the major system parameters are tuned by a GA with the goal of optimizing four performance measures: (1) minimal use of supporting forces, (2) target step length (i.e., 22 cm, as determined by empirical measure), (3) minimal energy use, and (4) minimal muscle stress (or fatigue). Figure 5.13b presents the findings from the simulated model. Between 0 and 5,000 search steps (i.e., simulated developmental time), the infant relies on supported walking (dark line), while consuming low energy levels (thin line) and generating minimal muscle stress (dashed line). Between 5,000 and 10,000 search steps, however, the transition to independent walking begins, and by 10,000 steps the infant can walk without external support. In particular, it is interesting to note that independent walking comes at a price: energy and fatigue levels initially rise at the onset of independent walking, but then continue to decline afterward.



1: Newborn stepping
Neural system
Activity of neural oscillators
Body movements
PC
RG
Time (s)
Height (m)
Distance (m)
2: Acquisition of standing
3: Acquisition of walking
4: Change to adult-like pattern of walking

Figure 5.12

The CPG model proposed by Taga (2006) to account for stages of walking by freezing and freeing DOFs.

We conclude this section by returning to a skill that we briefly described in section 5.1.4, that is, bouncing, which involves coordination of the same joints and muscles as those recruited for crawling and walking, but in a qualitatively different pattern. Because bouncing is a rhythmic behavior, like crawling and walking it can also be captured and described mathematically with CPGs. Lungarella and Berthouze (2003, 2004) investigate the bouncing behavior produced by a twelve-DOF humanoid robot that is suspended in a harness with springs (see figure 5.14a). Like other models of locomotion, Lungarella and Berthouze also use a network of CPGs to control the motor activity of the robot, which produces kicking movements (i.e., flexions and extensions of the knee joint). Figure 5.14b illustrates the system in which the CPG network is embedded, which includes sensory input, motor activity, as well as interaction with the skeletomuscular system and the external environment (i.e., ground and harness-spring system). An important finding from the model results from a comparison of bouncing with versus bouncing without sensory feedback: with feedback, the robot is more successful at maintaining a stable bouncing regime than without feedback. Thus, sensory feedback is used by the model to modulate the output of the CPG network, resulting in a self-sustaining limit-cycle pattern. It is important to note, however, that this result depends on hand-tuning of the model. As figure 5.14b suggests, a motivational or value system can be implemented within the model that drives exploration of the parameter space and selects parameter configurations that produce “desirable” patterns (e.g., stable bouncing, maximal bounce height, etc.).

5.5 Conclusions

We began the chapter by proposing that manipulation and locomotion are two fundamental skills that develop in early infancy. They are essential because they provide the means for probing, exploring, and interacting with both the physical and social world, and they therefore create a “motor” that drives not only physical, but also perceptual, cognitive, social, and linguistic development. While our brief survey of motor-skill development in human infants focused on reaching, grasping, crawling, and walking, we also noted there are a number of additional motor skills—some that are necessary for survival and appear universally, and others that are not survival-related and vary widely across cultures and historical time periods—which have not yet been modeled or studied from the developmental robotic perspective. We suspect that as the state of the art continues to improve, and the field moves toward a more domain-general approach (e.g., Weng *et al.* 2001), researchers will seek to capture a wider spectrum of motor-skill development in their models.

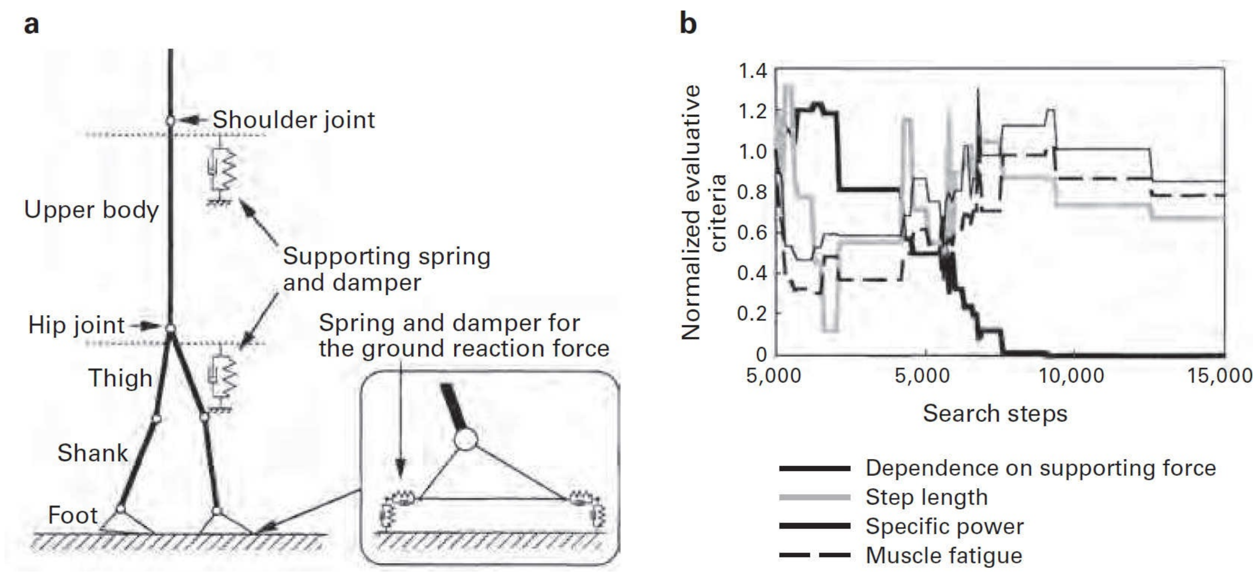


Figure 5.13

Simulated twelve-month-old studied by Hase and Yamazaki (1998) (a), and performance of the model during training (b). Figures reprinted with permission of The Anthropological Society of Nippon.

The review of reaching and grasping in infants identified a number of important themes, some of which have been incorporated into computational models of development. First, both skills initially appear as simple, reflex-like behaviors, and eventually become transformed into volitional actions that are adapted to the ongoing goals of the infant. A unique aspect of reaching development is that its initial form (i.e., prereaching) first declines in frequency, and subsequently reemerges as an intentional or goal-directed behavior. Second, both reaching and grasping demonstrate a developmental trend toward *differentiation*: early behaviors are somewhat ballistic, open-loop behaviors that once triggered, unfold in a stereotyped fashion. In contrast, more mature reaching and grasping movements are flexible and varied as a function of the task constraints (e.g., location and size of the target object). Figure 5.2, which illustrates the changes in infants' grasping ability from ages six to twelve months, provides a clear example of this pattern. A third and related aspect is not only an increasing use of visual information during reaching and grasping, but also the use of closed-loop movement strategies, in which flexible adjustments or corrective movements are produced in the face of changing task demands.

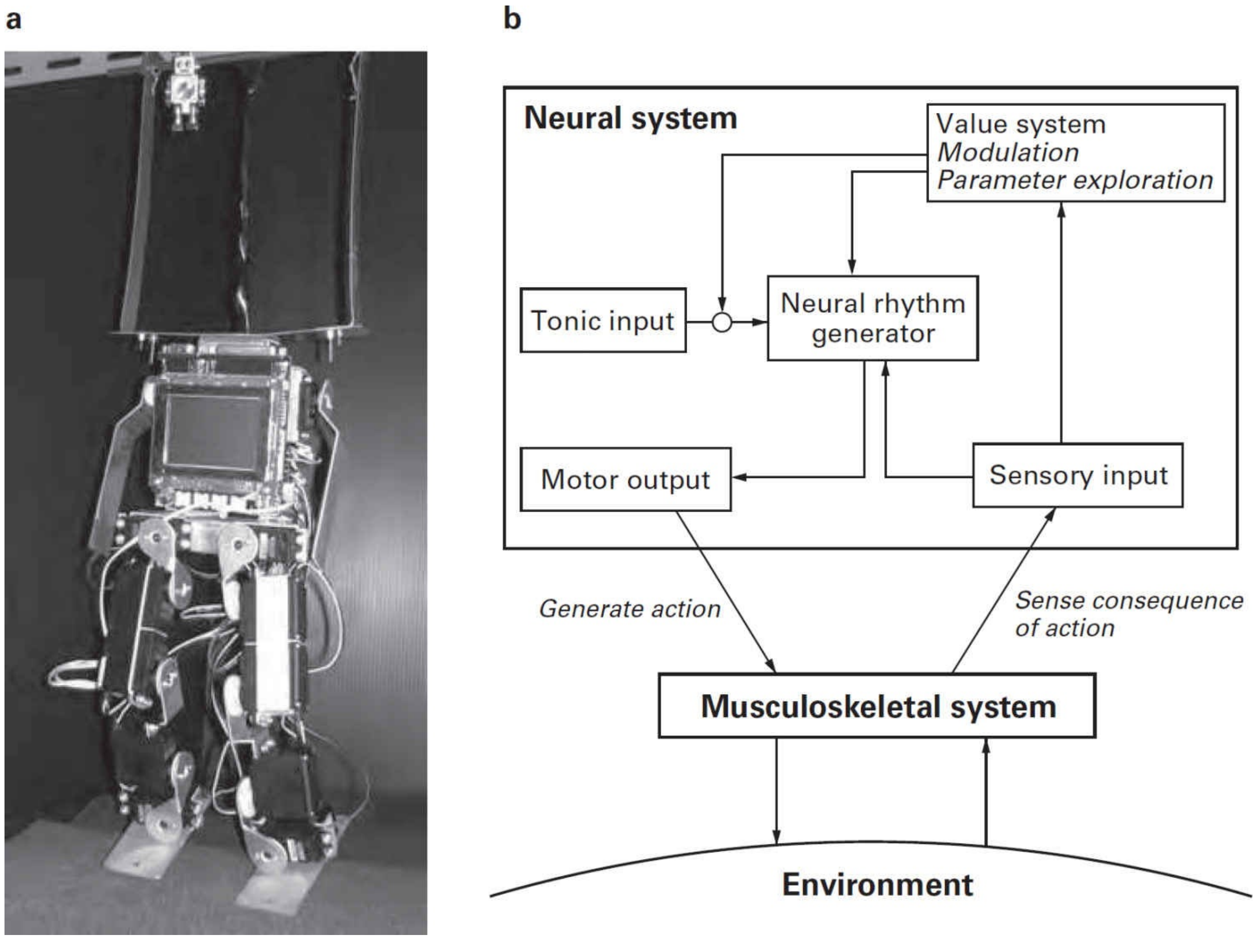


Figure 5.14

The “bouncing” robot designed by Lungarella and Berthouze (2004) (a), and the neural controller used to produce bouncing behavior (b). Figures courtesy of Luc Berthouse.

We also described the development of crawling and walking, the two earliest forms of locomotion. Like manipulation, self-produced locomotion also has long-ranging consequences for development. For example, in chapter 4 we discussed how the emergence of crawling transforms infants’ perception and experience of space (i.e., the onset of the fear of heights on the visual cliff). An important theme in the development of crawling is the idea of posture control as a rate-limiting factor. In particular, infants must first gain the strength and coordination necessary to produce the component actions (e.g., lift and support the head, alternate leg and arm movements) before they begin to crawl. In addition, we noted that infants explore a diverse range of movement patterns, such as creeping and rotating, before the canonical form of hands-and-knees crawling appears. Within two months of crawling, infants then quickly transition to pulling themselves upright, and using stable surfaces in their environment to provide balance as they master supported walking. After two months of supported walking, the typical infant then lets go of the couch or coffee table, and begins independent walking. An important concept highlighted in the development of walking was the central pattern generator or CPG, which we subsequently noted plays a central role in developmental models of locomotion.

Our review of research from the developmental robotics perspective on motor-skill acquisition focused on the same four abilities. First, we described a series of models that incorporate the properties, strategies, or constraints found in human infants, and demonstrate that these features help simplify or facilitate the task of learning to reach. A ubiquitous example is the use of motor babbling, which enables the simulated infant or robotic agent to simultaneously experience —and thus learn to correlate or coordinate——a wide range of arm postures and visual inputs. Another important issue addressed by developmental models is the DOF problem. A common computational strategy for addressing this problem, which mirrors the strategy exploited by human infants—is to “freeze” a subset of the joints available for generating a reaching movement, such as the elbow, and to subsequently “free” the joints after the reduced movement space has been explored.

Despite the availability of several child-sized robot platforms, the use of these robots for studying the development of reaching is still at an early stage; as we noted, for example, much of the work to date on the iCub platform has concentrated on more general issues, while only a few studies have specifically modeled the developmental process in infants. A similar pattern emerges from the review on developmental models of grasping. Nevertheless, there are several important findings from this work. First, as with reaching, a fundamental challenge is to relate visual information from the target object into not simply a corresponding grasp configuration, but to complicate matters, into a series of finger movements that result in the desired configuration. While there are only a few models thus far that explicitly adopt a developmental approach to this problem, they each suggest a potential solution that is not only available to human infants, but also succeeds in either simulation or on a real robot platform.

Second, a key ingredient in the learning process, across each of the models we described, is variability in movement and a learning mechanism that benefits from trial-and-error learning.

Finally, there are also several developmental robotic models of crawling and walking, some of which take advantage of available robot platforms like the iCub and NAO. It is worth noting that this work is also at a relatively early stage, and that the full spectrum of locomotion behaviors has not yet been captured by existing models. In particular, most models have focused on a subset of locomotion skills, such as hands-and-knees crawling, rather than attempting to account for the entire timespan from the onset of crawling to the mastery of independent walking. Analogous to the use of motor babbling in models of reaching and grasping, a common element in most models of infant locomotion is the CPG. A recurring theme in this work is that development consists of solving two problems: first, appropriately linking excitatory and inhibitory connections across CPG units or neurons, in order to optimally coordinate the movement of corresponding limbs, and second, learning to use input from sensory systems (e.g., visual, vestibular, and proprioceptive) to modulate the output of the CPG neurons.

Additional Reading

Thelen, E., and B. D. Ulrich. “Hidden Skills: A Dynamic Systems Analysis of Treadmill Stepping during the First Year.” *Monographs of the Society for Research in Child Development* 56 (1) (1991): 1–98.

Thelen and Urich’s comprehensive study of the development of stepping behavior illustrates a number of key phenomena, including U-shaped development, the stability of motor patterns in the face of perturbation, and the emergence of new forms of sensorimotor coordination. While the theoretical perspective tilts toward dynamic systems theory, many of the core ideas—like embodied cognition and learning through exploratory movement—resonate clearly with ongoing work in developmental robotics.

Asada, M., K. Hosoda, Y. Kuniyoshi, H. Ishiguro, T. Inui, Y. Yoshikawa, M.

Ogino, and C. Yoshida. “Cognitive Developmental Robotics: A Survey.” *IEEE Transactions on Autonomous Mental Development* 1, no. 1 (May 2009): 12–34.
Metta, G., L. Natale, F. Nori, G. Sandini, D. Vernon, L. Fadiga, C. von Hofsten, K. Rosander, J. Santos-Victor, A. Bernardino, and L. Montesano. “The iCub Humanoid Robot: An Open-Systems Platform for Research in Cognitive Development.” *Neural Networks* 23 (2010): 1125–1134.

Asada and Metta and their respective research teams have authored two excellent surveys of developmental robotics. While each article goes beyond the topic of motor-skill acquisition, both provide outstanding introductions to the issue, as well as numerous examples of state-of-the-art research. A unique feature of Asada’s overview is the discussion of fetal movements and their role in postnatal motor development. Metta’s article, meanwhile, highlights the use of the iCub platform, and in particular, it provides a detailed discussion of how the physical structure of the robot is designed to provide a testbed for exploring critical questions, such as how vision and hand movements become coordinated.

6 Social Robots

The child psychology studies on motivational, visual, and motor development in children, and the numerous developmental robotics models of intrinsic motivation and sensorimotor learning, focus on the acquisition of individual capabilities. However, one of the fundamental characteristics of human beings (as well as of other highly social animal species) is the fact that the human infant, from birth, is embedded in the social context of parents, caregivers, and siblings, and naturally reacts to this social presence and has an instinct to cooperate with others (Tomasello 2009). Evidence exists that newborn babies have an instinct and capability to imitate the behavior of others from the day they are born. After just thirty-six minutes old, the newborn can imitate complex facial expressions such as happiness and surprise (Field *et al.* 1983; Meltzoff and Moore 1983; Meltzoff 1988). As the child cannot walk until nearly her first birthday, she is dependent on the continual care, presence, and interaction of her parents and caregivers. This further reinforces the social bonding between infants and their parents, family members, and caregivers. Moreover, social interaction and learning is a fundamental mechanism for the development of empathic and emotional skills, as well as for communication and language.

The infant's social development depends on the gradual acquisition, refinement, and enrichment of various social interaction skills. Eye contact and joint attention support the establishment of the emotional bonding with the caregivers, as well as the cognitive capabilities to create a shared context of interaction. For example, the infant first learns to establish eye contact with the adult, and later develops an ability to follow the adult's gaze to look at objects placed within the child's own field of vision, but later also to look for an object outside her view. In addition to eye contact, the child also gradually learns to respond to, and then produce, pointing gestures initially to draw the adult's attention and request an object such as food or toy (imperative pointing), and then just to draw attention toward an object (declarative pointing). Imitation capabilities, as in the face imitation studies with one-day-old newborns, also go through various developmental stages, with qualitative changes of imitation strategies, from simple body babbling and body part imitation, to the inferring of goals and intentions of the demonstrator when repeating an action (Meltzoff 1995). The acquisition of advanced joint attention and imitation skills creates the bases for the further development of cooperation and altruistic behavior. Children learn to collaborate with adults and other peers to achieve shared plans. Finally, the parallel development of all these social competences and skills leads to the acquisition of a complex ability to correctly attribute beliefs and goals to other people, and the emergence of a "theory of mind" that supports the children's social interaction until they reach adulthood.

In the sections that follow we will first look at the developmental psychology studies and theories on the acquisition of joint attention, imitation, cooperation, and theory of mind. These sections are followed by the analysis of current developmental robotics models mirroring developmental shifts in the emergence of these social capabilities in robotic agents. Such skills are essential to support a fluid interaction between robots and humans, as mechanisms like gaze following and imitation are essential to allow robots to understand and predict the goals of the humans. At the same time, the social cues and feedback from the robots can be used by human agents to adapt their behavior to the perceived robot's sensorimotor and cognitive potential.

6.1 Children's Social Development

6.1.1 Joint Attention

Joint attention is based on the ability to recognize the face of another agent and their position, to identify the direction of their gaze and then to simultaneously look toward the same object gazed at by the partner. However, this goes well beyond a simple perceptual act. In fact, as Tomasello *et al.* (2005) and Kaplan and Hafner (2006b) stress (see also Fasel *et al.* 2002), within the context of social interaction between two intentional agents, joint attention must be seen as a coupling between two intentional actions. In a developmental context, this implies that a child looks at the same target object gazed at by the parent with the shared intention to perform an action on the object or discourse about properties (e.g., name, visual or functional features) of the object. Therefore in child development joint attention plays the fundamental function to support the acquisition of social and cooperative behavior.

In chapter 4 (sections 4.1.2 and 4.2) we looked at the child's (and robot's) capability to recognize faces. So if we start with the assumption that a child has a capability, and preference, to recognize and look at faces, we should then look at the developmental stages in gaze following to support intentional joint attention. Butterworth (1991) has investigated the early stages of gaze following, and has identified four key developmental stages (figure 6.1): (1) *Sensitivity Stage*, around six months, when the infant can discriminate between the left or right side of the caregiver's gazing direction; (2) *Ecological Stage*, at nine months, which is based on the strategy of scanning along the line of gaze for salient objects; (3) *Geometrical Stage*, at twelve months, when the infant can recognize the orientation angle of the caregiver's eyes to localize the distal target; (4) *Representational Stage*, reached at around eighteen months, when the child can orient outside the field of view, to gaze precisely at the target object that the caregiver is viewing.

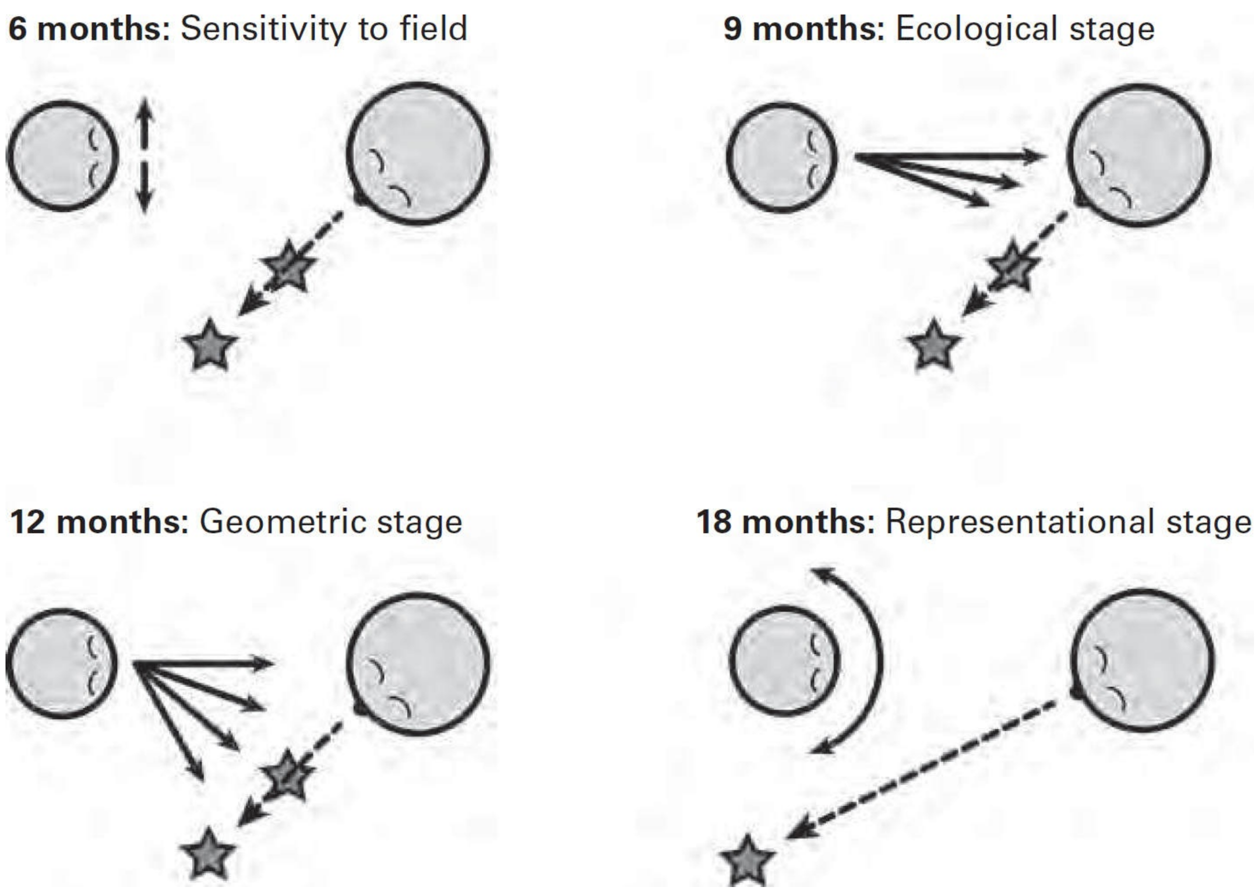


Figure 6.1

Developmental progression of gaze following. Adapted from Scassellati 2002.

Scassellati (1999) uses these four stages to identify the contribution of gaze following capabilities in agents for a theory of mind in humanoid robots. Kaplan and Hafner (2006b) have also proposed an illustration of different joint attention strategies, which include some of the key developmental stages summarized in table 6.1 and based on the developmental literature on gaze and pointing. The four strategies are as follows: (1) *mutual gaze*, when both agents are attending to each other's eyes simultaneously; (2) *gaze following*, when one agent looks at the object, and the other watches the first robot's eyes to detect where the partner is looking; (3) *imperative pointing*, when the first agent points to the object regardless of whether the other agent is attending to it; and (4) *declarative pointing*, when the first robot points to the object, while the second is also looking at it, thus achieving shared attention. These are represented in the four attentional strategies of the SONY AIBO robot (see section 6.2 below for a full discussion).

Kaplan and Hafner (2006b) have also proposed a developmental timescale for shared attention and social skills based on four key prerequisites: (1) attention detection, (2) attention manipulation, (3) social coordination, and (4) intentional understanding. These cognitive capabilities, whose developmental milestones are summarized in table 6.1, constitute the prerequisite for full achievement of shared attention between two agents. *Attention detection* refers to the capability of an individual to perceive and track the attentional behavior of other agents. In infants this starts as a simple capability of mutual gaze through detecting of the eyes of a social partner and establishing eye contact (first three months), and reaches a stage where the agent can look at an object outside the field of view by following the gaze of the other agent (eighteen months). *Attention manipulation* involves a more active capability to influence and direct the attentional behavior of others. In addition to mutual gaze, attention manipulation is achieved around nine months with imperative pointing (e.g., the infant points at food when she is hungry), at twelve months with declarative pointing (e.g., gesture to draw attention to an object), up to the eighteen-month stage when she can use predications based on word-gesture combinations, and later with complex linguistic interactions.

Table 6.1

Developmental timescale for joint attention skills (adapted from Kaplan and Hafner 2006b)

Age (months)	Attention detection	Attention manipulation	Social coordination	Intentional understanding
0–3 months	Mutual gaze through eye contact	Mutual gaze through maintaining eye contact	Protoconversation, simple turn taking mediated by caregiver	Early identification with other persons
6 months	Sensitivity only to the left/right side that the caregiver is gazing at	Simple forms of attention manipulation	Shared routines: caregiver-child conversational games	Animate-Inanimate distinction; physical/social causality distinction
9 months	Gaze angle detection, fixation of first salient object	Imperative pointing to ask for object/food	Joint activities, imitative games of caregiver's movement	First goal-directed behavior
12 months	Gaze angle detection, fixation of any salient object	Declarative pointing, draw attention with gestures	Joint activities and imitative games for goal sharing	Goal understanding, behavior understood as goal directed
18 months	Gaze following toward object outside field of view	First predications with words and gestures	Coordination of joint action plans	Intentional understanding, same goal for different action plans

The capacity of *social coordination* allows two agents to engage in coordinated interaction. In the very early stages of development the infant can take turns through the mediation of the caregiver. Later the child can perform joint activities such as imitation games of caregiver's actions (at nine months) and imitative games for goal sharing (twelve months), up to social coordination for action plans (see section 6.1.3 for more discussion on social coordination). Finally, *intentional understanding* refers to the development of a capability of the agent to understand that she, as well as other agents, can have intentions and goals. Developmentally, this first manifests with the identification of the physical presence of other people (zero–three months) and with the distinction between animate and inanimate agents (six months). This then proceeds to the understanding of the goals of action and prediction of the behavior of other agents in terms of joint action plans for common goals (eighteen months).

This detailed developmental timescale and milestones of social development in human infants have also provided a roadmap for developmental robotics research on shared attention (Kaplan and Hafner 2006b).

6.1.2 Imitation

The consistent evidence of the existence of imitation capabilities in neonates, even in the first hours after birth (Field *et al.* 1983; Meltzoff and Moore 1983), provides a bridge between the nature and nurture views of sensorimotor, social, and cognitive development (Meltzoff 2007). In addition to supporting the development of motor skills, imitation is a fundamental capability of social agents. As infants have been shown to be able to imitate facial gestures as early as forty-two minutes following birth (Meltzoff and Moore 1983, 1989), this provides support for the existence of a basic mechanism for comparing states across modalities, and for the instinct to imitate other agents.

Given the wide uses of terms such as “imitation,” “emulation,” and “mimicry” in the developmental and comparative psychological literature, Call and Carpenter (2002) have proposed an operational definition of imitation that differentiates imitation from other forms of copying behavior such as mimicry and emulation. When considering the situation of two social agents where one (the imitator) copies the other agent (the demonstrator), we need to distinguish three sources of information: the goal, the action, and the result. For example, if the demonstrator shows the action of opening a wrapped gift box, this implies several hierarchically organized goals (unwrap the box, open the box, get the present), hierarchical actions (unfold or tear the wrapping paper, open the box, take the present) and hierarchical results (the box is unwrapped, the box is open, I hold the present). Call and Carpenter propose to use the term “imitation” only for the case when the imitator copies all the three sets of goals, actions, and results. “Emulation,” in contrast, implies the copying of the goal and the results, but not the exact copying of the action itself (e.g., I use scissors to get the present out of the box). And “mimicry” involves the copying of the action and results, but not the goal (I unwrap and open the box, but leave the present inside). The distinction among these different types of copying behavior, and how the three sources of information are involved in each, allows us to better differentiate various imitation capabilities in animals and humans, and between different developmental stages of imitation strategies in infants. Moreover, this can better inform the modeling of imitation in robotics experiments (Call and Carpenter 2002).

Meltzoff and colleagues have identified four stages in the development of imitation abilities: (1) body babbling, (2) imitating body movements, (3) imitating actions on objects, and (4) inferring intentions (Rao, Shon and Meltzoff 2007). With *body babbling*, the infant randomly (by trial and error) produces body movements, and this allows her to learn about the sensorimotor consequences (proprioceptive and visual states) of her own actions and gradually develop a body schema ("act space"). In stage 2, the infant can *imitate body movements.* Studies with infants in their first month of age show that neonates can imitate facial acts (e.g., tongue protrusion) that they have never seen themselves perform, and twelve-to twenty-one-day-old infants can identify body parts and imitate differential action patterns with the same body part. This is referred to as "organ identification" in child psychology (Melzoff and Moore 1997) or "self-identification" in the robotics literature (Gold and Scassellati 2009). These studies demonstrate that newborns have an innate observation-execution mechanism and representational structure that allows infants to defer imitation and to correct their responses without any feedback. Stage 3 regards the *imitation of actions on objects.* Infants between one-year to one-and-a-half-years old can imitate not only movements of face and limbs, but also actions on objects in a variety of contexts. In stage 4, *inferring intentions*, the child can understand the underlying goal and intention behind the demonstrator's behavior. In an experiment by Meltzoff (2007), eighteen-month-old children were shown unsuccessful acts involving a demonstrator trying but failing to achieve his goal. Because children are able to imitate what the adult intended to achieve, and are not just copying the behavior, this indicates that children can understand the intentions of others. These incremental stages of the development of imitation skills show how the understanding and inference of the goal and intention of the others are crucial in adult imitation capabilities. And referring again to Carpenter and Call's classification of imitation terminology, proper imitation requires the full capability to understand the goals of demonstrated actions, as in stage 4, inferring intentions. As for stages 1 to 3, further investigations are needed to distinguish the stage when the child goes from simple emulation of action to full intentional imitation.

Meltzoff and Moore (1997) have proposed a developmental model that can explain the imitation of both facial and manual actions, called the Active

Intermodal Matching (AIM) model (figure 6.2). This model consists of three main subsystems: (1) perceptual system, (2) motor acts system, and (3) supramodal representational system. The *perceptual system* specializes for visual perception of the observed facial acts, or motor behavior. The *motor acts system* involves the imitator's active copying of the demonstrated act, supported by the essential feature of the proprioceptive information. The proprioceptive feedback permits the core matching to target between the visual input and the infant's own acts, and serves as a basis for correction. What is crucial here is the role of the *supramodal representational system*, which provides a common (supramodal) framework to encode, and detect the equivalence, between the perceived and the produced behavior. Given the benefits of the AIM model to provide a functional, operational description of the sensorimotor and the representation mechanisms involved in imitation, it has inspired the design of developmental robotics studies of imitation in mobile and humanoid robots (Demiris and Meltzoff 2008).

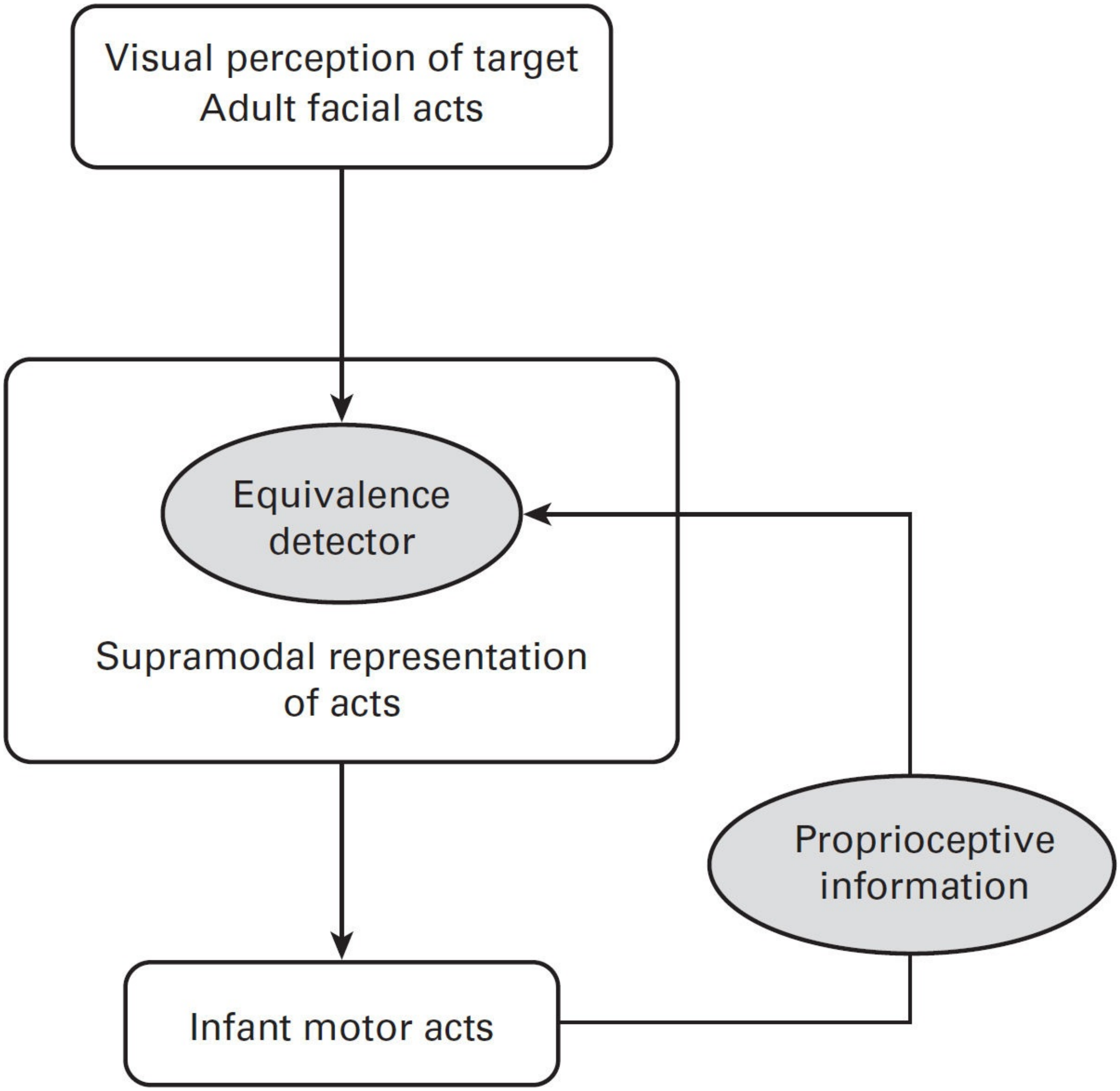


Figure 6.2

The Active Intermodal Matching model for imitation of Meltzoff and Moore 1997.

Significant progress has also been achieved in the last decade on theories and experimental evidence on the neural bases of imitation. In particular, the discovery of “mirror neurons” by Rizzolatti and colleagues (Rizzolatti, Fogassi, and Gallese 2001) has contributed to the renewed interest in this field. The mirror neurons, first studied in the monkeys’ premotor cortex (area F5), are neurons that fire both when the animal performs an action, and when it observes the same action being performed by another animal or a human experimenter. These neurons—which are involved in both the perception and production of an action—are obvious candidates for supporting tasks that require the matching of the visual and motor systems, as in the AIM model. Moreover, it has been demonstrated that in monkeys a mirror neuron fires only when the goal of the action is the same, as in the goal-based definition of imitation. However, as monkeys have a mirror system too primitive to code the details of the observed action, they cannot therefore replicate the observed action (Rizzolatti and Craighero 2004).

The existence of the mirror neuron system in humans, and its specific involvement in imitation tasks, has recently received experimental evidence (Iacoboni *et al.* 1999; Fadiga *et al.* 1995). This follows early theoretical stances on the anatomic and evolutionary similarities between the monkey's F5 area and the humans' Broca area, and the role that these play in motor and language imitation and in the evolution of human language (Rizzolatti and Arbib 1998).

6.1.3 Cooperation and Shared Plans

Cooperating with other people to achieve a common goal is another fundamental milestone in the development of social skills. Cooperation requires the capability of building and using shared plans and shared intentions between two or more interacting individuals. This can also explain forms of altruistic behavior observed in children, and in some cases also observed in nonhuman primates.

The study of the development of social cooperation capabilities in children has been closely associated with comparative psychology experiments carried out with both human children and nonhuman primates, such as chimpanzees. One of the key findings in the developmental comparative psychology of cooperation is that human children appear to have a unique ability and motivation to share goals and intentions with others. In nonhuman primates, however, this capability is absent. Tomasello and colleagues (Tomasello *et al.* 2005; Tomasello 2009) have proposed that human children's ability to share intentions emerges from the interaction of two distinct capabilities: (1) intention reading and (2) motivation to share intentions. *Intention reading* refers to the ability to infer the intentions of other people through observation of their behavior. This implies the more general ability to understand that others are intentional goal-directed agents. The *motivation to share intentions* implies that once we identify the intention of the other agent, this is then shared in a cooperative way. Tomasello has demonstrated in numerous experiments that both nonhuman and human primates are skilled at reading the intentions of others through observation of their actions and gaze direction. However, only human children possess the additional capability to altruistically share intentions.

One seminal study that has clearly demonstrated this difference between human children and other primates is the work by Warneken, Chen, and Tomasello (2006). They carried our comparative experiments with eighteen-to-twenty-four-month-old children and with young chimpanzees of thirty-three and fifty-one months of age. In this study they used two goal-oriented problem-solving tasks and two social games that required cooperation (see box 6.1 for more details). They also manipulated the condition of complementary versus parallel roles. In activities requiring complementary roles, the child and the adult have to perform different actions to achieve the same problem-solving or ludic goal. In parallel role tasks, the two partners must perform similar actions in parallel to achieve the joint task. For example, in the double-tube game task, the experimenter (cooperating adult) starts by inserting a wooden block in the upper hole of one of the two tubes. The block slides down the inclined tube, and finally has to be caught by the child, or chimpanzee, holding a tin cup at the other end of the tube. This task requires complementary roles, that is, one agent has to insert the block, and the second agent uses the container to catch it. In the trampoline game, both agents instead perform the same task: tilting their half of the trampoline border to make the wooden block jump.

Box 6.1

Cooperation Skills in Humans and Chimpanzees (Warneken, Chen, and Tomasello 2006)

Overview

This study compares cooperation behavior in human children and young chimpanzees to identify the existence of a form of cooperative activity involving shared intentionality, and to establish if this is a uniquely human capability. Four different cooperative tasks were used (two joint problem-solving activities and two social games), with either complementary or parallel roles with a human adult partner. Complementary role tasks require the child and the adult to perform different actions, while parallel role tasks require the two to perform the same action in parallel. In the second part of each experiment, the adult participant is instructed to stop the cooperative behavior, for example, by walking away or not responding to the child's (or chimpanzee's) requests. This condition aims at testing the capacity of the participants to reengage the human adult in the cooperative task.

Participants

In the four experiments, the group of young human participants consisted of sixteen eighteen-month-old children and sixteen twenty-four-month-old children. The two age groups were chosen to test the hypothesis that older children can better adjust their cooperative behavior to that of the adult, and that older children can better regulate the activity during interruption periods.

The animal group consisted of three young chimpanzees. Two were fifty-one-month-old female chimpanzees (Annet and Alexandra) and one was a thirty-three-month-old male chimpanzee (Alex), all housed together at the Leipzig Zoo. The materials used in the four experiments were subject only to minor adjustments (e.g., change in material and dimension, and food reward instead of toys) and directly matched the four cooperative tasks used with the human children.

Tasks

Complementary role **Parallel role**

Problem solving

Task 1—Elevator

The goal of this task is to retrieve an object placed inside a vertically movable cylinder. A single person cannot solve this, as it requires two complementary actions on the opposite sides of the apparatus. One person must

Task 2—Tube with handles

The goal of this task is to retrieve a toy placed inside a long tube with two handles. A single person cannot solve this, as the length of the tube makes it impossible for a person to grasp and pull both handles at the same first push the cylinder up and hold it in place (role 1), and only then the other person can access the object through the opening of the cylinder from the opposite side (role 2).


Elevator

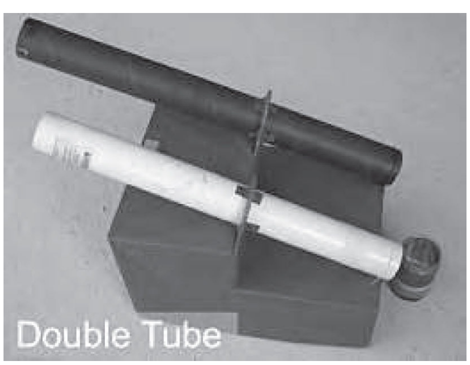
time. This tube can only be opened by two persons playing simultaneously the two parallel roles of pulling at each end until the tube opens and releases the toy.


Tube with Handles

Social game

Task 3—Double tube

The game requires one person to insert a wooden block in either of two tubes and let the other person catch it from the end of the correct tube. It requires one participant to insert the block in the top opening of the tube (role 1), and the other person to catch the block in a tin cup at the bottom end of the tube (role 2).


Double Tube

Task 4—Trampoline

The game requires two people to make a wooden block jump on the trampoline by holding the rim on opposite sides. Because the trampoline is made of two C-shaped hoses connected with flexible joints, covered with cloth, it requires parallel roles of synchronously shaking the hose ring.


Trampoline

Results Summary

• When the cooperation task is very simple, human children can achieve coordination by eighteen to twenty-four months of age; chimpanzees too can engage in simple cooperation.
• Children spontaneously cooperate and are motivated not just by the goal but also by the cooperation itself.
• With interruption conditions, all children attempted to reengage the partner, but no chimpanzee made a communicative attempt to reengage the partner.

Using these experimental tasks, Warneken, Chen, and Tomasello (2006) first studied cooperation in normal conditions, when both agents consistently cooperate in the game. They also observed the children's and chimpanzees' behavior in disrupted cooperative settings, such as when the adult experimenter stops performing the collaborative task by refusing to use the trampoline or to insert the block in the rube.

Results of the experiments show that in normal cooperative settings all the children enthusiastically participate both in goal-directed, joint problem-solving tasks and in social games. They engage in cooperation not only for the aim of achieving the joint goal, but also for the sake of cooperation itself. Chimpanzees can also cooperate is simple tasks. But in the condition when the adult experimenter stops cooperating, results show that children spontaneously and repetitively attempt to reengage the adult, while chimpanzees appear disinterested in non-goal-directed social games. The animals are only focused on obtaining the food goals, independently of cooperation. Warneken, Chen, and Tomasello (2006) thus conclude that there is a very early and unique human motivation and capacity for actively engaging in cooperative activities.

In a follow-up study, Warneken, Chen, and Tomasello (2006) demonstrated that eighteen-month-old infants spontaneously and altruistically help adults in a variety of situations, for example, when the adult is struggling to achieve the goal (instrumental help) and even if the child receives no direct benefit from his action. Children were tested with ten different situations in which an adult was having trouble performing a task, manipulating the difficulty across four conditions: (1) an out-of-reach object, (2) an object obstructed by an obstacle, (3) achieving the wrong goal when this can be corrected by the child, and (4) using the wrong means that the child can correct. Results show clear evidence of altruistic behavior in the children, with twenty-two of the twenty-four infants helping in at least one of the tasks. They also carried out a comparable experiment with three young chimpanzees using the same four types of tasks. All three chimpanzees consistently helped in the task with out-of-reach objects, even if the target object was not food. However, they did not help the human in the types of tasks with obstacles, wrong results, or wrong means. The chimpanzee's altruistic behavior with the reaching task is explained by the fact that in this task the goal is easier to detect than in the other conditions. This suggests that both children and chimpanzees are capable of altruistic behavior, but that they differ in their ability to interpret the other's need for help.

The results of these studies on cooperative behavior are consistent with Carpenter, Tomasello, and Striano's (2005) role reversal analysis. They observe the emergence of a "triadic" cooperative strategy in role reversal, which involves the child, the collaborative adult/peer partner, and an object. This is for example the case in which the adult holds out a container so the child can place toys into it. In subsequent interactions, reversing the roles, the child can then hold out the basket to the adult so that he can put toys into it. This also implies that the child has the capacity to read the adult's intended goal and to perform, on his behalf, the action the adult would have wanted to perform. The role reversal capacity corresponds to a bird's-eye view, or third-person representation of the interaction, that allows the child to take either role in the cooperation task. These child studies have inspired the design of developmental robotics models implementing different cooperation strategies (Dominey and Warneken 2011—see section 6.4).

6.1.4 Theory of Mind

The parallel development of social learning capabilities, including skills such as eye-gaze detection, face recognition, observation and imitation of other people's actions, and cooperation gradually leads to the acquisition of a complex ability to correctly attribute beliefs and goals to other people. This is normally referred to as the theory of mind (ToM), which is the capacity to understand the actions and expressions of others and to attribute mental states and intentionality to the other social agents. The understanding of the cognitive mechanisms leading to

ToM development is crucial for the design of social robots capable of understanding the intention and mental stages of human agents and of other robots. Here we will follow Scassellati's (2002) analysis of two of the most influential ToM hypotheses, proposed by Leslie (1994) and by Baron-Cohen (1995), and their influence in social developmental robotics. In addition, Breazeal *et al.* (2005) have proposed a ToM based on simulation theory and Meltzoff's AIM model that has been applied to developmental robotics. Moreover, work on theory of mind in nonhuman primates also provides useful insights on mechanisms involved in the (evolutionary) development of the theory of mind (Call and Tomasello 2008).

Leslie's (1994) ToM is based on the core concept of the attribution of causality to objects and individuals during the perception of events. Leslie distinguishes three classes of events according to the causal structure involved: (1) mechanical agency, (2) actional agency, and (3) attitudinal agency. *Mechanical agency* refers to the rules of mechanics and physical interaction between objects. *Actional agency* describes events in terms of the agent's intent and goals and their manifestation in actions. *Attitudinal agency* explains events in terms of the attitudes and beliefs of agents.

Leslie (1994) claims that the human species has evolved three independent, domain-specific cognitive modules to deal with each type of agency, and that these gradually emerge during development. The theory of body module (ToBY) handles mechanical agency, for the understanding of the physical and mechanical properties of the objects and the interaction events they enter into. This reflects the infant's sensitivity to the spatiotemporal properties of object-interaction events. Classical examples of mechanical agency phenomena are Leslie's experiment on infants' perception of causality between two animated blocks. He manipulates conditions such as direct launching (where one moving block hits a second static object and this immediately starts to move), delayed reaction (same collision, but delayed movement of the second object), launching without collision, collision with no launching, and static objects. Children with fully developed ToBY, at six months of age and later, can perceive causality of interaction in the first condition, and not in the others. Leslie suggests that this might be an innate ability, as mechanical agency is seen in the very first months of life (table 6.2).

Table 6.2

Developmental timescale for theories of mind by Leslie and by Baron-Cohen

Age (months)	Leslie	Baron-Cohen
0–3 months	Sensitivity to spatiotemporal properties of events for theory of body (innate?)	Intentionality detector for self-propelled agents vs. inanimate objects (innate?)
6 months	Detecting of actions and their goals (through eye gaze) for ToM-System1	Eye direction detector
9 months		Appearance of shared attention mechanism
18 months	Initial development of attitudinal agency for ToM-System2	Initial development of ToM mechanisms
48 months	Fully developed ToM-System2; meta-representations	Full development of ToM mechanisms

The second module is called theory of mind system 1 (ToM-S1), and is used for actional agency to explain events in terms of goals and actions. This is manifested through eye-gaze behavior, and leads to the child's identification of the actions and their goals. This capacity starts to appear at six months of age. The third module is called theory of mind system 2 (ToM-S2), and is used for attitudinal agency for the representations of other people's beliefs that might differ from our own knowledge or from the observable world. Children develop and use meta-representations, where the truth properties of a statement depend on mental states, instead of the observable world. This module starts to develop at eighteen months, until its full development at around forty-eight months.

Baron-Cohen's theory of mind, called the "mindreading system," is based on four cognitive capabilities: (1) intentionality detector, (2) eye direction detector, (3) shared attention mechanism, and (4) theory of mind mechanism. *Intentionality detector* (ID) is specialized for the perception of stimuli in the visual, auditory, and tactile senses that have self-propelled motion. As such it distinguishes between animate entities (i.e., agents) versus nonanimate entities (i.e., objects). This leads to the understanding of concepts such as "approach" and "avoidance," and for representations such as "he wants food," "he goes away." The intentionality detector appears to be an innate capability in infants (table 6.2). The *eye direction detector* (EDD) specializes in face perception and the detection of eye-like stimuli. Baron-Cohen identifies various functions for the EDD. These include the detection of eye gaze, the detection of the target of eye gaze (looking at an object or at another person), and the interpretation of gaze direction as a perceptual state (the other agent is looking at me). The eye detection capability is available in the first nine months of age. Both ID and EDD produce dyadic representations, with one agent and one object or another agent, as in the "he wants food" and "the other agent is looking at me" cases.

The *shared attention mechanism* (SAM) combines dyadic representations to form triadic concepts. For example two dyadic percepts "I see something" and "you want food" can be combined into the "I see (you want food)" representation. In particular, combinations of ID and EDD representations allow the infant to interpret the gaze of others as intentions. SAM develops between nine and eighteen months of age. Finally, with the *theory of mind mechanism* (ToMM) the triadic representations are converted into meta-representations (as in Leslie's ToM-S2) through the understanding and representation of the mental states and beliefs of other agents. ToMM permits the construction of representations of the form "Mary believes (I am hungry)," as well as representation of knowledge that might not correspond to true states in the world, such as "Mary believes (dogs can speak)." The advanced ToMM starts to appear around eighteen months, until it fully develops by forty-eight months. An important advantage of such a theory is that it is possible to identify ontogenetic impairments in the development of the four capabilities, which can in turn explain various autism spectrum disorders (ASDs).

In addition to Leslie and Baron-Cohen's explanations of the mechanisms involved in the development of theory of mind in infants, other theoretical stances on ToM focus on imitation and simulation theory (Breazeal *et al.* 2005; Davies and Stone 1995). Simulation theory claims that we can make predictions about the behaviors and mental states of others by simulating another person's actions and sensory state. We can use our own imitation skills and cognitive mechanisms to recreate how we would think, feel, and act in the other agent's situation, thus inferring the emotions, beliefs, goals, and actions of the others. Simulation theory is also consistent with the embodied cognition approach (Barsalou 2008) and the role of mirror neurons in linking action perception with action execution (Rizzolatti, Fogassi, and Gallese 2001).

In addition to the theory of mind development in humans, there has been an important debate on the evolutionary origins of the theory of mind, and the existence of theory of mind capabilities in animals. One of the main contributions in this field has come from Call and Tomasello's (2008) investigation of the capacity to infer the goals and intentions of other agents in nonhuman primates such as chimpanzees. They review extensive evidence in support of the hypothesis that at least chimpanzees understand both the goals and intentions of other agents (humans and chimpanzees), as well as the perception and knowledge of others. Primates use these social capabilities to produce intentional action. No evidence is available, however, to support the fact that primates can understand false belief, as in the meta-representation of Leslie's and Baron-Cohen's theories, or to support the view that primates can appreciate that other agents might use mental representations of the world to drive their actions and that do not correspond to the observable reality.

The operationalization of various cognitive mechanisms involved in the gradual development of the theory of mind, as in Leslie's and Baron-Cohen's theories, and evolutionarily in animal studies, provides a useful framework for the modeling of theory of mind in cognitive robots (Scassellati 2002) and for the use of robots in the treatment of autism disorder (François, Dautenhahn, and Polani 2009a; François, Powell, and Dautenhahn 2009b; Tapus, Matarić, and Scassellati 2007).

6.2 Joint Attention in Robots

The study of joint attention in robots has been a key focus in developmental robotics, for its link between social skills and human robot interaction and communication. The developmental classification of attentional and social skills proposed by Kaplan and Hafner (2006b) provides a useful framework for the review of developmental robotics models of joint attention. They use the example of the two AIBO robots facing each other to show different types of gaze sharing and pointing gestures. Figure 6.3a–b illustrates two attention-detection strategies of the robots, namely (1) mutual gaze when the two robots establish mutual eye contact, and (2) gaze following, when the partner looks at the object gazed at by the first agent. In figure 6.3c–d, two attention manipulation behaviors are shown, i.e., (3) imperative pointing to request an object or food even when the other agent is not initially looking at it, and (4) declarative pointing to put emphasis and create shared attention on an object focus of the interaction.

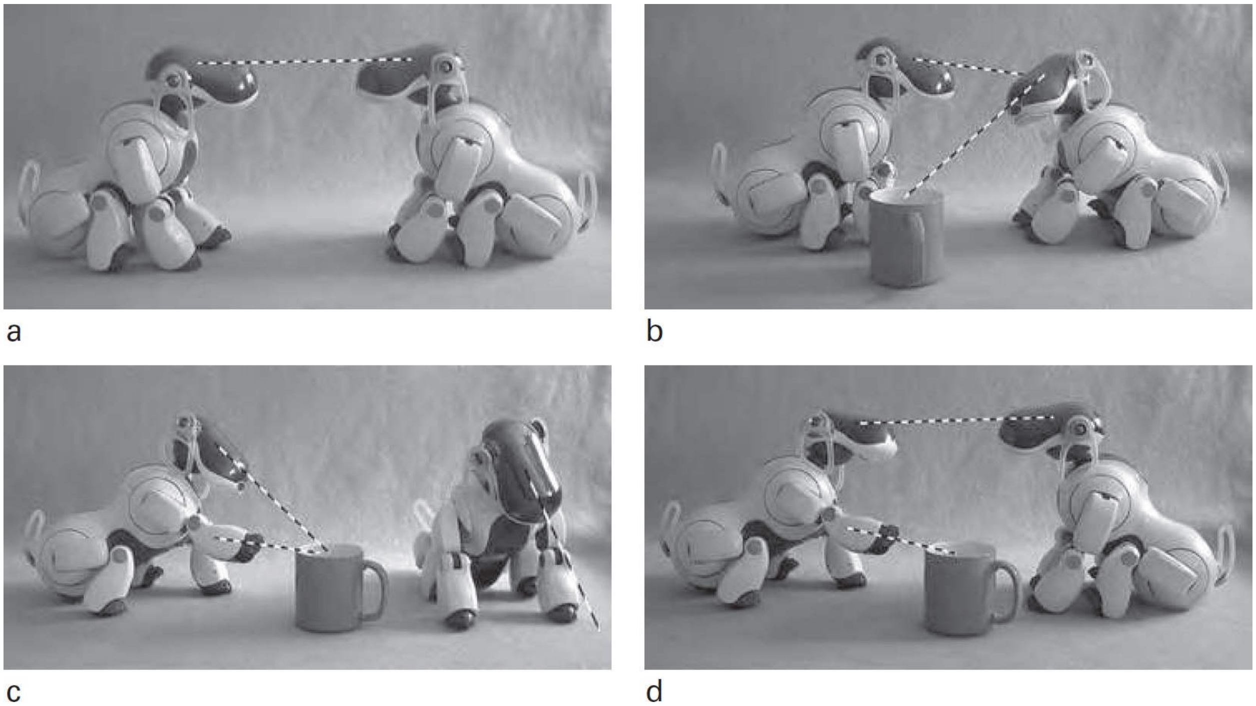


Figure 6.3

Different joint attention strategies: (a) mutual gaze, (b) gaze following, (c) imperative pointing, (d) declarative pointing (from Kaplan and Hafner 2006b). Figure courtesy of Verena Hafner. Reprinted with permission from John Benjamins.

A developmental robotics investigation into the learning recognition of pointing gestures was originally carried out by Hafner and Kaplan (2005) with the AIBO robots, and more recently by Hafner and Schillaci (2011) with the NAO. In the original Hafner and Kaplan (2005) study, two Sony AIBOs sit on the floor and face each other, with an object in the middle. The "adult" robot is equipped with a capacity to recognize the object location and point at it. The "child" robot can learn to recognize the partner's pointing gesture. It first looks at the pointing gesture of the adult, guesses the direction of the object, and turns its head to look at it. A supervision signal is given to check if the learner looks at the correct direction, and this is used to update the neural control architecture. To train the robot's neural controller, the learner robot's camera captures 2,300 images of the partner's pointing gesture (half for left and half for right pointing) with a variety of backgrounds, lighting conditions, and distances between the robots. Each image is divided into a left and right side, and then processed to extract two levels of brightness and the horizontal and vertical edges through Sobel filtering. Further operators are then applied to identify the vertical and horizontal centers of mass of the image pixels. The selected features intuitively correspond to the detection of the vertical shift of brightness when the robot lifts its arm, to the increase of horizontal edges and to the decrease of vertical edges on the side of the pointing. Through a pruning method based on greedy hill climbing, three key features are selected out of the combination of the various features and operators, leading to a pointing recognition performance of over 95 percent.

To train the robot to recognize the left/right direction of the pointing gesture, Hafner and Kaplan use a multilayer-perceptron with three input neurons for the selected visual features, three neurons in the hidden layer, and two outputs for the left/right pointing direction. The backpropagation algorithm used to train the multilayer perceptron is considered comparable to a reward-based system, when a binary left/right decision is involved. Hafner and Kaplan (2005) argue that this capacity to learn to recognize the direction of pointing is at the basis of manipulative attention capability, which can further develop to include imperative and declarative pointing behavior. Other robotics models have focused on the developmental emergence of shared gaze, as in Nagai and collaborators (Nagai *et al.* 2003; Nagai, Hosoda, and Asada 2003) model of the gradual extension of the gaze-followable area. Nagai and colleagues follow Butterworth's (1991; Butterworth and Jarrett 1991) developmental framework based on the incremental acquisition of ecological (the infant looks at an interesting object regardless of the caregiver's gaze direction), geometric (joint attention only when the object is in the infant's field of view), and representational (the infant can find a salient object outside its own field of view) gaze strategies.

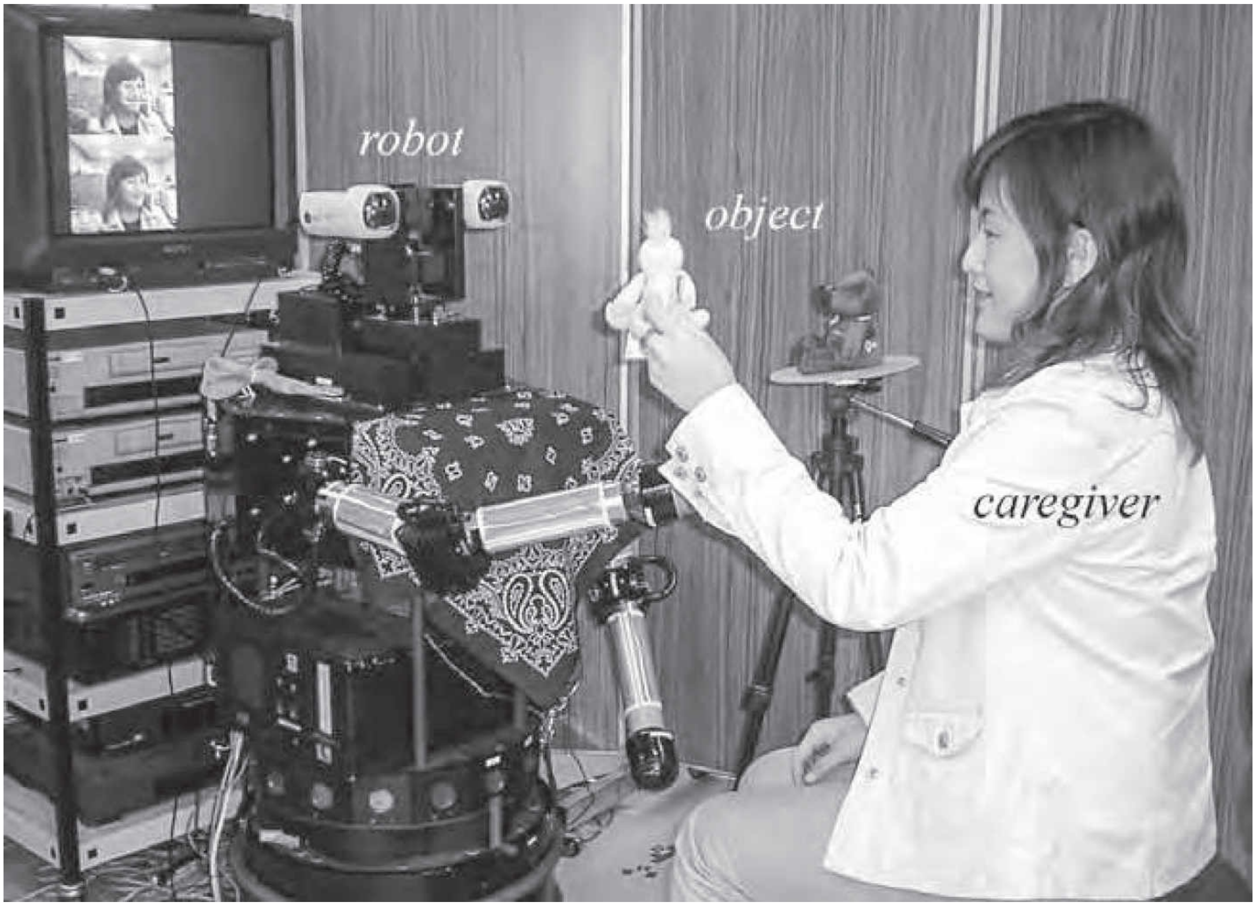


Figure 6.4

Experimental setup for Nagai, Hosoda, and Asada (2003) experiment. Figure courtesy of Yukie Nagai.

The experimental setup consists of a robot head with two cameras, which rotate on the pan and the tilt axes, and a human caregiver with various salient objects (figure 6.4). In each trial, the objects are randomly placed, and the caregiver looks at one of them. She changes the object to be gazed at every trial. The robot first has to look at the caregiver by detecting her face through template matching and extracting a face image. It then locates the salient, bright-colored objects by using thresholds in color space.

Through the cognitive architecture as in figure 6.5, the robot uses its camera image and the angle of the camera position as inputs, to produce in output a motor command to rotate the camera eyes. The architecture includes the visual attention module, which uses the salient feature detectors (color, edge, motion, and face detectors) and the visual feedback controller to move the head toward the salient object in the robot's view. The self-evaluation module has a learning module based on a feedforward neural network and the internal evaluator. The internal evaluator gauges the success of the gaze behavior (i.e., whether there is an object at the center of the image, regardless of the success or failure of joint attention) and the neural network learns the sensorimotor coordination between face image and current head position, and the desired motor rotation signal. The gate module selects between outputs from the visual feedback controller and the learning module. This uses a selection rate that is designed to choose mainly the output of the attention module at the beginning of the training, and then, as learning advances, gradually select the learning module's output. The selection rate uses a sigmoid function to model the nonlinear developmental trajectory between bottom-up visual attention and top-down learned behavior.

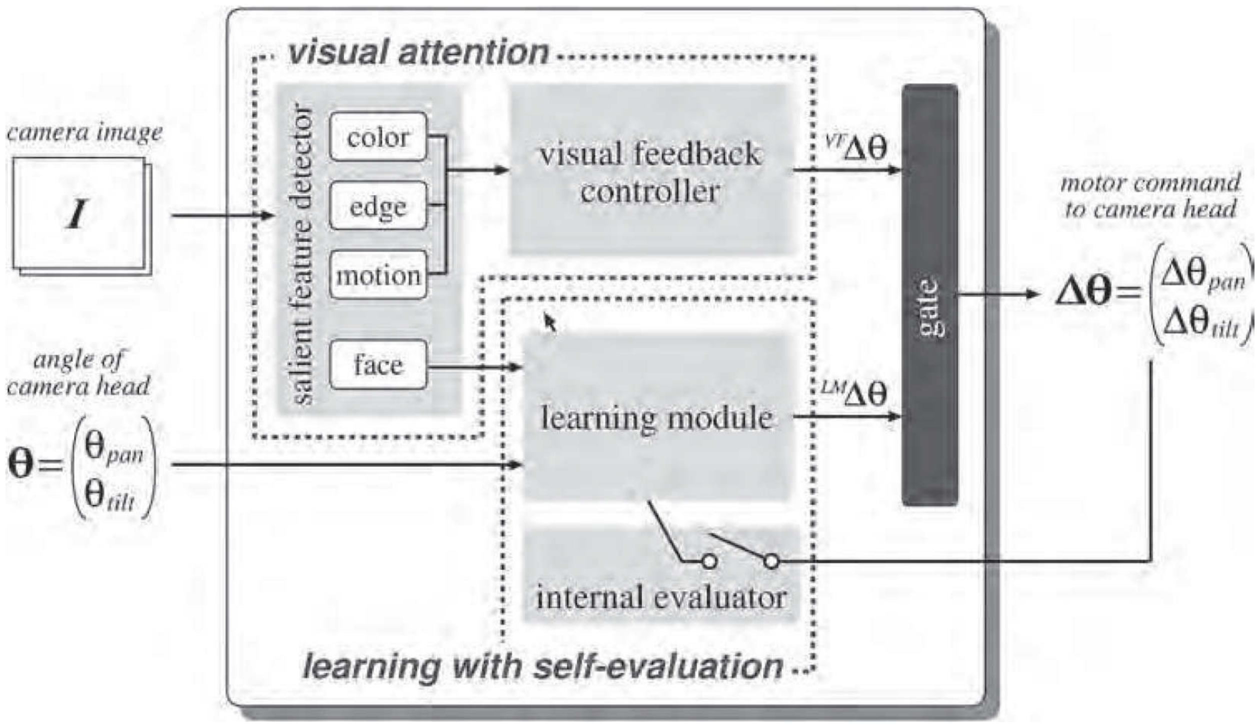
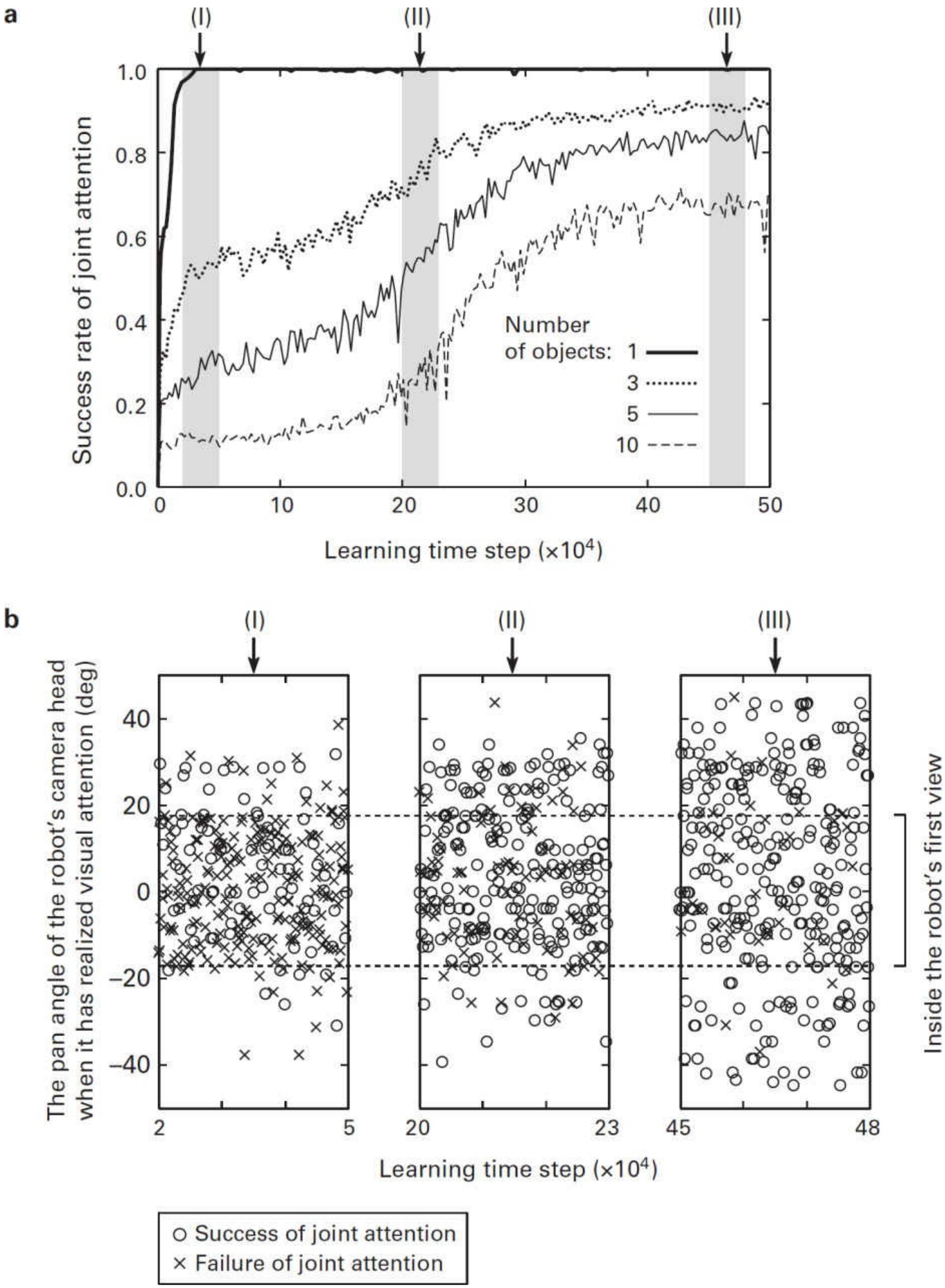


Figure 6.5

Cognitive control architecture for shared gaze in the Nagai, Hosoda, and Asada (2003) experiment. Figure courtesy of Yukie Nagai.

To train the robotic agent, when a face is detected, the robot first looks at the caregiver and captures the image. The filtered image and the camera angles are used in input to the visual attention module. If the attention module detects one salient object, the robot produces the motor rotation signal to look at this object. In parallel, the learning module uses the head image and camera angles to produce its own motor rotation output. The gate module uses the selection rate to choose either the attention module's or the learning module's motor output signal, and the camera is then rotated to gaze at the object. If the robot has successfully gazed at one object, the learning module uses the motor rotation output as training signal for the feedforward neural network. Successful gaze is defined as the action to center the camera on any object in the scene regardless of whether this is the one gazed at by the caregiver. However, the feedforward network is able to learn the correlation between joint gazed objects due to the systematic correlation between the image of the face's eye direction and the object position (when the wrong object is looked at, the position of the object that the robot has gazed at does not uniquely correspond to the image of the caregiver’s face). This mechanism has the advantage that the robot can develop the ability of joint attention without any task evaluation or direct feedback from the caregiver. And as the gate module gradually allows the learning module to take over control of gazing direction, this produces the incremental improvement of the shared gaze behavior.



a
(I)
(II)
(III)
Success rate of joint attention
1.0
0.8
0.6
0.4
0.2
0.0
0
10
20
30
40
50
Learning time step (×10⁴)
Number
of objects: 1
3
5
10
b
(I)
(II)
(III)
The pan angle of the robot's camera head
when it has realized visual attention (deg)
40
20
0
–20
–40
2
5
20
23
45
48
Learning time step (×10⁴)
Inside the robot's first view
○ Success of joint attention
× Failure of joint attention

Figure 6.6

(a) Learning performance as success rate during the Nagai, Hosoda, and Asada (2003) experiment. (b) Data on the three stages, showing the emergence of ecological (I), geometrical (II) and representational (III) joint attention strategies. Figure courtesy of Yukie Nagai.

Nagai *et al.* (2003) and Nagai, Hosoda, and Asada (2003) carried out a series of experiments with this robot head varying the number of objects from one to ten. When only one object is used, success is easy and the robot achieves 100 percent success. When the experimenter uses five objects, in the first stage of learning joint attention is only possible for 20 percent, in other words, due to random choice of one of the five objects. However, at the end of the training, the success rate reaches 85 percent, well above chance, when the learning module output has achieved low training error and it has taken over the bottom-up visual attention preference for the most salient visual object. With ten objects the task is quite hard, and the training only reaches a performance of just above 60 percent success.

The most important result from a developmental perspective are the analyses of the emergence of Butterworth's (1991) three stages of gaze and shared attention—I: ecological, II: geometrical, and III: representational. Figure 6.6a shows the increase of the rate of successful joint attention occurrences during the whole experiment, with a highlight of the three stages selected for further analysis in figure 6.6b. Figure 6.6b shows the number of successes (symbol o) and failures (symbol ×) of joint attention events at three different developmental stages (sample analyses on the case with five objects). At the beginning of training (stage I), the robot mostly looks at objects located within the robot's view, and can only achieve joint attention at a chance level. This is due to the predominance of choices by the bottom-up visual attention module, as per the gate module's sigmoid selection rate. In the intermediate steps of training (stage II), the agent is capable of achieving joint attention in the great majority of cases when the object is within the image, and at the same time the robot increases the gazing at location outside the eye's view. Finally (stage III), the robot achieves joint attention in almost all trials and positions.

How does the robot achieve the capability to look at the target (caregiver's gazing direction) object outside the robot's own field of view, as in stage III?

During training, the robot's learning module gradually acquires the capability to detect the sensorimotor correlation between the eye position of the caregiver's face image and a direction of camera rotation. This association is learned especially during successful joint gazes when the object is visible as in stages I and II. However, even when no objects are visible, the robot tends to produce a motor rotation signal consistent with the caregiver's eye direction. The robot's head rotation toward the direction of gaze will gradually lead to the visualization of the target object on the border of the image. Once the object is detected in the image, the robot will be able to identify its location and gaze directly on its center.

The Nagai *et al.* (2003; Nagai, Asada, and Hosoda 2006) study is an elegant example of a developmental robotics model directly investigating known developmental stages, as the joint attention stages proposed by Butterworth (1991). Moreover, it shows how the changes between these qualitative stages are the results of gradual changes in the robot's neural architecture. This is due to the subsymbolic and distributed nature of the robot's neural controller, that is, trained through small changes to the network parameter (weights). However, a gradual accumulation of changes can result in nonlinear learning phenomena, as in the well-known connectionist models of learning past tense (Plunkett and Marchman 1996) or the vocabulary spurt (Mayor and Plunkett 2010) and general U-shape modeling in robots (Morse *et al.* 2011) (see also chapter 8). Numerous other developmental robotics models of joint attention have been proposed. A few have a focus on human-robot interaction and how a robot can achieve and support joint attention with a human. For example, Imai, Ono, and Ishiguro (2003) carry out experiments on pointing for joint attention. Their Robovie robot (Ishiguro *et al.* 2001) is able to attract the attention of a human participant by pointing at an object and establishing mutual gaze. Kozima and Yano (2001) used the Infanoid baby robot, and modeled the robot's capacity to track human faces and objects, to point to and reach for objects, and to alternate the gaze between faces and objects. Jasso, Triesch, and Deak (2008) and Thomaz, Berlin, and Breazeal (2005) modeled social referencing, meaning, the phenomenon when an infant is presented with a novel object and consults the adult's facial expression before reacting to this object. If the adult's facial expression is positive (e.g., smile), the infant touches and interacts with the object, while she avoids it when the adult’s face shows a negative reaction. Jasso, Triesch, and Deak (ibid.) use a reward-driven modeling framework, based on temporal-difference reinforcement learning, for social referencing in simulated agents. Thomaz, Berlin, and Breazeal (ibid.) use the humanoid robot Leonardo to model social referencing dependent on both visual input and an internal affective appraisal of the object.

Developmental models of joint attention are also relevant to the investigation of normal and atypical development, given the importance of shared attention and social interaction in disorders such as autism spectrum disorders. For example, in this field, Triesch *et al.* (2006; see also Carlson and Triesch 2004) have modeled healthy, autistic, and Williams syndrome infants by changing characteristics of their preferences for gaze shift in simulated agents. They propose a computational model of the emergence of gaze-following skills in infant-caregiver interactions, as the infant’s learning of his caregiver’s gaze direction allows him to predict the locations of salient objects. The modeling of shared attention for normal and atypical development is also relevant to the robotics models of the theory of mind, as in section 6.5.

6.3 Imitation

The study of social learning and imitation has been one of the main topics of research in cognitive robotics and human-robot interaction (e.g., Demiris and Meltzoff 2008; Breazeal and Scassellati 2002; Nehaniv and Dautenhahn 2007; Schaal 1999; Wolpert and Kawato 1998). Robots provide a useful tool to investigate the developmental stages of imitation as they require the explicit operationalization of the various components and mechanisms necessary to achieve. To imitate, a robot must be able to possess the following skills: (a) motivation to observe and imitate the others, (b) perception of movement, and (c) conversion of the observed actions into their own body schema (correspondence problem) (Breazeal and Scassellati 2002; Hafner and Kaplan 2008; Kaplan and Hafner 2006a).

For studies on the evolutionary and developmental origins of the motivation to imitate, most developmental robotics models start from the assumption that the robot is equipped with an innate motivation (instinct) to observe and imitate others. Although numerous comparative psychology and neuroscience studies have looked at the origins of imitation capabilities in animals and humans (e.g., Ferrari *et al.* 2006; Nadel and Butterworth 1999) and through the involvement of the mirror neuron systems (Rizzolatti, Fogassi, and Gallese 2001; Ito and Tani 2004), few computational models exist that have explicitly explored the origins of the imitation capabilities. For example, Borenstein and Ruppin (2005) used evolutionary robotics to successfully evolve adaptive agents capable of imitative learning, through the emergence of a neural mirror device analogous to the primates' mirror neuron system. In existing developmental robotics models, the imitation algorithm implicitly implements an instinct to observe others and use this input to update the models' own imitation system.

For the perception of movement, various motion capture methods and artificial vision systems have been used. Motion capture technologies include the Microsoft Kinect, exoskeleton technology, or digital gloves that measure joint angles positions (e.g., the Sarcos SenSuit system for the simultaneous measurement of 35 DOFs of the human body; Ijspeert, Nakanishi, and Schaal 2002), and tracking with the use of magnetic or visual markers (Aleotti, Caselli, and Maccherozzi 2005). In particular, the easy-access, low-cost Microsoft Kinect apparatus and open software system offer a great opportunity for gestural, teleoperation, and imitation studies in robotics (Tanz 2011). Vision-based motion detection systems are typically based on the automatic detection and tracking of body parts (e.g., Ude and Atkeson 2003). Alternatively, Krüger *et al.* (2010) use parametric hidden Markov models for the unsupervised discovery of action primitives by analyzing the object state space—that is, inferring human action primitives that induce the same effect on the object, rather than focusing on human body part movements.

In addition to a motion perception system, an imitating robot must have the capability to apply selective attention to the specific actions and objects that are the focus of the interaction. This might depend on a combination of bottom-up processes (e.g., saliency of the object/action) and top-down processes (e.g., expectations and goal-directed aspects). In the imitation experiments by Demiris and Khadhouri (2006) described as follows, we see an example of the contribution of bottom-up and top-down mechanisms, in particular where attention helps reduce the cognitive load of the robot.

Finally, to study imitation the experimenter needs to address the correspondence problem (Nehaniv and Dautenhahn 2003), that is, the knowledge required by the robot to convert an action that has been observed into a sequence of its own motor responses to achieve the same result. Breazeal and Scassellati (2002) identify two main approaches to the correspondence problem and the representation of the perceived movements: (1) motor-based representations and (2) task-based representations. The first method uses representations of the perceived movement in motor-based terms, e.g., though the encoding of the demonstrator's movement trajectory into the imitator's motor coordinates. This is the method used by Billard and Matarić (2001) where the excentric frame of reference (relative to the visual tracking system) used for the coordinates of the demonstrator's joints is projected into an egocentric frame of reference for a simulated humanoid robot. The second method represents perceived movements in the imitator's own task-based system. This is the case of the use of predictive forward models, where movement recognition is directly accomplished by the same process that generates the agent's own movements (e.g., Demiris and Hayes 2002).

A variety of combinations of methods for imitation motivation, action perception, and the correspondence problem have led to the proposal of numerous robot imitation experiments. In this section we will focus on some seminal work on robot imitation that takes direct inspiration from developmental psychology studies on imitation. Demiris and colleagues have proposed a computational architecture that incorporates Meltzoff and Moore's (1997) active intermodal matching (AIM) model of the development of imitation abilities in infants. This architecture is called Hierarchical Attentive Multiple Models (HAMMER) (figure 6.7) and incorporates various aspects of the AIM model, primarily the principle of "understanding others by analogy with the self" (Demiris and Hayes 2002, Demiris and Johnson 2003; Demiris and Khadhouri 2006). It also models the developmental stages of imitation behavior in infants, such as the fact that younger infants first imitate only the surface behavior of the demonstrator, and later understand their underlying intentions and therefore can imitate the goal with different behavioral strategies. The AIM component of the HAMMER cognitive architecture has been used for various robot imitation experiments, such as a robotic head that observes and imitates human head movements (Demiris *et al.* 1997) and a mobile robot capable of learning to navigate by imitating and following another robot (Demiris and Hayes 1996).

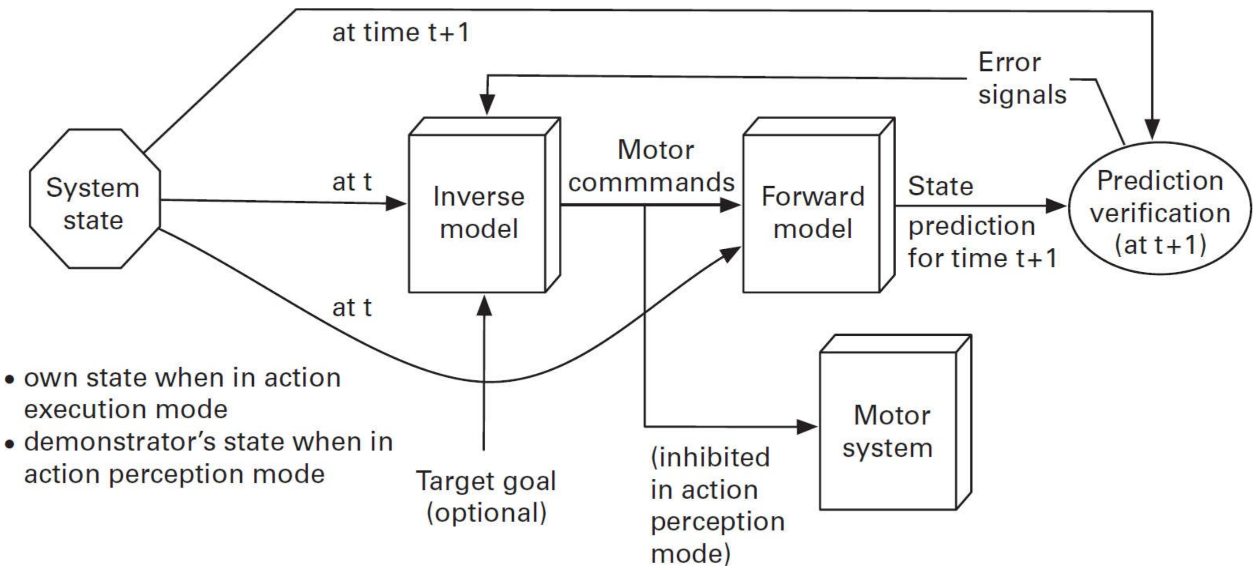


Figure 6.7

Demiris's HAMMER architecture for imitation. Figure courtesy of Yiannis Demiris.

The HAMMER architecture is based on the following principles:

• Basic building blocks consisting of pairs of inverse and forward models, for the dual role of either executing or perceiving an action.

• Parallel and hierarchical organization of multiple pairs of inverse/forward models.

• A top-down mechanism for the control of attention during imitation, to deal with limited access to the sensory and memory capacities of the observer.

Each building block is constituted by an inverse model paired with a forward model. An inverse model takes as inputs the current state of the system and the target goal, and outputs the motor control commands that are needed to achieve the goal. A forward model takes as inputs the current state of the system and a control command to be applied to it and outputs the predicted next state of the controlled system. The forward model works as an internal predictor simulation model. These models can be implemented as artificial neural networks, or other machine learning methods. HAMMER uses multiple pairs of inverse/forward models to observe and execute action. This combination of inverse and forward models has been proposed as a general internal mechanism for motor control, first proposed by Wolpert and Kawato (1998) in the MOSAIC (modular selection and identification for control) model. Wolper and Kawato propose that the brain uses a series of multiple paired modules of forward (predictor) and inverse (controller) models. Demiris's hierarchical model is based on the same idea of paired forward/inverse modules.

When a robot endowed with the HAMMER architecture is asked to imitate a new action via demonstration, the inverse model receives in input the demonstrator's current state as perceived by the imitator. The inverse model generates the associated motor commands necessary to achieve the target goal (the action itself is not executed by the robot during perception/imitation learning). The forward model then uses these motor commands to provide an estimation of the demonstrator's future state at timestep $t + 1$. The comparison between the actual and the predicted states generates an error signal that can be used to adjust the parameters of the action execution and to learn the demonstrator's actions. Learning is achieved through the increase/ decrease of the inverse model's confidence value, which indicates how closely the demonstrator's action matches the imitator's action. During imitation learning, many of these pairs of inverse/forward models are active in parallel during a demonstration, with a continuous adjustment of the predictor's model confidence value, strengthening the confidence values of those models that best match the demonstrator's action with its own predictions. The prediction model with the highest confidence value is then chosen for the action execution at the end of the demonstration. If no existing internal models are found that can generate the demonstrated action, the architecture uses its AIM component to learn a new one, using the surface behavior as a starting point.

These pairs of inverse/forward models can be organized hierarchically, where higher-level nodes encode increasingly abstract behavioral aspects, such as goal states (Johnson and Demiris 2004). This has the advantage of simulating the demonstrated action not by following the exact demonstrated movements, but rather their effects on the environment to achieve the goal. This permits the solution of the correspondence problem in imitation, by allowing the robot to choose its own actions to achieve the imitation goal.

To model the effects of selective attention and limited memory capabilities, a top-down attentional mechanism is implemented. Each inverse model only requires a subset of the global state information, that is, some models might specialize for arm movement, others for the torso, and so on. The selection of the states and features of the task to be passed to the inverse model depends on the hypotheses that the observer has on the task being demonstrated. And as there might be multiple parallel hypotheses and state requests, the saliency of each request depends on the confidence value of each inverse model. In addition, this top-down attentional system can be integrated with bottom-up attentional processes, as those depending on the salience properties of the stimulus itself. Here we briefly describe two robot imitation experiments conducted by Demiris and collaborators on the HAMMER architecture. Demiris follows a clear developmental robotics approach by performing comparative analysis between child psychology studies on infants' imitation from a human demonstrator and robotics experiments replicating such phenomena (Demiris and Meltzoff 2008). In particular the child/robot comparison focuses on the initial conditions necessary for imitation (i.e., what is innate in infants, and what functionality must be prewired in the robot) and developmental pathways (i.e., how the performance of infants changes over time, and the corresponding changes in the mechanisms used by the robot to extend imitation skills).

The first experiment (Demiris *et al.* 1997) explicitly models the face imitation behavior studied by Meltzoff in young infants. The robotic head ESCHeR (Etl Stereo Compact Head for Robot vision) (Kuniyoshi *et al.* 1995) was used as this is constrained to the human vision system with binocular, foveated wide-angle lenses for a 120-degree field of view, high-resolution fovea of twenty pixels per degree, and velocity and acceleration parameters comparable to human head movements. During the human experimenter's demonstrations, the human head's pan and tilt rotations are estimated first by using an optical flow segmentation algorithm for the vertical and horizontal coordinates, and then a Kalman filtering algorithm to determine the approximate pan and tilt values. To estimate the robot's own head posture, the values of the encoders are recorded, after the head is initialized to its default coordinates of looking straight ahead.

A qualitative imitation approach is used by matching the observed target posture with the current posture. Depending on the difference between the pan and tilt values of the target and of the proprioceptive information on the current head posture, the system activates a series of “move upward” and “move leftward” commands until the target posture has been reached. To extract the representative postures of the sequence of movements necessary to imitate the target behavior, a simple algorithm is used that keeps the posture at time *t* in memory if either the *x* or *y* angle value of the posture represents a local minimum or maximum. During imitation experiments, the robot head successfully imitated the vertical/horizontal movement of the experimenter’s head movements, relying only on representations known to exist in primate brains. The model configuration permitted the imitation of a variety of movements, with varying duration and speed. Moreover, the use of the algorithm for extraction of only representative postures allowed the smoother reproduction of demonstrated movements.

A second experiment that tests the HAMMER architecture for the imitation of object manipulation tasks was carried out with the ActivMedia PeopleBot (figure 6.8) (Demiris and Khadhouri 2006). This is a mobile robot platform with an arm and a gripper for object handling. In this experiment, only the on-board camera was used as input sensor, with an image resolution of 160 × 120 pixels and a sampling rate of 30 Hz for a two-second-long demonstration. The human participant demonstrated actions such as “pick X,” “move hand towards X,” “move hand away from X,” and “drop X,” where X was either a soft drink can or an orange. The visual properties of these two objects and of the human hand (i.e., hue and saturation histograms) are preprocessed for the objects, to be used later by the inverse models.

To implement the inverse models for these four actions the ARIA library of primitives provided with the ActivMedia PeopleBot was used, in addition to the specification of the preconditions necessary to perform the action (e.g., before picking up an object, the hand needs to move closer). A set of eight inverse models was used, one for each of the above four actions in combination with each of the two objects. The forward models were implemented using hand-coded kinematic rules to predict the qualitative prediction of the next state of the system expressed as two possible states: “closer” or “away from.”

Figure 6.8

A PeopleBot observing an object manipulation act, selectively attending the relevant parts of the demonstration (from Demiris and Khadhouri 2006). Figure courtesy of Yiannis Demiris. Reprinted with permission from Elsevier.

To choose which of the eight inverse models will produce an action (i.e., will win the robot's selective attention), the top-down attentional arbitration mechanism is used, taking into consideration the confidence value of each model (e.g., using the inverse models with higher confidence, or in the alternative "round-robin" equal share method, choosing at each time step one model at a time, in sequential order). Once an inverse model has been selected, this requires a set of object properties related to the objects in the scene: color, motion, and size of the objects (can, orange, or hand). These properties act as biases in the calculation of a combined saliency map, such as with highlighted regions for the positions of the hand and the target object. Using these values, the selected inverse model generates a motor command, which is then passed to the paired forward model to generate the qualitative, binary prediction of the next close/away state. The confidence value of the inverse model is increased/decreased depending on the correct/incorrect binary error value.

To test this implementation of the HAMMER architecture for manipulation behavior, eight video sequences of a demonstrator performing different tasks with the two objects were used with different arbitration methods (round-robin, highest-confidence choice or combinations of both). Experimental results and analyses of the different arbitration methods show that the addition of the attention mechanism produces a significant savings in terms of computational resources. Moreover, the combination of the round-robin and high-priority methods allows an efficient dynamic switch to the highest-confidence inverse model, after some initial model optimization steps.

The testing of the HAMMER model with robot imitation experiments provides a validation of the various developmental and neuroscience phenomena data (Demiris and Hayes 2002), and the AIM theoretical model of imitation proposed by Meltzoff. In particular, the learning of inverse and forward models can be considered part of the infant's developmental processes. The acquisition of forward models is similar to the motor babbling stage of infant development. Robots, like infants, before they fully master reaching behavior go through stages where they generate random movements, and these are associated with their visual, proprioceptive, or environmental consequences. The learning of these associations between actions and consequences can then be inverted to create approximations to the basic inverse models, by observing and imitating others, that is, learning how certain goals correspond to input states (Demiris and Dearden 2005). During later developmental stages, various basic inverse models can be combined in parallel to create multiple inverse models of the interaction with the environment and their hierarchical grouping to handle complex goals and actions.

The HAMMER architecture has also been used to model a range of biological data related to the action perception and imitation systems in primates (Demiris and Hayes 2002; Demiris and Simmons 2006) and extended for a variety of imitation tasks and robotics platforms, such as human-robot collaborative control and imitation for robotic wheelchairs (Carlson and Demiris 2012) and imitation of dancing routines in human-children interaction experiments (Sarabia, Ros, and Demiris, 2011). In addition to this robot imitation architecture, other researchers have proposed developmental-inspired robotics experiments on imitation based on Meltzoff and Moore's AIM model. For example Breazeal *et al.* (2005) have modeled facial mimicry between robots and adult caregivers, as they see this as a significant milestone in building natural social interactions between robots and humans and a theory of mind. Other researchers have focused on imitation and learning of emotional states. Hashimoto *et al.* (2006) investigated how a robot can learn to categorize different emotions by analyzing the user's facial expressions and labels for emotional states. Watanabe, Ogino, and Asada (2007) proposed a communication model that enables a robot to associate facial expressions with internal states through intuitive parenting, by imitating human tutors who mimic or exaggerate facial expressions.

6.4 Cooperation and Shared Intention

The development of cooperative and altruistic behavior in children, based on the capability to represent shared intention and to construct shared plans, has been the target of developmental robotics models of social interaction. Specifically, Dominey and collaborators (Dominey and Warneken 2011; Lallée *et al.* 2010) have modeled the cognitive and sensorimotor skills involved in a cooperative task like the "block launching" task of Warneken *et al.* (2006) (box 6.1).

In Dominey and Warneken's (2011) experiments, the robotic agent (a 6-DOF Lynx6 robotic arm [www.lynxmotion.com] with a gripper) and a human participant jointly construct a shared plan that allows them to play a game with objects on a table with goals such as "put the dog next to the rose" or "the horse chases the dog." The human and the robot can move four objects (a dog, a horse, a pig, and a duck) and have to place them next to six fixed landmarks (picture of a light, turtle, hammer, rose, lock, and lion). Each moveable object is a wooden puzzle piece with the image of the animal drawn on it, with a vertical bar for the human or robot to grasp. The six landmarks consist of puzzle pieces glued to the table. Their fixed positions allow the robot to more easily determine the location of the objects and its grasping posture.

The cooperating robot's cognitive architecture, and the corresponding experimental setup, are shown in figure 6.9. The central component of this cognitive architecture is the Action Sequence Storage and Retrieval System. The actions of the animal game are organized in a sequential structure (i.e., the shared plan), where each action is associated with either the human or the robot agent. Dominey and Warneken propose that the ability to store a sequence of actions, each tagged with its agent, corresponds to the shared plan. This constitutes part of the core of collaborative cognitive representations and is a unique ability of human primates. The Action Sequence Storage and Retrieval System design is inspired by neuroscience studies on the involvement of the human brain's cortical area BA46 in real-time storage and retrieval of recognized actions, and its link with sequence processing, language areas, and the mirror neuron system (Rizzolatti and Craighero 2004; Dominey, Hoen, and Inui 2006).

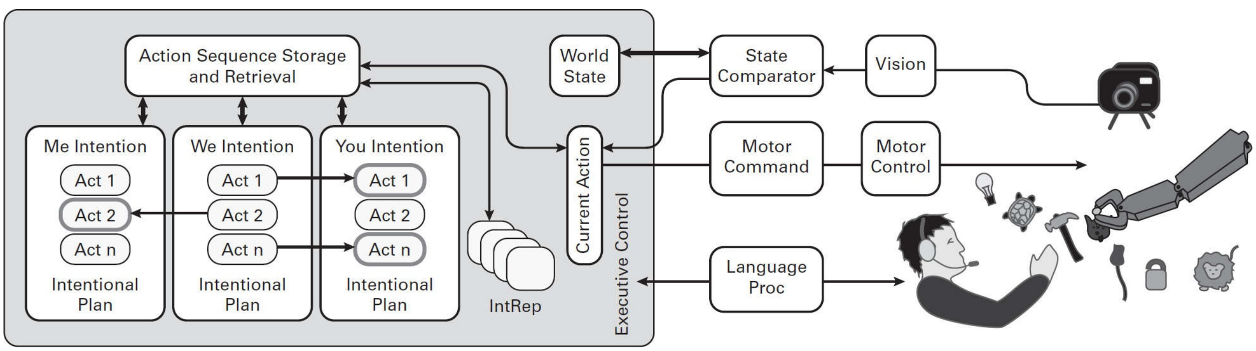


Figure 6.9

Architecture for cooperation system from Dominey and Warneken (2011). Figure courtesy of Peter Dominey. Reprinted with permission from Elsevier.

An intentional, goal-directed action representation is used, with the agent specifying each action and with the object and its goal as target location. The goal-directed representation formalism *Move(object, goal location, agent)* can then be used for a variety of tasks such as requesting an action and describing it. Three types of intentional plans are possible: (1) I Intention, (2) We Intention, and (3) You Intention. In the "I" and "You" intention plans, either the robot or the human execute all the actions in a sequence. In the We Intention plan, each action in the sequence is by default attributed either to the robot or the human agent, and the turn taking order is initially fixed. However, following the Carpenter, Tomasello, and Striano (2005) study on role reversal, the robot is equipped with the same capability to reverse the turn-taking order. When the robot is ready to execute a plan, it asks the user if she wants to go first. If the user responds yes, the roles of user and robot remain fixed as in the memorized sequence during the demonstration. Alternatively, the roles are reversed and the robot systematically reassigns the agents to each action.

Another core component of the robot's cognitive architecture is the *World Model*. This encodes the physical locations of the objects in the world, and corresponds to a 3D simulation of the grounded mental model of the agent (Mavridis and Roy 2006). The World Model is continuously updated when the robot detects a change of location of the objects carried out by either the human agent or the robot itself. A vision recognition system allows the tracking of the object locations, and a speech recognition and dialogue management system allows the collaborative interaction between the human and the robot (see box 6.2 for the overview of technical implementation details).

At the beginning of each game, the robot uses the vision system to update the location of each visible object in the world model. To check the correctness of its World Model, the robot lists the object positions by saying "The dog is next to the lock, the horse is next to the lion." Then it asks "Do you want me to act, imitate, play or look again?" If the object description is correct, the human user can ask to act by naming the game (e.g., "Put the dog next to the rose"), and the robot demonstrates it. Alternatively, the human will give a demonstration of a new game involving the four objects. In this second case, the robot memorizes the sequence of actions performed by the human user and then repeats it. During each action demonstration, the human indicates to the agent who has to perform the action by saying "You do this" or "I do this." These roles are assigned in the sequence as the default action roles in the We Intention plan.

A set of seven experiments was carried out to investigate various types of games, interactions, and collaborative strategies (see table 6.3 for a summary overview of the experiment's procedures and main results). Experiments 1 and 2 served to validate the system as a whole and the capability of the robot to play and imitate a single action. Experiments 3 and 4 tested the capability of the robot to build the We Intention plan for a sequence of multiple actions, with the systematic assignment of each action to either “I” (the robot) or “You” (the human user). In particular, in experiment 4, when the user does not perform one of its assigned actions, the robot can use the We Intention plan to substitute the user in the missing action.

Box 6.2

Implementation Details of Dominey and Warneken’s (2011) Experiments

Robot and Actions

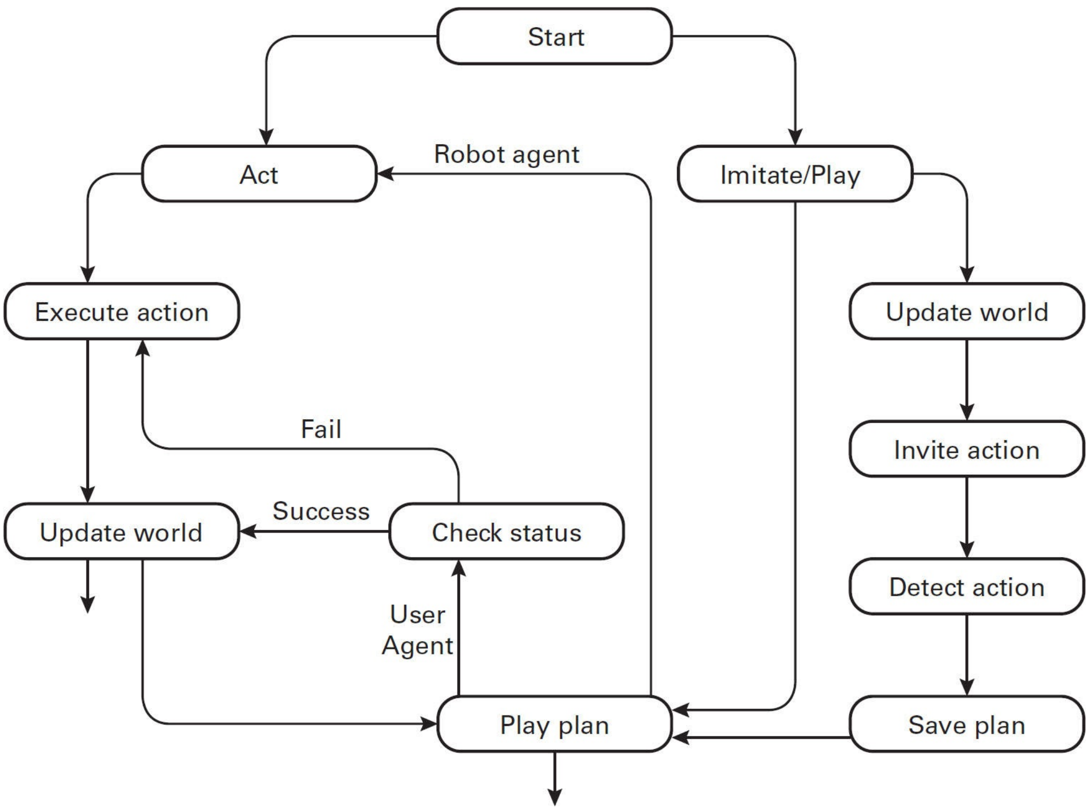
The Lynx6 arm (www.lynxmotion.com) robotic arm with two finger grippers was used in the experiment. Six motors control the degrees of freedom of the arm: motor 1 rotates the shoulder base of the robot arm, motors 2–5 control upper and forearm joints, and motor 6 opens/closes the gripper. The motors are controlled by a parallel controller connected to a PC, through the RS232 serial port. The robot was equipped with a set of action primitives that are combined to (a) position the robot at any of the six locations to grasp the corresponding object (e.g., Get(X)), and (b) move to a new position and release the object (e.g., PlaceAt(Y)).

Vision

To recognize the ten images of the four target objects and six landmarks, the SVN Spikenet Vision System (http://www.spikenet-technology.com) was used. A VGA webcam located at 1.25 m above the robot workspace captures a bird’s-eye view of the object arrangement on the table. For each of the ten images, the SVN system was trained offline with three recognition models at different orientations of the objects. During real-time vision processing, once the SVN recognizes all the objects, it returns the reliable (x, y) coordinates of each of the four moveable objects. Subsequently the system calculates the distance of each moveable object to the six fixed landmarks and identifies for each the nearest landmark. Both the human users and the robot are constrained to place the object they move in one of the zones designated next to the six landmarks. This facilitates the robot’s capability to grasp that object at the prespecified location (nearest the landmark). During the initial calibration phase, the six target locations are marked next to each of the fixed landmarks. These are arranged on an arc equidistant to the center of rotation of the robot base.

Natural Language Processing (NLP) and Dialogue Management

To communicate with the robot, an automatic speech recognition and dialogue management system is used. This is implemented through the CSLU Rapid Application Development toolkit (http://www.cslu.ogi.edu/toolkit/). This system allows interaction with the robot, via the serial port, and with the vision processing system, via file i/o. To manage the spoken language interaction with the robot, a structured flow of control of the dialogue is predetermined in CSLU (see figure below—courtesy of Peter Dominey). At the start of each interaction, the robot can either choose to Act or Imitate/Play. In the Act state, the human participant utters a request such as "Put the dog next to the rose." Using a grammatical construction template (Dominey and Boucher 2005b) an action is identified through the predicate(argument) formalism as in *Move(object, location)*. To execute the action, the robot has to update the representation of the environment (Update World). In the Imitate state, the robot first has to verify the current state (Update World) and then invite the user to demonstrate an action (Invite Action). The Detect Action procedure is triggered when the robot determines changes in the object location, leading to a saved action (Save Plan) represented by the same "predicate(argument)" formalism. During the demonstration, the user says who the agent should be when the game is to be played (e.g., "You/I do this"). Finally, the save action is executed by the robot (Play Plan).



Example of Experiment 1: Validation of Sensorimotor Control

Act state

• User command "Put the horse next to the hammer."
• The robot requests confirmation and extracts the predicate-argument representation: *Move(Horse, Hammer).*

Execute Action state

• *Move(Horse, Hammer)* is decomposed into the two primitive components of *Get(Horse)*, and *PlaceAt(Hammer)*.
• *Get(Horse)* queries the World Model in order to localize Horse with nearest landmarks.
• Robot performs a grasp of Horse at the corresponding landmark target location.
• *PlaceAt(Hammer)* performs a transport to target location Hammer and releases the object.
• Update World memorizes the new object location.

Table 6.3

Summary of the seven experiments in Dominey and Warneken's (2011) study on collaboration

Experiment	Description	Results
1: Sensorimotor control	User chooses Act and says "Put the horse next to the hammer"; robot extracts *Move(Horse, Hammer)*, and decomposes it into the two primitive *Get(Horse)*, and *Place-At(Hammer)*; robot executes action with World Model checks and update	Ability to transform a spoken sentence into a *Move(X to Y)* command and its constituent primitives; ability to perform visual localization of the target object; ability to grasp the object and put it at the specified location
2: Imitation	User chooses the Imitate state; user performs one action; robot builds a *Move(object, location)* action representation by detecting object location changes in vision system; robot verifies action representation with user; performs action	Ability to detect the final "goal" of user-generated actions as defined by visually perceived state changes; imitation defined as achievement of goal; utility of a common representation of action for perception, description, and execution
3: Cooperative game	Same as imitation, but with a sequence of multiple actions; for each action the user specifies "you do this" or "I do this"; "We Intention" plan with different agents for different actions; robot and user alternate in sequence of actions	Ability to learn a simple intentional plan as a stored sequence of multiple actions with roles assigned to the human and the robot; cooperative, turn-taking execution of actions by user/robot
4: Interrupting cooperative game	Same as before, with one imitation of full alternating sequence; at second imitation, the user does not perform one of her assigned actions; the robot says "Let me help you" and executes the action	The robot's stored representation of the action allows it to help the user
5: Complex game	Same as experiment 3, but with complex game "dog chases horse"; user moves the dog, and robot "chases" the dog with the horse until they both return to their starting places	Learning by demonstration of a complex intentional plan in a coordinated and cooperative activity
6: Interrupting complex game	Same as experiment 4, with complex dog chasing sequence User fails to perform final move, dog back to fixed landmark Robot can substitute user to achieve final goal	Robot's generalized ability to help whenever it detects that the human agent has difficulties
7: Role reversal in complex game	Same game from experiment 5; robot asks, prior to playing the game, "do you want to go first?"; user responds "no" (user was first in demonstrated game); robot starts game and systematically reassigns roles	Ability to benefit from the bird's-eye view representation of the shared intentional plan and take either role in the plan

Figure 6.10

Cooperation game between the robotic arm and the human: “the horse chases the dog” in Dominey and Warneken (2011): (a) human participant demonstrating the chasing game, and (b) robot executing the learned game. Figure courtesy of Peter Dominey.

In experiments 5 and 6 the sequence learning capability is extended for a more complex game where the target goal of each action is not a fixed landmark, but a dynamically changing target defined by the user. The robot must learn to move the horse to chase the dog moved by the human user (figure 6.10). The robot can also successfully substitute the user in the interrupted chasing game of experiment 6, and return the dog to the fixed landmark. This task is related to the learning-by-demonstration scenario (Zöllner, Asfour, and Dillmann 2004) where agents define a complex intentional plan in a coordinated and cooperative way.

Finally, in experiment 7 Dominey and Warneken (2011) demonstrate the feasibility of the robot’s role reversal capability using the “birds’ eye view” representation of the shared intentional plan. When the human user fails to start the dog chasing game, as she had done during the previous game demonstration, the robot is able to swap roles with the user and initiate the game by moving the dog. This implements the Carpenter, Tomasello, and Striano (2005) role reversal capability observed in eighteen-month-old children.

This cognitive architecture can be extended to other types of human-robot collaborative tasks. For example, in Lallée *et al.* (2010), the humanoid robot iCub learns to assemble a table, attaching the four legs to the main board, with the help of the human experimenter (figure 6.11). To achieve this, the robot learns by experience, allowing it to anticipate the repetitive activities as the four legs are successively attached. By allowing the iCub the ability to learn shared plans, Lallée *et al.* (ibid.) provided the robot with the ability to perform the joint task with the human, to demonstrate role reversal, and even to share this acquired knowledge with another iCub remotely over the Internet.

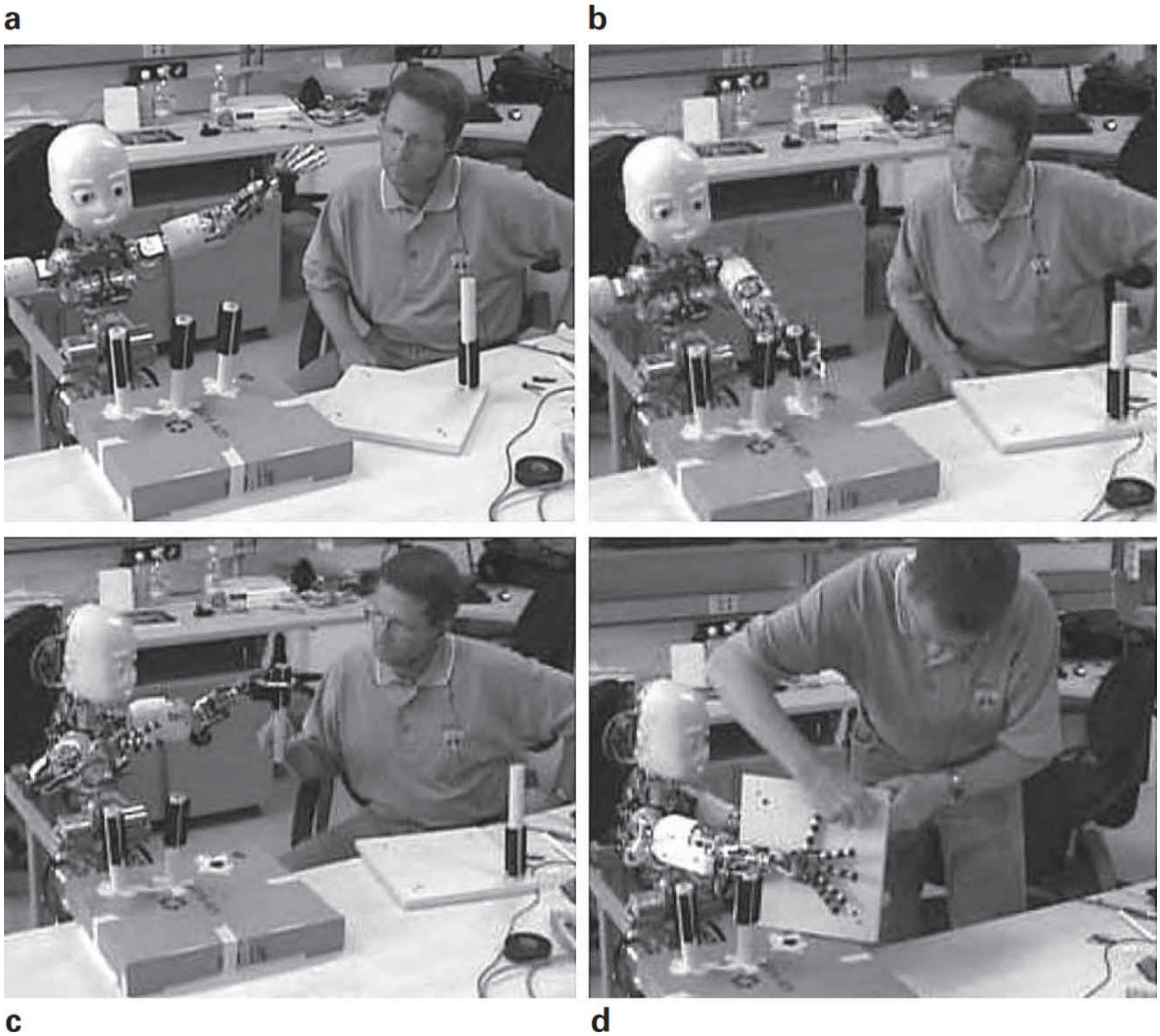


Figure 6.11

The cooperative table construction task using iCub platform in Lallée *et al.* (2010). Robot and human have to cooperate in order to build a table (a). The robot has to grasp the table legs (b), it passes them to the user (c), and holds the table while the user screws on the legs (d). Figure courtesy of Peter Dominey.

This approach demonstrates that it is possible to build the cognitive architecture of a social robot that is able to observe an action, determine its goal, and dynamically attribute roles to agents for a cooperative task. The design of such a sociocognitive architecture benefits from its direct inspiration from developmental and comparative psychology on the role of altruistic and social skills in early development.

6.5 Theory of Mind (ToM)

The design of theory of mind capabilities in interactive robotic agents is an important extension of social and cognitive capabilities in robots as it allows them to recognize the goals, intentions, desires, and beliefs of others. A robot can use its own theory of mind to improve the interaction with human users, for example, by reading the intention of the others and reacting appropriately to the emotional, attentional, and cognitive states of the other agents, to anticipate their reactions, and to modify its own behavior to satisfy these expectation and needs (Scassellati 2002).

In the previous sections we have looked at the robotic implementation of various capabilities that combined together contribute to the full development of theory of mind in cognitive robots. For example, all the work on gaze behavior modeling (section 6.2) implements a core prerequisite for development of a complete theory of mind. Moreover, the review of the work on face perception in chapter 4 (section 4.2) contributes to the design of key components in the robot's theory of mind. However, notwithstanding the numerous developmental robotic models of individual social skills, there are only a few attempts to explicitly model the integration of many processes for a general robot's theory of mind (Scassellati 2002; Breazeal *et al.* 2005). Here we will look at Scassellati's (2002) theory of mind architecture for the COG humanoid robot. Scassellati explicitly models theory of mind principles consistent with infants' developmental theories of Leslie and Baron-Cohen (see section 6.1.4). For example, Scassellati focuses on the implementation of Leslie's distinction between the perception of animate and inanimate objects, with subsequent differentiation among mechanical, action, and attitudinal agency. This approach also puts great emphasis on Baron-Cohen's eye detection mechanism.

This robotic theory of mind model is based on the COG robot, an upper-torso humanoid platform with two six-DoF arms, a three-DoF torso, and seven DoFs for the head and neck (Breazeal and Scassellati 2002). The model implements the following behavioral and cognitive mechanisms necessary for theory of mind development:

- Pre-attentive visual routines

• Visual attention
• Face and eye detection (Baron-Cohen's eye direction detector)
• Discrimination of animate and inanimate entities (Leslie's mechanical agency)
• Gaze following
• Deictic gestures

The pre-attentive visual routines are based on saliency map analyses that implement the infant's natural preference for bright and moving objects. The three basic feature detectors implemented in COG are color saliency, motion detection, and skin color detection (Breazeal and Scassellati 2002). Using four color-saturated areas filters (red, green, blue, and yellow), the algorithm generates four opponent-color channels that are subsequently thresholded to produce a smooth-output color saliency map. The robot's visual input is processed at thirty Hertz to extract these three saliency features, because this speed is suitable for handling social interaction with human participants. For motion detection, temporal differencing and region growing is used to generate the bounding boxes of moving objects. For skin detection, the images are filtered using a mask whose color values are the result of the hand classification of skin image regions.

The next stage of visual attention selects the objects in the scene (including human limbs) that require an eye saccade and neck movement. This is achieved by combining the three bottom-up detectors for skin, motion, and colors, with a top-down motivation and habituation mechanism (time-decayed Gaussian representing habituation effects). These visual attentional mechanisms are based on the model of human visual search and attention proposed by Wolfe (1994).

Eye and face detection allow the robot to maintain eye contact with the human experimenter. First a face detection technique is used to identify locations that are likely to contain a face using a combination of the skin and motion detection maps. These regions are processed using the "ratio templates" method (Sinha 1995), which is based on a template of sixteen expected frontal face regions and twenty-three relations among them. The robot then gazes toward the detected face region, which then leads to the identification of the eye subregion (as in Baron-Cohen's EDD module).

The function to discriminate animate and inanimate entities from visual perception of self-generated motion is based on Leslie's mechanical agency mechanism of the Theory of Body module. A two-stage developmental process is modeled. The first stage only uses the spatiotemporal features of object size and motion to track the objects. The second stage uses more complex object features, such as color, texture, and shape. Motion tracking is implemented through the multiple hypothesis tracking algorithm proposed (Cox and Hingorani 1996), where the output of the motion saliency map is processed to produce a labeled trajectory of the coordinates of the centroid of an object over a series of temporal frames. The system is also capable of handling object disappearance from the visual input, for example due to object occlusion, head rotation, or the limited size of the field of view. When a movement is interrupted, a "phantom point" can be created that can later be linked to trajectories of objects that enter, exit, or are occluded within the visual field. A more advanced learning mechanism to detect animate entities has been developed by Gaur and Scassellati (2008).

The gaze following function requires the implementation of three subskills that further process the eye detection operation: (1) extracting the angle of gaze, (2) extrapolating the angle of gaze to a distal target object, and (3) motor routines for alternating between the distal object and the experimenter. This allows the modeling of the incrementally complex infant's gaze-following strategies proposed by Butterworth (1991), starting from a simple sensitivity to the field of gaze toward the fully developed representational capability (see section 6.1.1).

Scassellati (2002) also suggests that a complementary cognitive capability to gaze following is that of understanding, and responding to, deictic gestures. These include imperative pointing and declarative pointing. Imperative pointing involves the pointing gesture toward an object that is out of reach, to implicitly ask the other agent to pick it up and give it to the infant. Developmentally the imperative pointing can be considered a natural extension of the infant's own reaching behavior. Declarative pointing uses a gesture of an extended arm and index finger, to draw attention to a distal object without an implicit request to have it. The implementation of such gesture understanding is core in social robotics, for example to operationalize requests and declarations consistent with the robot's own, and the agent's, beliefs. Although pointing gestures have not been implemented in the cognitive theory of mind model, other researchers have proposed methods to interpret point gestures, as in Hafner and Kaplan 2005.

In addition to the mechanisms proposed by Scassellati in 2002, a robot with a complete theory of mind mechanism also requires additional capabilities, such as self-recognition. This has been recently explored by Gold and Scassellati (2009), with Nico, an upper-torso humanoid robot with the arm and head kinematics of a one-year-old. This baby robot is trained to recognize its own body parts, as well as their reflections in a mirror, using a Bayesian reasoning algorithm. This self-recognition ability allows the robot to recognize its image in a mirror, and to distinguish the experimenter as an “animate other” and static objects as “inanimate.” These recent developments on theory of mind capabilities, as well as general progress on developmental robotics models of social skills, are important to support the design of robots capable of understanding the intentions of other agents, such as humans and robots, and integrate them with their own control system for effective human-robot interaction.

6.6 Conclusions

In this chapter we have focused on both developmental psychology and developmental robotics studies on the acquisition of social skills. The literature on child psychology demonstrates that infants are endowed with a strong instinct to interact with other people, as in the case of their capability to imitate facial gestures within the first days of life. This social instinct is strongly supported, and reinforced, by the adults’ caregiving behavior of continuous interaction with and stimulation of the infant. This strictly coupled adult-child interaction allows the child to gradually acquire ever more complex joint attention skills (shared eye gaze and pointing gestures), increasingly articulated imitation skills (from body babbling and body movement imitation to repeating the actions on objects and inferring the demonstrator’s intentions), altruistic and cooperative interactions with the others (spontaneous help and role reversal behavior), up to developing a full theory of mind (attributing beliefs and goals to other people).

Developmental robotics models have taken direct inspiration from child psychology literature (Gergely 2003), sometimes even through close roboticist-psychologist collaborations (e.g., Demiris and Meltzoff 2008; Dominey and Warneken 2011), to design social skills in robots. Table 6.4 provides an overview of the various skills involved in designing social robots, and how these have been addressed in the robotics studies analyzed in this chapter.

This overview shows that their shared/joint attention, a fundamental capability for social agents, is one of the key phenomena more extensively modeled in robotics experiments. In some studies, shared attention is primarily operationalized as mutual gaze between the caregiver adult (human experimenter) and the infant (robot) as in Kaplan and Hafner (2006b), Imai, Ono, and Ishiguro (2003), and Kozima and Yano (2001). In Triesch *et al.* (2006), the manipulation of normal and impaired gaze shift patterns is also used to model socio-attentional syndrome such as autism and Williams syndrome. In other experiments, shared attention is achieved by gaze following, as in the Nagai *et al.* (2003) model. In particular this study provides a nice demonstration of the developmental emergence of different gaze following strategies, as in the study on human infants (Butterworth 1991). The analysis of the robot's gaze following at different stages of the developmental learning process show the robot face first uses an ecological gaze strategy (i.e., looks at an interesting object regardless of the experimenter's gaze direction), then this becomes a geometric strategy (the robot face and human participant achieve joint attention only when the object is in the infant's field of view), and finally leads to the adoption of representational gaze strategies (the infant robot can find a salient object outside own field of view). In addition, joint attention is modeled through the use of pointing behavior, as in Hafner and Kaplan 2005.

Another area of social competence that has attracted much attention in developmental robotics is imitation learning. Imitation has also been one of the main research issues in the wider field of cognitive robotics and human-robot interaction (Breazeal and Scassellati 2002; Nehaniv and Dautenhahn 2007; Schaal 1999). Among the studies with a clear focus on the developmental stages of imitation, the models proposed by Demiris (Demiris and Meltzoff 2008; Demiris *et al.* 1997) and Breazeal *et al.* (2005) have explicitly implemented the active intermodal matching model of infant development proposed by Meltzoff and Moore (1997). In Demiris and Hayes (2002), the AIM model is incorporated into the HAMMER architecture, an ensemble of pairs of inverse and forward models, as a means to imitate and learn new inverse models. This robotic architecture also includes a top-down attentional mechanism for the control of attention during imitation, which allows the robot to deal with limited access to the sensory and memory capacities. This allows the robot to integrate top-down attentional biases and bottom-up visual attention cues.

Table 6.4

Mapping of developmental robotics model of social skills and individual social capabilities (two ++ signs indicate main focus of the study, and one + sign a partial explicit inclusion of the cognitive/social skill)

Social and cognitive skills	Kaplan and Hafner 2006b	Nagai et al. 2003	Imai, Ono, and Ishiguro 2003	Kozima and Yano 2001	Triesch et al. 2006	Demiris et al. 1997	Demiris and Khadhouri 2006	Breazeal et al. 2005	Watanabe, Ogino, and Asada 2007	Dominey and Warneken 2011	Lallee et al. 2012	Scassellati 2002	Gold and Scassellati 2009
(robot)	AIBO	Robot head	Robovie	Infanoid	Simu-lation	Robot head	PeopleBot	Leo	Virtual face	Robot arm	iCub	COG	Nico
Mutual gaze	+		++	++	++								
Gaze following		++		+	++							+	
Pointing gesture	++		++	++									
Attention (visual)		++					++					+	
Attention (top-down)		+					++						
Shared/koint attention	+	++	+	+	++							+	
Imitation: face expressions						++		++	+				
Imitation: face emotions									++				
Face detection								+	+			+	
Imitation: body movements							++						++
Cooperation										++	++		
Role reversal										++	++		
ToM								+				++	+
Self-recognition (mirror)													++

Another areas of social development thoroughly investigated through robotic experiments is collaborative and altruistic behavior. Dominey and Warneken (2011) propose a cognitive architecture for human-robot collaboration based on developmental theories and replicate the tasks in the seven infant and chimpanzee experiments carried out by Warneken, Chen, and Tomasello (2006). In the subsequent studies of Lallée *et al.* (2012), they extend this model for collaborative tasks with the iCub humanoid robot. These experiments also provide a demonstration that the robot is capable of role reversal and bird's-eye view of the collaboration setting (Carpenter, Tomasello, and Striano 2005), in other words, dynamically taking on the demonstrator's role to help her achieve the task.

Finally, some models explicitly address the issue of developing theory of mind capabilities in the robots. In Scassellati 2002, this is achieved by endowing the robot with multiple sociocognitive skills, such as pre-attentive visual routines and visual attention, face and eye detection, discrimination between animate and inanimate entities, gaze following, and deictic gestures. This architecture explicitly tests some of the components in the psychology literature on theory of mind development, as with the operationalization of Baron-Cohen's eye direction detector in the robot's face and eye detection capabilities, and the sensitivity to discriminate between animate and inanimate agency, as in Leslie's mechanical agency concept. The agency animate/inanimate distinction is also used to model robot's self-recognition in Gold and Scassellati's (2009) study.

Overall, this chapter demonstrates that social learning and interaction is one of the most articulated fields of developmental robotics, because the design of social capabilities is an essential precondition for human-robot interaction with robot companions. These experiments on social learning establishes the foundation for the investigation of more advanced capabilities in robots, such as the theory of mind capability to read the intention of the others, and to predict their needs and behavior, thus facilitating effective human-robot collaboration.

Additional Reading

Tomasello, M. *Why We Cooperate.* Cambridge, MA: MIT Press, 2009.

This volume presents Tomasello's theory of human cooperation. It reviews a series of studies on young children and primates aiming at the identification of the specific mechanisms supporting human infants' natural tendency to help others and collaborate. This unique feature, not observed as a spontaneous behavior in our closest evolutionary ancestor, provide the basis for our unique form of cultural organization based on cooperation, trust, group membership, and social institutions.

Nehaniv, C., and K. Dautenhahn, eds. *Imitation and Social Learning in Robots, Humans and Animals.* Cambridge: Cambridge University Press, 2007.

This highly interdisciplinary volume includes chapters on theoretical, experimental, and computational/robot modeling approaches to imitation in both natural (animals, humans) and artificial (agents, robots) systems. This is the successor to the volume edited by Dautenhahn and Nehaniv, *Imitation in Animals and Artifacts* (MIT Press, 2002), and the follow up in the international series of Imitation in Animals and Artifacts workshops organized by the two editors. The 2007 volume includes contributions from developmental psychologists (e.g., M. Carpenter, A. Meltzoff, J. Nadel), animal psychologists (e.g., I. Pepperberg, J. Call), and numerous robot imitation researchers (e.g., Y. Demiris, A. Billard, G. Cheng, K. Dautenhahn and C. Nehaniv).

7 First Words

Language, as the capacity to communicate with others through speech, signs, and text, is one of the defining features of human cognition (Barrett 1999; Tomasello 2003, 2008). As such the study of language learning and language use has attracted the interested of scientists from different disciplines ranging from psychology (for psycholinguistics and child language acquisition) and neuroscience (for the neural bases of language processing) to linguistics (the formal aspects of human languages). Therefore it is not surprising that even in developmental robotics, and in cognitive modeling in general, there has been a great deal of research on the design of language learning capabilities in cognitive agents and robots.

An important issue in language research is the "nature" versus "nurture" debate, that is the opposition between those (nativists) who believe that we are born with knowledge of universal linguistic principles, and those (empiricists) who propose that we acquire all linguistic knowledge through interaction with a language-speaking community. Within the nativist position, some influential researchers have proposed that there are universal syntactic rules or generative grammar principles, and that these are innate in the human brain (Pinker 1994; Chomsky 1957, 1965). For example Chomsky proposed that we are born with a language "brain organ" called the language acquisition device. In Chomsky's Principles and Parameters theory, our linguistic knowledge consists of a series of innate, universal principles (e.g., we always use a fixed word order) with learnable parameters associated with them (e.g., in some languages, the verb always precedes the object, in others the verb follows after the object). The language acquisition device has a set of predefined parameter switches that are set during language development. If a baby develops in an English-speaking community, the word order parameters (switches) will be set to SVO (subject-verb-object) order, while in Japanese-speaking children, this parameter will be switched to SOV (subject-object-verb). Another important aspect of the nativist view is the poverty of stimulus argument. This argument states that the grammar of a language is unlearnable if we consider the relatively limited data available to children during development. For example, a child is never, or rarely, exposed to incorrect grammatical sentences, but she is able to distinguish grammatically correct sentences from those that are ungrammatical. Therefore, the nativist's explanation is that the input during development must be complemented by innate knowledge of syntax (i.e., the principles and parameters of the language acquisition device).

According to the nurture stance, the essence of the linguistic knowledge emerges from language use during development, without any need to assume the existence of innate language-specific knowledge. For example, grammatical competence is seen not as universal, prewired knowledge, as in nativist generative grammar. On the contrary, as Michael Tomasello, one of the primary supporters of the nurture stance, says: "the grammatical dimension of language is the product of a set of historical and ontogenetic processes referred to collectively as *grammaticalization*" (Tomasello 2003, 5). Children's language development depends on the child's own ontogenetic and maturational mechanisms, such as the critical period, and on cultural and historical phenomena that affect the dynamics on a continuously changing shared language. This view of language development (construction) does not exclude that there are innate maturational and sociocognitive factors affecting language acquisition. In fact, genetic predispositions such as the critical period and the biases in categorization and world learning (see section 7.1) do affect language acquisition. However, these are general learning biases, and not innate language- (i.e., syntax-) specific competences. For example, the critical period of language acquisition is one of the crucial phenomena in language development. Typically children only develop full command of a native language if they are exposed to it in during the first few years of life. This phenomenon, and in general the effects of age of acquisition in linguistic competence, has been extensively studied for second language acquisition (e.g., Flege 1987). As for the Poverty of Stimulus argument, in the literature there is evidence that children do get negative examples of impossible, grammatically incorrect sentences, and that parents do correct their children when they make grammar mistakes. In addition, in computational models it has been demonstrated that a reduced, impoverished input can act as a bottleneck that even helps the child discover syntactic regularities in the language (Kirby 2001).

This empiricist view of language learning is normally known as the constructivist, usage-based theory of language development (Tomasello 2003; MacWhinney 1998). This is because the child is seen as an active constructor of his own language system through implicit observation and learning of statistical regularities and logical relationships between the meaning of words and the words used. Within linguistics, this has helped promote cognitive linguistic theories (Goldberg 2006; Langacker 1987). This closely associates semantics with grammar, and demonstrates that syntactic categories and roles emerge out of usage-based regularities in the semantic systems. For example, the general grammatical category of verbs emerges from incremental and hierarchical similarities between verbs sharing common features (e.g., Tomasello's 1992 verb island hypothesis—see section 7.3 for more details).

The constructivist view of language is highly consistent with the embodied developmental robotics approach to the modeling of language learning (Cangelosi *et al.* 2010). Most of the principles of developmental robotics, as discussed in chapter 1, reflect the phenomena of gradual discovery and acquisition of language observed in studies of children's acquisition of linguistics capabilities, and the role of embodied and situated interaction with the environment in cognitive development. A fundamental concept in robotics and embodied models of language learning is that of the *symbol grounding* (Harnad 1990; Cangelosi 2010). This refers to the capability of natural and artificial cognitive agents to acquire an intrinsic (autonomous) link between internal symbolic representations and referents in the external word or in internal states. By default, linguistic developmental robotics models are based on the grounded learning of associations between words (which are not always encoded as symbols, but may be subsymbolic dynamic representations) and external and internal entities (objects, actions, internal states). As such, these models do not suffer from what Harnad (1990) calls the "Symbol Grounding Problem."

This chapter will explore the close link between embodied, constructivist theories and the developmental robotics model of language learning. In the next two sections we will first briefly review the main phenomena and milestones of linguistic development and the principles involved in conceptual and lexical acquisition (section 7.1). We next discuss in detail one seminal child psychology experiment on the role of embodiment in early word learning (section 7.2). These phenomena and principles will then be mapped to the various developmental robotics studies of language acquisition, respectively for the models of the development of phonetics competence through babbling (7.3), the robot experiments on early word learning (7.4), and the models of grammar learning (7.5).

7.1 Children's First Words and Sentences

7.1.1 Timescale and Milestones

The most significant events of language development are concentrated during the first three to four years. This is not to say that children stop progressing in their linguistic capabilities at the school age. On the contrary, there are important developmental stages associated with primary school age, and beyond, and they mostly regard metacognitive and meta-linguistics achievements (i.e., awareness of one's own language system) that gradually lead to adultlike linguistic competence. However, developmental psychology and developmental robotics both focus on the core early stages of cognitive development. These early milestones of language acquisition follow the parallel and intertwined development of incremental phonetics processing capabilities, increasing lexical and grammatical repertoires, and refined communicative and pragmatic faculties.

Table 7.1

Typical timescale and major milestones of language development (adapted from Hoff 2009)

Age (months)	Competence
0–6 months	Marginal babbling
6–9 months	Canonical babbling
10–12 months	Intentional communication, gestures
12 months	Single words, holophrases Word-gesture combinations
18 months	Reorganization of phonological representations 50+ word lexicon size, vocabulary spurt Two-word combinations

24 months	Increasingly longer multiple-word sentences Verb islands
36+ months	Adultlike grammatical constructions Narrative skills

Table 7.1 provides an overview of the main milestones during language development (Hoff 2009). In the first year, the most evident sign of linguistic development is vocal exploration, meaning, vocal babbling. Initially babbling consists of vocal play with sounds such as cooing, squeals, and growls (also known as “marginal babbling”). At around six to nine months of age, children go through the stage of “canonical babbling” (also known as “reduplicated babbling”) (Oller 2000). Canonical babbling consists of the repetition of language-like syllabic sounds such as “dada” or “bababa,” merging into variegated babbling This is hypothesized to play a role in the development of refined feedback loops between sound perception and production, rather than in communicative purposes, and the transition from the marginal to canonical babbling stage is a fundamental step in phonetic development. Also toward the end of the first year, children start to produce communicative gestures (e.g., pointing) and iconic gestures (e.g., a throwing motion to indicate a ball, or raising the fist to the ear, to mean telephone). These gestures are clear signs of the child’s prelinguistic intentional communication and cooperation skills, and first signs of a theory of mind (Tomasello, Carpenter, and Liszkowski 2007; P. Bloom 2000).

Toward the end of the first year, reduplicated babbling, subsequently followed by the richer phonetic combinations of a range of consonant and vowel sounds (variegated babbling), and the restructuring of the language-specific phonetic representations and repertoire, lead to the production of the first single words. The first words are typically used to request an object (e.g., say “banana” to request the fruit), indicate its presence (“banana” to indicate the presence of the fruit), name familiar people, indicate actions (“kick,” “draw”) and dynamic events (“up,” “down”), and ask questions “Whats-that” (Tomasello and Brooks 1999). These words are normally referred to as “holophrases,” as a single linguistic symbol is used to communicate a whole event. In some cases holophrases can correspond to an apparent word combination, as in “Whats-that," though at this stage the child has not yet developed a full independent use of the individual words and of their flexible combination in multiple combination.

During the first part of the second year, children slowly increase their single-word repertoire. This includes a variety of names of social agents (dad, mum), labeling of food, objects, and body parts, words for requests ("more"), and so on. The growth of the child's lexicon is characterized by a nonlinear increase in the number of words, and is called the "vocabulary spurt." The vocabulary spurt (a.k.a. naming explosion), typically observed between months 18 and 24, refers to a steep increase in rate of growth of the vocabulary that happens after the child has learned approximately fifty words (Fenson *et al.* 1994; L. Bloom 1973). This is typically hypothesized to depend on a restructuring of lexical-semantic representation, leading to qualitative changes in word learning strategies. As the child increases her lexicon repertoire, she is also able to produce two-word utterances. However, during the beginning of the second year, and before the capability to produce two-word combinations is fully developed, children go through a hybrid word/gesture stage when they combine one gesture with a word to express combinations of meanings. For example, a child can say the word "eat" and point to a sweet, to communicate "eat the sweet." Even at these early stages, gestures, and their combination with words, become predictors of future lexical and grammatical competence and general cognitive capabilities (Iverson and Goldin-Meadow 2005).

The first two-word combinations that appear at around eighteen months of age typically follow the structure of pivot-style constructions (Braine 1976). Children produce two-word combination based on a constant element (pivot), such as "more," "look," and a variable slot, such as "more milk," "more bread," "look dog," "look ball."

During the third year the child starts to develop ("construct") more complex grammatical competences. One seminal example of constructivist grammatical development is the verb island hypothesis (Tomasello 1992). Although children at this age are able to use a variety of verbs, these appear to exist as independent syntactic elements, called "verb islands." For example, for some verbs (e.g., "cut") the child is only able to use very simple syntactic combinations of the same verb with different nouns of objects ("cut bread," "cut paper"). Other verbs, instead, can have a richer syntactic use. For example, the verb “draw” is uttered with richer combinations such as “I draw,” “draw picture,” “draw picture for your,” “draw picture with pencil.” These differences in the level of complexity and maturity of different verb islands are due to usage-based experience. In the case of the well syntactically developed verb island “draw” the child is exposed to richer combinations of the verb with multiple participant types and multiple pragmatics roles and functions. At this stage, however, the child has not developed the general syntactic and semantic categories of agent, patient, instrument, as in mature adultlike verb categories. Instead, she acquires verb-island specific roles such as “drawer,” “drawn object,” “draw something for person,” and “draw something with.” These intermediate syntactic constructions also allow the child to develop more refined morphological and syntactic skills, since for some verb islands there is a richer use of prepositions links to verb as with “on,” “by,” and so on (Tomasello and Brooks 1999).

From four to six years of age, corresponding to the preschool period in most countries, the child gradually develops mature adultlike syntactic constructions such as simple transitives (agent-verb-patient as in “John likes sweets”), locatives (agent-verb-patient-locative-location as in “John puts sweets on table”), and datives (agent-verb-patient-dative-receiver as in “John gives sweets to Mary”) (Tomasello and Brooks 1999). This gradually leads to the development of ever more complex syntactic-morphologic constructions, more abstract and generalized grammatical categories, up to the formation of formal linguistic categories such as word classes. These syntactic skills are accompanied by extended pragmatics and communicative skills, thus leading to refined narrative and discursive capabilities.

7.1.2 Principles of Conceptual and Lexical Development

To be able to achieve the milestones we have outlined during language acquisition, and given that language is closely intertwined with the parallel development of other sensorimotor and social skills, it is important to know which other factors and competences support these developments. As discussed in the initial sections on the nature versus nurture debate, all theories of language development assume that the child relies on some (innate or previously developed) competence to learn the lexicon and syntactical categories. And although there is strong disagreement on the pre-existence of innate language-specific (i.e., syntax-specific) capabilities between the generativist and the constructivist view of language, all developmentalists agree that the child's acquisition of first words and grammar is supported by a set of prelinguistics capabilities. Some of these might be innate, species-specific behavior, while others might just be social and conceptual skills gradually acquired during the early stages of development.

These general cognitive capabilities, often referred to as "biases" or "principles" of conceptual and lexical development (Golinkoff, Mervis, and Hirshpasek 1994; Clark 1993), depend on a combination of perceptual and categorization skills (e.g., the capacity to discriminate and identify objects and entities, and to group them within a category) and social skills (e.g., the instinct to imitate and cooperate). These principles have the main function of "simplifying" the task of word learning by reducing the amount of information that children must consider when learning a new word.

Table 7.2 provides an overview of the main principles that have been demonstrated to contribute to lexical development. This list extends the original set of six principles, as proposed in Golinkoff, Mervis, and Hirshpasek 1994, by including more recent findings from developmental psychology.

Table 7.2

Language acquisition principles (biases) in word learning

Principles (Biases)	Definition	Reference
Reference	Child has some awareness that words are used to map entities in the real world	Golinkoff, Mervis, and Hirshpasek 1994 Mervis 1987
Similarity	Once a label is associated with one instance of an object, this is extended to functionally or perceptually similar exemplars	Clark 1993
Conventionality	Speakers of a common language tend to use the same words to express certain meanings	Clark 1993
Whole-object (Object scope)	Children assume that a novel label is likely to refer to the whole object and not to its parts, substance, or other properties	Markman and Wachtel 1988; Gleitman 1990
Whole-part juxtaposition	Children are able to interpret a novel label as referring to a part, when the novel part label is juxtaposed with a familiar whole-object label	Saylor, Sabbagh, and Baldwin 2002
Segmentation	Infants exploit highly familiar words to segment and recognize adjoining, previously unfamiliar words	Bortfeld et al. 2005
Taxonomic (categorical scope)	Words refer to things that are of the same kind	Markman and Hutchinson 1984
Mutual exclusivity (novel-name nameless category; contrast)	Children assume that nouns pick out mutually exclusive object categories, and so each object category should have only one label	Markman and Wachtel 1988 Golinkoff, Mervis, and Hirshpasek 1994 Clark 1993
Embodiment	Children use their body relationship with the objects (e.g. spatial location, shape of the object) to learn new object-word associations	Smith 2005; Samuelson and Smith 2010
Social cognition	Shared attention, imitation learning, cooperation	Baldwin and Meyer 2008 Carpenter, Nagel, and Tomasello 1998 Tomasello 2008

The *reference principle* is at the basis of word learning and reflects the fact that the child must develop some awareness that words are used to map objects and entities in the real word. Mervis (1987) first observed that at around twelve months of age children learn to name objects just for the sheer pleasure of it. With the additional *Similarity Principle*, once a label is associated with one instance of an object, the same word can be extended to exemplars other than those initially seen, and that share with the original object some functional or perceptual similarities (Clark 1993).

The *whole-object principle* (also known as the object scope principle) starts from the observation that children assume that a novel label that they hear for the first time is likely to refer to some object present in the scene. In particular, the label is assumed to refer to the whole object, rather than to its parts, its substance, or other properties (Markman and Wachtel 1988; Gleitman 1990). The *whole-part juxtaposition principle* is based on the observation that children are able to interpret a novel label as referring to a part, when the novel part label is juxtaposed with a familiar whole-object label (Saylor, Sabbagh, and Baldwin 2002).

The *segmentation principle* (Bortfeld *et al.* 2005) states that infants, as young as six-month-olds, can exploit highly familiar words, such as their own names or other people's names, to segment and recognize adjoining, previously unfamiliar words from continuous, fluent speech.

The *taxonomic principle* (also the categorical scope principle) states that children assume that a word refers to things that are of the same kind, and that this extends to the members of the basic category to which the original entity belongs (Markman and Hutchinson 1984; Golinkoff, Mervis, and Hirshpasek 1994).

The *mutual exclusivity principle* (also the contrast principle, or the novel-name nameless category principle) starts from the assumption that nouns pick out mutually exclusive object categories, so that each object category should have only one label associated with it (Markman and Wachtel 1988; Clark 1993). Therefore, when a child hears a novel label and sees a new, nameless object, she attaches the new word to the novel object. This is true even in the case when there are two objects, with one already labeled by the child and one with no word associated to it.

The *conventionality principle* refers to the fact that a child assumes that all the speakers of a common language tend to use the same words to express certain meanings, so a child must always use the same label to refer to the same object (Clark 1993).

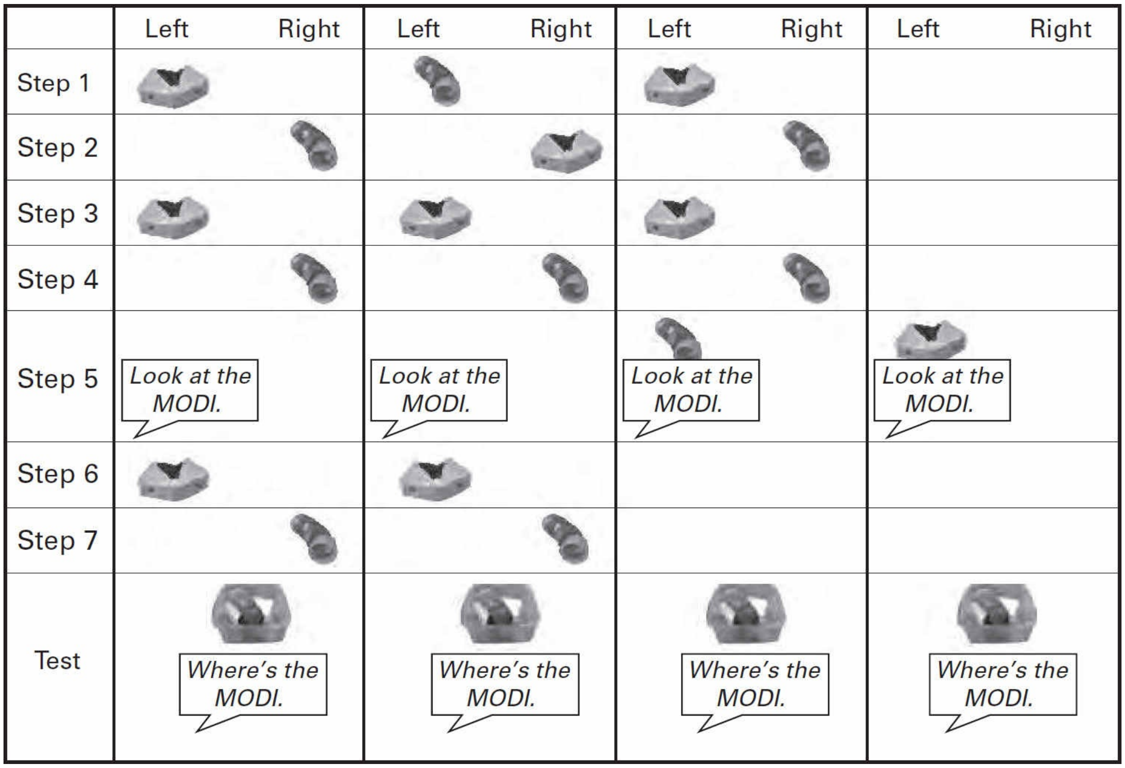
The *embodiment principle* is based on the observation that children use their body relationship with the external world to learn new object-word associations. For example, the child can use the relations between body posture and spatial location of the objects, even in the temporary absence of the object, to learn a new object-label association (Smith 2005). This principle will be discussed in detail in the next section, with the example of the experimental setup in box 7.1.

Box 7.1

The Modi Experiment (Smith and Samuelson 2010)

Procedure

The parent sits in front of a table, holding the child in her lap. The experimenter sits opposite and during the training she shows, one at a time, two novel, nameless objects (figures below). Two distinct locations on the table are used (left and right). During the test phase, the two objects are shown together in a new location of the table (center). All the participants are children between eighteen and twenty-four months of age, around the typical developmental stage of fast word learning and the vocabulary spurt. We briefly describe here four experiments using this paradigm (see table below for a diagram of the four experiments).



Experiments 1 and 2: Object Named in Its Absence

In these experiments, the experimenter shows the two novel objects, one at a time. The name of the object "modi" is only said in the absence of the object. In this first experiment (No-Switch condition) each object is always shown in the same location. The first object is consistently presented on the left of the peripersonal space in front of the child, and the other object is consistently presented on the right side. Two presentations of each individual object are given (steps 1–4). Subsequently (step 5), the child's attention is drawn to one of the now empty locations (left) and simultaneously the linguistic label "modi" is said aloud by the experimenter (e.g., "Look at the modi"). The two objects are then shown again, one at a time (steps 6–7). Subsequently, in the test phase, the child is presented with both objects in a new (central) location and asked: "Can you find me the modi?"

In the second experiment (Switch Condition), the same basic procedure is used, except that the consistency of the left/right location between the two objects is weakened. In the initial presentations, the first object is presented on the right side, with the second object on the left (steps 1–2). The objects' position is then switched in the following two presentations (steps 3–4). In the naming step (step 5) and the final two presentations of the objects (steps 6–7), the initial location of stages 1–2 is used.

Experiments 3 and 4: Object Named while in Sight

In these two experiments, the new label is said at the same time the object is shown to the child. In experiment 3 (Control Condition), a systematic left/right position is used for the two objects throughout the experiment, exactly as in the No-Switch Condition. However, in step 5, the word "modi" is said when the first (yellow) object is shown. This corresponds to the standard object-labeling setup of word naming experiments. In experiment 4 (Spatial Competition Condition), a different group of children is repeatedly presented with the two objects in a systematic left/right spatial location for steps 1–4. At step 5 the second (green) object is now labeled as “modi” while in sight. However, the green object is now located on the left side of the table, that is, the position used by the yellow object.

Results

In experiment 1 (No-Switch Condition), the majority (71 percent) of the children select the spatially correlated object (the one presented in the left side), despite the fact that the name is said in the absence of either object. In experiment 2 (Switch Condition), only 45 percent of the children chose the object shown in the same location highlighted when the word “modi” is said aloud. In the experiment 4 (Control Condition), 80 percent correctly picked the labeled object over the previously unseen object. In experiment 3 (the Spatial Competition condition), a majority of children (60 percent) selected the spatially linked object (yellow) rather than the green object that was actually being attended and labeled at the same time.

Finally, there are a series of observations based on *social cognition principles* that significantly contribute to word learning. These social cognition principles of language learning focus on the child-parent cooperative dyadic relationship, as well as child-peer interactions. For example, Tomasello (2008) and Carpenter (2009) have carried out comparative studies between child and animal (ape) experiments to look at the form and mechanisms of shared attention that exist in human children, but that are absent in primates, and which support language learning in human children. Similar studies have been carried out on the social imitation and cooperation skills (Tomasello 2008). The evidence in support of the core role of joint attention and shared gaze in early word learning is strong. For example, it has been demonstrated that at around eighteen months children pay attention to the speaker’s eye gaze direction as a clue to identify the topic of the conversation (Baldwin and Meyer 2008). Also the time infants spend on joint attention is a predictor of the speed of lexical development (Carpenter, Nagell, and Tomasello 1998). Some of these social-cognition biases, and related models in developmental robotics, were discussed in detail in chapter 6.

The word-learning biases discussed in this chapter can also be seen as a manifestation of intrinsic motivation, in this case specifically for the motivation that drives the infant to discover and learn language and communicative behavior. This has been explicitly modeled in developmental robotics, with Oudeyer and Kaplan’s (2006) experiments with the AIBO. Their model supports the hypothesis that children discover (vocal) communication because of their general instinct to engage in situations that result in learning novel situations, rather than for intentional communicative purposes. That is, while exploring and playing within their environment, the robots’ general motivation to learn makes them select novel tasks not previously learned, as when they are allowed to vocally interact with other agents.

7.1.3 A Case Study: The Modi Experiment

To conclude this concise overview of language development in children, and show how child psychology findings can inform the design of models of language acquisition in developmental robotics, we provide a detailed description of one of the seminal experimental procedures used in child language studies. A developmental robotics experiment, with the replication of the child psychology experimental results, will then be presented in section 7.4. This comparison will demonstrate how a close mapping between empirical and computational studies can benefit both our scientific understanding of language development mechanisms in children and robots, and the technological implication of developing plastic, language-learning robots. In this specific case, the use of a robotic model permits the explicit testing of the role of embodiment and sensorimotor knowledge in early conceptual and word learning.

The experiment is typically referred to as the Binding Experiment, or the “Modi” Experiment (box 7.1). This is an experimental procedure related to Piaget’s (1952) well-known A-not-B error paradigm, but more recently used by Baldwin (1993) and Smith and Samuelson (2010) specifically for language development studies. In particular, Smith and Samuelson chose this procedure to demonstrate the role of the Embodiment Principle in early word learning and to challenge the default hypothesis that names are linked to the object being attended to at the time the name is encountered.

The four experiments described in box 7.1 show the systematic manipulation of factors affecting word learning, in other words, the location where the object appears with the label being given in the absence of the object (experiments 1 and 2) and the competition between spatial and temporal associations when the label is presented while the object is in sight (experiments 3 and 4). Results show that children can associate a label to an object even in its absence. In addition, when the spatial/temporal conditions are in competition, as in experiment 4, the embodiment bias based on the child posture is stronger than the presentation of the label at the same time as the object.

Another important observation is that in each of the experiments, changes in the parent's posture from sitting to standing (producing a different schema of the child's spatial-body perspective) can disrupt the children's ability to link the absent object to the name through space, while other visual or auditory distracters do not. This further reinforces the mediation of embodiment factors in language learning. Overall, this study provides clear evidence challenging the simple hypothesis that names are associated to the things being attended to at the time the name is heard. In fact, the experiments provide strong evidence that the body's momentary disposition in space helps binding objects to names through the expected location of that object (Smith and Samuelson 2010; Morse *et al.* in preparation).

7.2 Robots Babbling

Numerous speech recognition and synthesis applications have been developed in the last twenty years, and these are typically used as natural language interfaces for computers, cars, and mobile phones. Most of the latest speech recognition systems rely on statistical methods, such as hidden Markov models (HMMs), which require offline training of the system with thousands of sample sounds for each word. However, developmental robotics models of speech learning propose an alternative approach to the emergence and development of speech processing capabilities. These developmental models rely on the online learning and imitation in teacher-learner interactions, as during child development, rather than on the offline training with a huge corpora. The design of developmental-inspired speech systems, and their scaling up to deal with large corpora, aims to overcome the bottleneck issues of current speech recognition applications and their limitations and unstable recognition performance in dynamic, noisy environments.

Most of the current robotics models of language learning rely on this type of pretrained speech recognition system, especially those that focus on the acquisition of words and syntax (cf. sections 7.3 and 7.4). However, a few robotics and cognitive-agent approaches to language learning have specifically focused on the emergence of a phonetic system through interaction between learners and teachers and via the developmental stages of vocal motor babbling. Most of these studies have been based on the use of simulated cognitive agents with physical models of the vocal tract and auditory apparatus, with a more recent focus on the use of developmental robotics approaches.

Oudeyer (2006) and de Boer (2001) have proposed some of the pioneering studies on the emergence of language-like phonetic systems through agent-agent interaction (see also the related work of Berrah *et al.* 1996; Browman and Goldstein 2000; Laurent *et al.* 2011). Oudeyer (2006) investigated the evolutionary origins of speech, and in particular the role of self-organization in the formation of shared repertoires of combinatorial speech sounds. This work is based on a brain-inspired computational model of motor and perceptual representations, and how they change through experience, in a population of babbling robots. The agents have an artificial ear capable of transforming an acoustic signal into neural impulses that are mapped into a perceptual neural map (figure 7.1). They are also endowed with a motor neural map that controls the articulatory movements of a vocal tract model. These two Kohonen-like maps are also mutually interconnected. Initially, internal parameters of all neurons and of their connections are random. To produce a vocalization, a robot randomly activates several motor neurons, in which internal parameters encode articulatory configurations to be reached in sequence. This produces an acoustic signal through the vocal tract model that can be perceived by the ear model. This is the basis of babbling. These neural networks are characterized by several forms of plasticity: (1) intermodal connections evolve in such a way that each agent learns the auditory-motor mapping when it is babbling; (2) neuron parameters in each map change to model the distribution of sounds heard by the agent; and (3) the distribution of sounds encoded in the motor map follows roughly the distribution of sounds encoded in the perceptual map. Thus, agents have the tendency to produce the same distribution of sounds as that heard in the group of agents. This architecture constitutes a basic neural kit for holistic vocal imitation.

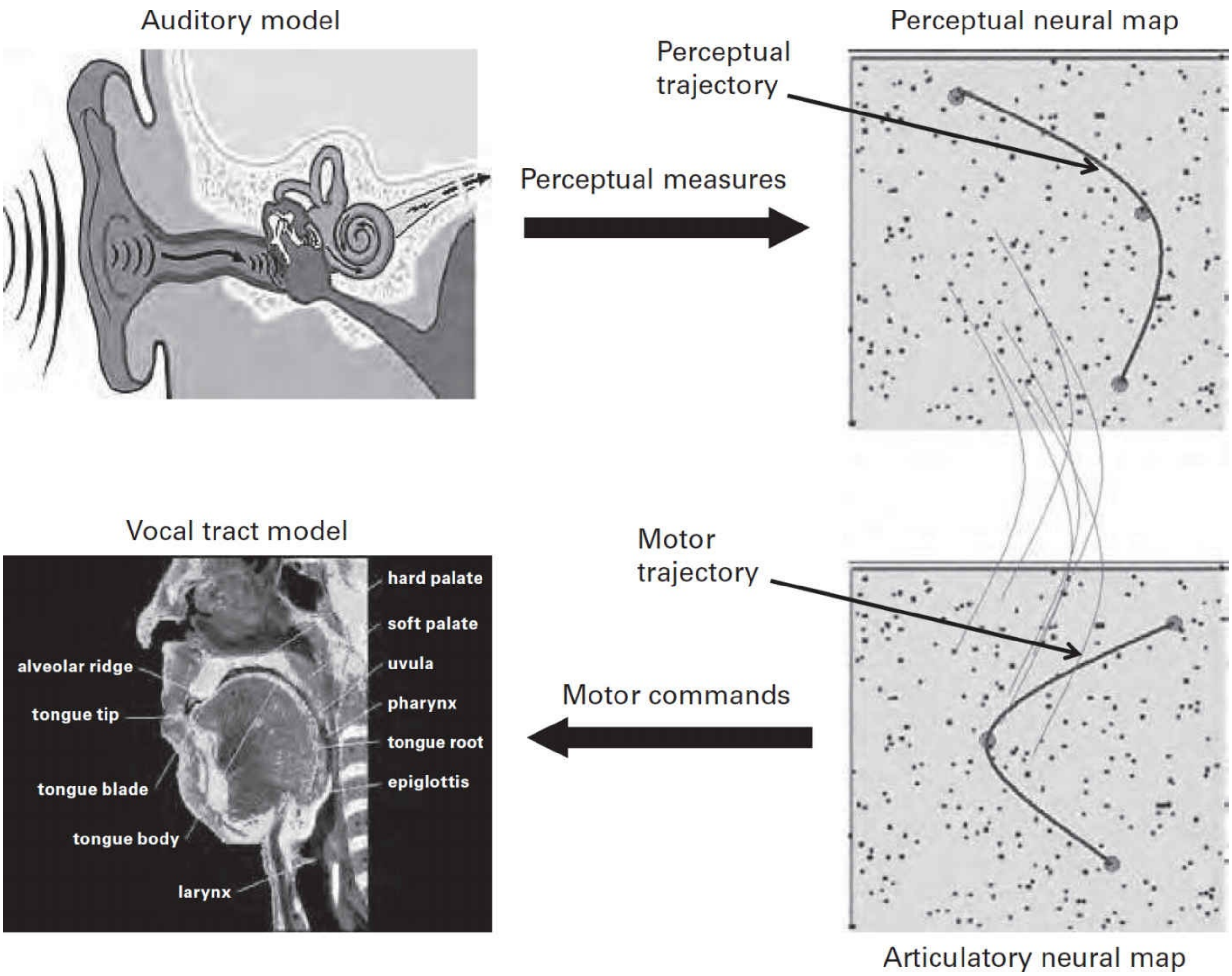


Figure 7.1

Architecture of the model of the self-organization of speech with the ear and articulation models and the perceptual and motor maps. Figure courtesy of Pierre-Yves Oudeyer.

Initially, the agents' random vocalizations are unorganized and spread through the whole speech continuum. This initial equilibrium is unstable and over time symmetry breaks: the population of agents spontaneously generates a shared combinatorial system of vocalizations that map some of statistical regularities and diversity in vocalization systems observed in human languages. The formation of such a discrete speech system also reproduces aspects of the transition from marginal to canonical babbling observed in infants (Oller 2000). These configurations are shown to depend on the interaction between innate morphological and physiological constraints (e.g., nonlinearity of the mapping of articulatory configurations to acoustic waves and auditory perceptions) and the self-organization and imitation mechanisms. In particular, this provides a unified framework to understand the formation of the most frequent vowel systems, which are approximately the same in the robot populations and in human languages.

A similar methodology was used by de Boer (2001) to model specifically the self-organization of the vowel system. More recently, these computational models of speech self-organization have been refined, for example through the use of more realistic models of the larynx position in the speech articulation system of male and female speakers (ibid.) and for babbling experiments (Hornstein and Santos-Victor 2007).

These models mostly focus on the evolutionary and self-organization mechanisms in the emergence of shared language sound systems. More recently, there has been a specific focus on modeling of the developmental mechanisms in speech learning through developmental robotics experiments. In particular, these models have specifically investigated the early stages of babbling and speech imitation in the acquisition of early word lexicons. To provide an overview of the main approaches in the field, we first review a developmental robotic model of the transition from babbling to word forms (Lyon, Nehaniv, and Saunders 2012) with the iCub robot, and then analyze a model of speech segmentation with the ASIMO robot (Brandl *et al.* 2008).

The study by Lyon, Nehaniv, and Saunders (2010, 2012; Rothwell *et al.* 2011) explicitly addresses the developmental hypothesis on the continuum between babbling and early word learning (Vihman 1996). Specifically, they carry out experiments to model the milestone when canonical syllables emerge and how this supports early word acquisition. This behavior corresponds to the period of phonetic development in children about six and fourteen months old. These studies model the learning of phonetic word forms without meaning, which can be integrated with the parallel development of referential capability.

The experiments were initially carried out on a simulated developmental cognitive architecture (LESA [linguistically enabled synthetic agent]), and then tested in human-robot interaction studies with the childlike iCub robotic platform. Contingent, real-time interaction is essential for language acquisition. The model starts with the assumption that agents have a hardwired motivation to listen to what is said, and to babble frequently in response. This intrinsic babbling motivation is similar to that shown to emerge developmentally in Oudeyer and Kaplan's (2006) model of the discovery of vocal communication instinct.

Table 7.3

Target words and phonetic transcription (adapted from Rothwell *et al.* 2011)

Words	Phonetic transcriptions
Circle	s-er-k-ah-l
Box	b-aa-ks, b-ao-ks
Heart	hh-ah-t, hh-aa-rt
Moon	m-uw-n
Round	r-ae-nd, r-ae-ah-nd, r-ae-uh-nd
Sun	s-ah-n
Shape	sh-ey-p
Square	skw-eh-r
Star	st-aa-r, st-ah-r

At the initial stages of the experiment, the robot produces random syllabic babble (Oller 2000). As the teacher-learner dialogue progresses, the robot's utterance is increasingly biased toward the production of the sounds used by the teacher. The teacher's speech is perceived by the robot as a stream of phonemes, not segmented into syllables or words, using an adaptation of Microsoft SAPI. Teachers are asked to teach the robot the names of shapes and colors based on the names of six pictures printed on the sides of boxes (see table 7.3), using their own spontaneous words. It happens that most of the shape and color names are one-syllable words (red, black, white, green, star, box, cross, square, etc.). The teacher is asked to make an approving comment if he/she hears the robot utter one of these one syllable words, and then the reinforced term is added to the robot's lexicon. This process models the known phenomenon that infants are sensitive to the statistical distribution of sounds (Saffran, Newport, and Aslin

1996). The frequency count of each syllable heard by the robot is updated in an internal phonetic frequency table. The robot will continue to produce quasi-random syllabic babble, or novel combinations of syllables, with a bias toward the most frequently heard sounds. This will gradually result in the robot producing words and syllables that match the teacher's target lexicon.

The phonetic encoding is based on four types of syllables: V, CV, CVC and VC (where V stands for vowel, C for consonant or a cluster of consonants), which correspond to the phonetic structure developed early by the infant. It differs in that an infant's phonetic inventory is much more limited by articulatory constraints. Infants can recognize phonemes before they can produce them. The consonant clusters are constrained by the possible combinations in the English language phonetic system. Some combinations only occur at the start of a syllable, such as *skw* as in "square," others only at the end, such as *ks* as in "box," and others in either position, such as *st* as in "star" or "last." Phonemes are represented by the CMU set, using fifteen vowels and twenty-three consonant sounds (CMU 2008). Table 7.3 shows a few target words and their phonetic transcription. Some words can have more than one encoding, reflecting variability in speech production.

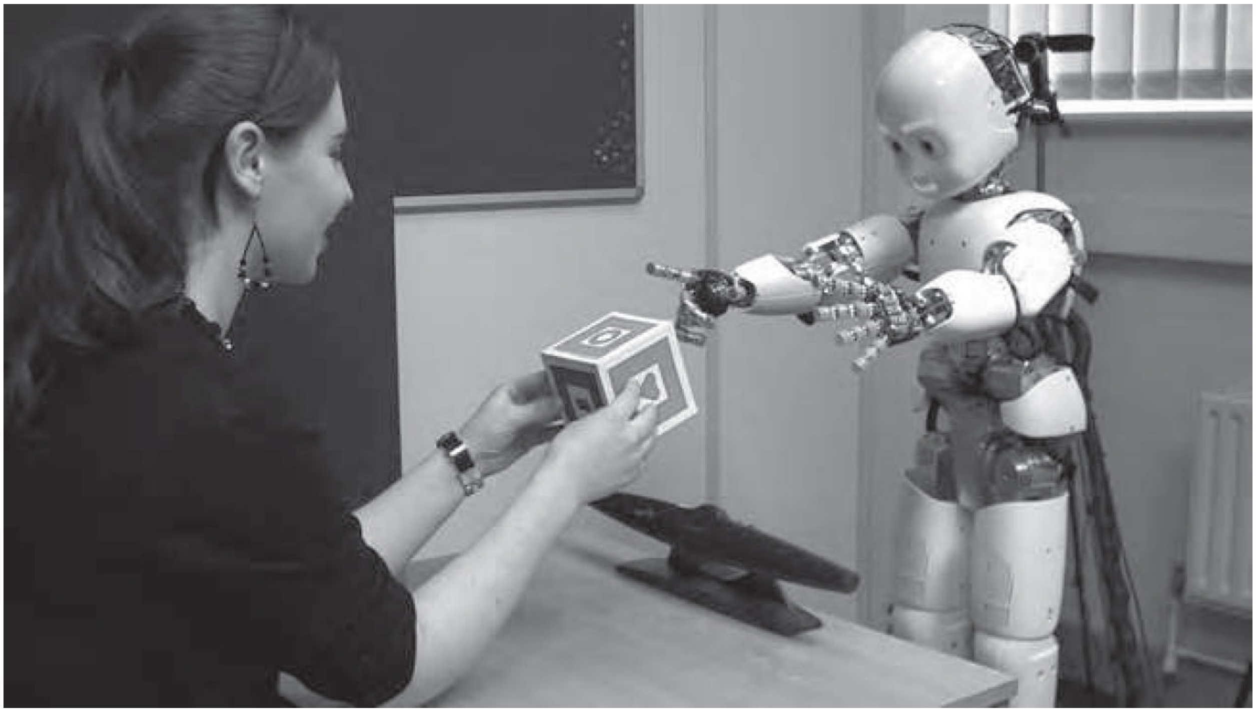


Figure 7.2

A participant interacting with the iCub during phonetic babbling experiments in Lyon, Nehaniv, and Saunders's 2012 study. Figure courtesy of Caroline Lyon and Joe Saunders.

In Lyon, Nehaniv, and Saunders (2012), experiments with thirty-four naïve (not familiar with robots) participants are reported. Participants were randomly assigned to one of five sets. The process was the same for each set except that participants were given slightly different guidelines, for instance whether or not they should take notice of the iCub's expression. During these experiments, the expression of the iCub's mouth (LED lights) was set to "talking" when producing syllables, and reverted to a "smile" expression when listening to the teacher (figure 7.2). The iCub babbled at three-second intervals, through the eSpeak synthesizer (espeak.sourceforge.net).

At the end of the experiments, each lasting two sessions of four minutes each, the robot was, in almost all cases, able to learn some of the word forms. Although the overall learning of the names of shapes and colors was not very high (a contributory factor was the low recognition rate of the phoneme recognizer), some interesting results were observed as a result of the teacher's interaction style. For instance, in experiments reported by Rothwell *et al.* (2011), a naïve student participant used single-word utterances, such as "moon," repeating these in order to get the robot to learn them. The second participant, who was used to teaching children, embedded the salient words (names of the shapes and colors) within a communicative utterance, such as "do you remember the smile shape it's like your mouth." The repetitive style of the first participant allowed the robot to learn most effectively, with the shortest time and the largest number of words achieved. In the later experiments (Lyon, Nehaniv, and Saunders 2012) this correlation was not significant. Some of the best results came from more verbose teachers, who seemed to produce the salient words in a pronounced manner.

A significant result of the experiments was that teachers often failed to notice when the robot produced a proper word, and so did not reinforce it. There is an issue over perception in human-robot interaction (HRI): in this case it seemed hard to pick out word forms from quasi-random babble; audio perception may be related to intelligibility (Peelle, Gross, and Davis 2013).

Other developmental models of speech learning have specifically focused on the roles of the caregiver's imitation in guiding language acquisition. For example, Ishihara *et al.* (2009) propose a simulated developmental agent model of vowel acquisition through mutual imitation. This considers two possible roles of the caregiver's imitation: (1) informing of vowel correspondence ("sensorimotor magnet bias") and (2) guiding infant's vowels to clearer ones ("automirroring bias"). The learned agent has an immature imitation mechanism that changes over time due to learning. The caregiver has a mature imitation mechanism, and these depend on one of the two biases. Computer simulation results of caregiver–infant interactions show the sensorimotor magnet strategy helps form small clusters, while the automirroring bias shapes these clusters to become clearer vowels in association with the sensorimotor magnets. In a related model by Yoshikawa *et al.* (2003), a constructivist human-robot interaction approach to phonetic development in a robotic articulation system is proposed. This study investigates the hypothesis that the caregiver reinforces the infant's spontaneous cooing by producing repetitive adult phoneme vocalizations, which then lead the child to refine her vocalizations toward the adultlike sound repertoire. The robotic agent consists of a mechanical articulation system with five degrees of freedom (DOFs) to control and deform a silicon vocal tract connected to an artificial larynx. The learning mechanisms uses two interconnected Kohonen Self-Organizing Maps respectively for auditory and articulatory representations. The weights of these two maps are trained using associative Hebbian learning. This learning architecture based on Kohonen maps and Hebbian learning has been extensively used in developmental robotics (see also box 7.2). Experiments on the sound imitation interactions between a human caregiver and the robotic agent demonstrate that by simply relying only on the repetitive vocal feedback by the caregiver (with no previous "innate" phonetic knowledge) the robot acquires a gradually refined human-like phonetic repertoire. To resolve the arbitrariness ins selecting the articulation that best matches the perceived human's vocalization sound, the Hebbian learning has to be modified to minimize the toil involved in the articulation (i.e., the torque to deform the vocal tract and the resulting larynx deformation). This toil parameter decreases the arbitrariness between perceived and produced sound, and improves the correspondence between the human's and the robot's phonemes. The work by Yoshikawa *et al.* (2003) is one of the first developmental robotics models to employ a physical robotic articulation system for the learning of human-like phonetic sounds via direct interaction with human caregivers. For a more recent example of a robot head with a physical model of the vocal tract, see also Hofe and Moore 2008.

Box 7.2

Neurorobotics Model of the Modi Experiment

This box provides some technical details on the implementation of Morse, Belpeame, *et al.* (2010) model, to facilitate replication of the neurocognitive experiments on the Modi setup.

Network Topology, Activation Functions, and Learning Algorithm

The neural model can be implemented easily as two separate network types, first the self-organizing map (SOM) and field, which use standard equations, and second the spreading activation model. One SOM receives three inputs corresponding to the average R, G, and B values from the center of the input image, and the posture map receives six inputs corresponding to the pan-tilt of the eyes, head, and torso of the iCub robot. For each SOM, the best matching unit (BMU) has the shortest Euclidean distance between its weights (initially random) and the input pattern at that time (see equation 7.1). The weights of all units within the neighborhood of the BMU are then updated pulling them closer to the input pattern (see equation 7.2).

$$BMU = Max_i\left(1 - \sqrt{\Sigma(\acute{a}_j - \grave{u}_{ij})}\right) \tag{7.1}$$

$$\Delta\grave{u}_{ij} = \acute{a}exp\left(-\frac{dist^2}{2size}\right)(a_j\grave{u}_{ij}) \tag{7.2}$$

Speech input is processed using the commercial speech to text software dragon dictate. Each word (as text) is compared to a dictionary of known words (initially empty) and if novel a new entry is made with a corresponding new node in a field. As each word is heard the unique corresponding unit in the word field is activated.

The spreading activation model then allows activity to spreads bidirectionally between the body posture SOM and the other maps (following standard IAC spreading activation, see equation 7.3) via connections (initially at zero) modified online with a Hebb-like learning rule (see equation 7.4), and within each map via constant inhibitory connections.

$$net_i = \Sigma\grave{u}_{ij}a_j + \hat{a}BMU_i \tag{7.3}$$

$$\text{If } net_i > 0,\ \Delta a_i = (\max - a_i)net_i - decay(a_i - rest)$$

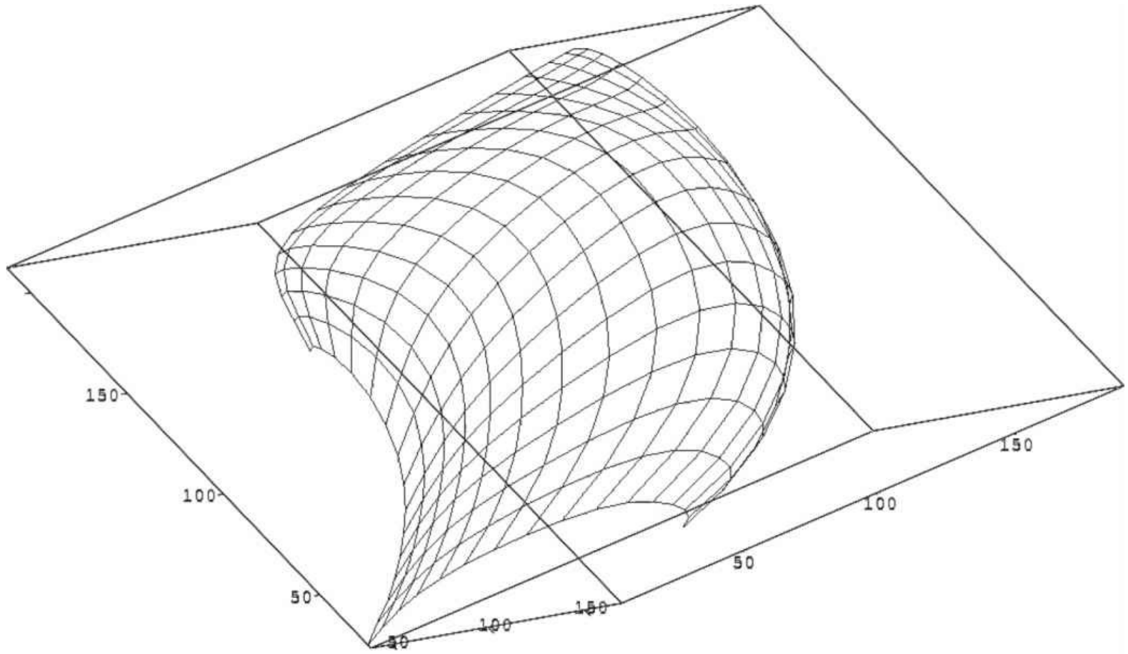
$$\text{Else } \Delta a_i = (a_i - \min)net_i - decay(a_i - rest)$$

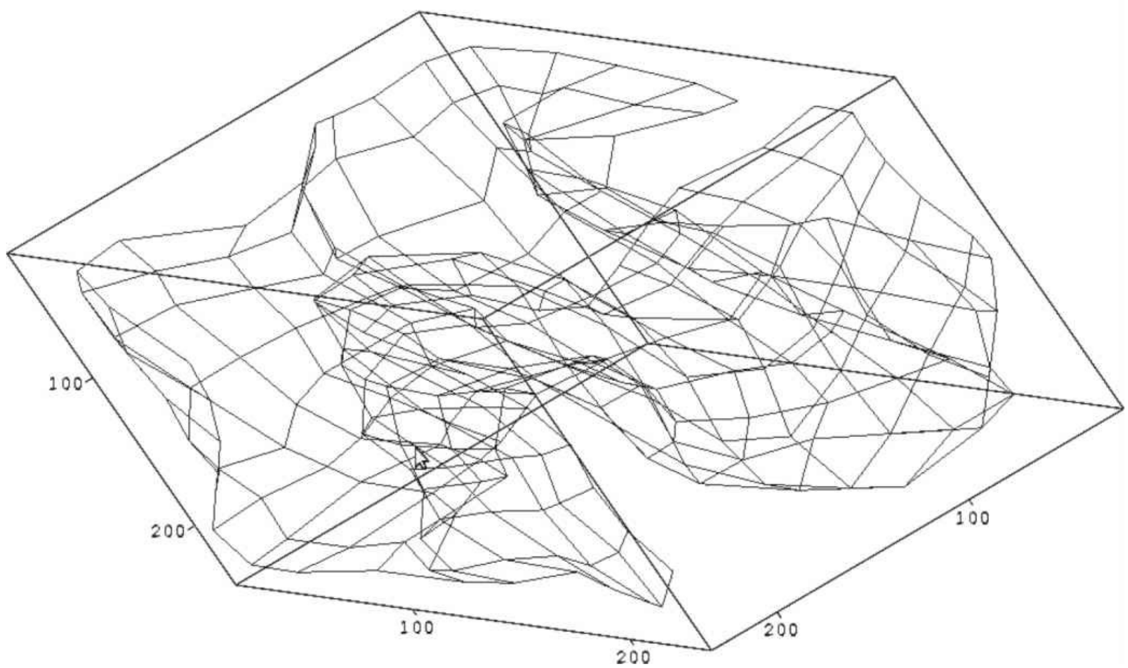
$$\text{If } a_i a_j > 0,\ \Delta\grave{u}_{ij} = \ddot{e}a_i a_j(1 + \grave{u}_{ij}) \tag{7.4}$$

$$\text{Else } \Delta\grave{u}_{ij} = \ddot{e}a_i a_j(1 - \grave{u}_{ij})$$

Training Procedure

The SOMs are partially trained using random RGB values, and random joint positions until the neighborhood size is 1, the model then runs with real input from the iCub as it interacts with people in a replication of the experiment described in box 7.1, in other words, we treat the iCub as the child and interact with it in exactly the same way as with the child in the original experiments. The learning rules are continually active and there is no separation between learning and testing phases, the model simply continues to learn from its ongoing experiences. An example of the color SOM, in early pretraining top) and during the experiment (bottom) is shown in the figures below.





Test and Overview of Results

When the iCub robot is asked to “find the modi” the spread of activation from the “modi” word unit in the word field primes a color map unit via the body posture map. The weights of that externally activated SOM unit correspond to an RGB color and the image is then filtered according to closeness to this target value. If any of the image pixels are a good match to the primed color (above a threshold) then the iCub moves its head and eyes to center those pixels in the image, thus looking at and tracking the appropriate object. In the experiment we simply recorded which object, if any, iCub looked at when asked to find the modi. The experiment was run twenty times in each condition, each time starting with new random connection weights.

Finally, as developmental robotics is based on the principle that cognition is the result of the parallel acquisition and interaction of various sensorimotor and cognitive capabilities, we describe here a model of babbling development that has been extended to include the simultaneous acquisition of phonetic, syllabic, and lexical capabilities. This is the case of the study by Brandl and colleagues (Brandl *et al.* 2008) on the childlike development of phonetic and word learning in the humanoid robot ASIMO, and other related studies as in the experiments from the ACORN European project (Driesen, ten Bosch, and van Hamme 2009; ten Bosch and Boves 2008). In particular, Brandl and colleagues' work directly addresses the issue of the segmentation of speech into words, which allows infants as young as eight-month-olds to bootstrap new words based on the principle of subtraction (Jusczyk 1999; Bortfeld *et al.* 2005; see also table 7.2).

Brandl et al.'s (2008) model is based on a three-layered framework for speech acquisition. First the robot develops representations of speech sound primitives (phonemes) and a *phonotactic model* by listening to raw speech data. Second, a *syllable representation model* is learned based on the syllabic constraints implied by the phonotactic model, and by the properties of infant-directed speech. Finally, the robot can acquire a lexicon based on the syllabic knowledge and the word acquisition principles of early-infant language development. This hierarchical system is implemented through a cascade of HMM-based systems, which use statistical information of incomplete speech unit representations at the phonetic, syllabic, and lexical levels.

The raw speech data consists of segments of utterances of different complexity, ranging from isolated monosyllabic words up to complex utterances comprising many multisyllabic words. The model first converts speech segments into sequences of phone symbol sequences based on high frequency concatenations of single state HMMs. These phone representations are the prerequisite to learn the phonotactics of language, that is, the rules that govern the structure of syllables in a particular language. The robot uses the phonotactics model to learn syllable models, as a concatenation of phone

HMMs. To bootstrap the early stages of syllable acquisition, the input speech occasionally contains isolated monosyllabic words. The developmental principle of segmentation (Bortfeld *et al.* 2005) is used to exploit the knowledge of initial syllables to generate new ones. Brandl and colleagues use the example of the segmentation of the "asimo" word into more syllables to explain such a bootstrapping mechanism. Let's assume the robot has already acquired the syllable "si." Given as new speech input the word "asimo," the model starts from the detection of the previously known syllable [si], and then subtracts this spotted syllable generating the sequence [a] [si] [mo]. This allows the robot to learn the two additional syllabic segments [a] and [mo]. Using such an incremental method, the robot acquires increasingly complex and richer syllabic elements. This allows the agent to learn further concatenations of syllables, as for the names for objects.

Brandl *et al.* (2008) used this to model speech segmentation and syllable use in language grounding experiments with the ASIMO robot, though only monosyllabic words. The ASIMO is able to recognize an object, and detect properties such as object motion, height, planarity, and object location relative to the robot's upper body. It can also use gestures, such as pointing and nodding, to communicate with the human participant (Mikhailova *et al.* 2008). During the speech segmentation and word learning experiments, the robot first restricts its attention to one of the properties of the objects that should be labeled, such as the object height. To learn the name for this property, each new word is repeated between two and five times. Using the segmentation and novelty detection mechanisms of speech, the robot was able to learn up to twenty words through contingent verbal and gestural interactions alone. Ongoing work with the ASIMO robot at the Honda Research Institute in Germany is now focusing on the extension of such a developmental linguistic mechanism, also using brain-inspired learning architectures (Mikhailova *et al.* 2008; Gläser and Joublin 2010).

This experiment with ASIMO proposes the explicit exploration of the interaction between phonetics development and word acquisition, based on childlike learning mechanisms. In the next section we will review numerous developmental robotics models of the acquisition of words, with the main focus on the acquisition of referential and symbol grounding capabilities.

7.3 Robots Naming Objects and Actions

Most of the current developmental robotics experiments on lexical development typically model the acquisition of words to name the objects visually presented in the environment and to label their properties (e.g., color, shape, weight). Only a few models investigate the learning of the names of actions performed by the robot or by the human demonstrator (e.g., Cangelosi and Riga 2006; Cangelosi *et al.* 2010; Mangin and Oudeyer 2012).

In this section we will first review some seminal robotics models of early word acquisition for object labeling. Subsequently, to demonstrate the fruitful close interaction between experimental and modeling data, a detailed description of a study on the direct developmental robotics replication and extension of the Modi Experiment will be given (as described in section 7.1, box 7.1). This child psychology modeling study explicitly addresses a series of core issues within the developmental robotics approach, such as the modeling of the role of embodiment in cognition, the direct replication of empirical data from child psychology literature, and the implementation of an open, dynamic human-robot interaction system. Finally, we will review related work on the robotics modeling of lexical development for the naming of actions, with some directly addressing developmental research issues, while others are more generally related to language learning.

7.3.1 Learning to Name Objects

A rich series of computational cognitive models, typically based on connectionist simulations of category and word learning, has preceded the design of robotics models of lexical development. These include, for example, the neural network models of the categorization and naming of random dot configurations of Plunkett *et al.* (1997), a modular connectionist model of the learning of spatial terms by Regier (1996), a model of the role of categorical perception in symbol grounding (Cangelosi, Greco, and Harnad 2000) and more recent neural network models for the learning of image-object associations using realistic speech and image data (Yu 2005).

Another important development in computational modeling of language learning, which precedes and has also directly influenced the subsequent work on developmental robotics, is the series of multiagent and robotics models on the evolution of language (Cangelosi and Parisi 2002; Steels 2003). These models investigate the emergence of shared lexicons through cultural and genetic evolution and use a situated and embodied approach. Rather than providing a communication lexicon already fully developed, the population of agents evolves a culturally shared set of labels to name the entities in their environment. These evolutionary models, as in the self-organization models of speech imitation and babbling in Oudeyer (2006) and de Boer (2001), have provided important insights on the biological and cultural evolution of language origins.

Steels and Kaplan's (2002) study with the AIBO robot is one of the first robotics studies on the acquisition of first words that builds directly on previous evolutionary models and employs a developmental setup modeling the process of ontogenetic language acquisition. This study includes a series of language games based on human-robot interaction. A language game is a model of interaction between two language learners (e.g., robot-robot or human-robot) involving a shared situation in the world (Steels 2003). This is based on a routinized protocol of interaction between the speaker and the learner. For example, in the "guessing" language game the listener must guess which object, out of many, is being referred to by the speaker. In the "classification" language game used in this study, the listener only sees one object and must learn to associate the internal representation of the object with a label. In this study the AIBO robot has to learn the labels for a red ball, a yellow smiley puppet and a small model of the AIBO called Poo-Chi. The experimenter uses words such as "ball," "smiley" and "poochi" to respectively teach the robot the names of these objects, while the robot interacts or sees them. The AIBO can recognize other predefined interactional words used to switch between different stages of the interaction in the language game ("stand," "look," "yes," "no," "good," "listen," and "what-it-is"). For example, "look" initiates a classification language game and "what-it-is" is used to test the robot's lexical knowledge. An instance-based method of classification of the objects is used, using multiple instances (views) of the objects, which are classified using the nearest neighbor algorithm. Each image is encoded as a 16 × 16 2D histogram of the red-green-blue (RGB) values (no segmentation is applied to the image of the object). An off-the-shelf speech recognition system was used to recognize the three object labels and the interactional words. The word-object association and learning is implemented through an associative memory matrix mapping objects' views with their words. During learning, the "yes," "no" words are used respectively to increase/decrease the grade of association between the object in view and the word heard.

Three different conditions are considered for the language learning experiments (figure 7.3): (1) social interaction learning; (2) observational learning with supervision; and (3) unsupervised learning.

In the first condition (social interaction learning), a model of full situated and embodied interaction, the robot navigates in the environment, where the experimenter is also present, and uses an attentional system to interact with the experimenter, the three objects, and the surrounding room layout. Human-robot language games, dependent on both the experimenter's and the robot's motivational system, are played to teach the robot the names of the three objects. In the second condition (observational learning with supervision), the robot is left wandering the environment following its own motivational system, with the human experimenter only acting as language teacher when the robot, by chance, encounters any of the three target objects. This generates a set of pairings of a view of an object and of a verbal utterance of the object's name, used for the supervised training. Finally, in the third condition (unsupervised learning) the robot is static and is given a series of images of the objects, which are used by an unsupervised algorithm to classify what is in the image.

a b c

Figure 7.3

Three experimental conditions in Steels and Kaplan's (2002) study: (a) social interaction learning; (b) observational learning with supervision; (3) unsupervised learning. Figure reprinted with permission from John Benjamins.

This study specifically examines the hypothesis that social learning, rather than individual learning, helps the child bootstrap her early lexicon, and that initial meanings are situated and context dependent. This is highly consistent with the defining principles of developmental robotics, as discussed in chapter 1. The experimental data clearly support the hypothesis. In the social interaction learning experimental condition, after 150 repeated language games, AIBO is able to learn the names of the three objects correctly in 82 percent of the cases. The red ball naming reaches a higher success rate of 92 percent due to the simplicity of the recognition of a uniform red object, with respect to the articulated puppet and the small robot replica. In the observational learning condition, when the experimenter plays a passive role of naming the objects that the robot encounters by chance, a lower average naming rate of 59 percent is achieved. Finally, in the unsupervised condition, the lowest result of 45 percent correct classification and naming is achieved.

Steels and Kaplan's (2002) explanation of the best performance in the social learning condition is based on the analysis of the dynamics of the classification clustering algorithm. Full interaction with the human user allows the robot to gather a better sampling of the objects' views and of label-image instances. In the observational learning condition, the reduced, passive role of the experimenter reduces the quality of the object's view data collected during unguided interactions. Social interaction is therefore seen as a scaffolding mechanism that guides and supports the exploration of the learning space and constraints. As the authors state, "the social interaction helps the learner to zoom in on what needs to be learned" (ibid., 24).

Various other robotics models of language learning, though not necessarily addressing developmental research issues, have been proposed. For example, Billard and Dautenhahn (1999) and Vogt (2000) both use mobile robots for experiments on the grounding of the lexicon. Roy and collaborators (Roy, Hsiao, and Mavridis 2004) teach the RIPLEY robot (a peculiar arm robot with cameras in the wrist) to name objects and their properties relying on an analogical mental model of the state of the physical word in which they interact.

More recently, robotics models of lexicon acquisition have started to directly address developmental research issues and hypotheses. One of the first models in this line of research is Lopes and Chauhan's (2007) work on a dynamic classification system for the incremental acquisition of words (OCLL: One Class Learning System). This study directly addresses the early stages of lexical development for the naming of concrete objects, referring directly to the embodiment language learning bias of the shape properties of early named objects (Samuelson and Smith 2005). This developmental robot model, based on an arm manipulation platform, incrementally develops a lexicon of between six and twelve names through the dynamic adjustment of category boundaries. The robot successfully learns to recognize the names of objects as pens, boxes, balls, and cups relying on the shape categorization bias, and to respond by picking up the named target element out of a set of objects. The use of the open-ended OCLL algorithm is particularly suited, as language development implies a dynamic, open-ended increase of the lexicon size. However, the performance of this learning algorithm diminishes when the lexicon goes above a size of ten or more words. Moreover, this study generically refers to principles of child development, not specifically addressing the current hypotheses and debates in the literature.

A more recent developmental robotics model of early lexicon development has directly targeted the replication and extension of child psychology studies, using the experimental paradigm of the Modi Experiment (Smith and Samuelson 2010; Baldwin 1993), as discussed in section 7.1. This model will be extensively discussed in the following section, to provide a detailed example of a developmental robotics model of language acquisition.

7.3.2 The iCub Modi Experiment

The Modi Experiment described in box 7.1 is directly based on the Embodiment Principle of language acquisition, and strongly supports the hypothesis that the body posture is central to the linking of linguistic and visual information (Smith 2005; Morse, Belpaeme, *et al.* 2010). For example, Smith and Samuelson (2010) reported that large changes in posture, such as from sitting to standing, disrupt the word-object association effect and reduce the performance in the first experiment to chance levels. In the developmental robotics model of the Modi Experiment (Morse, Belpaeme, *et al.* 2010) this embodiment principle is taken quite literally, using information on the body posture of the robot as a "hub" connecting information from other sensory streams in ongoing experience. Connecting information via this embodiment hub allows for the spreading of activation and the priming of information across modalities.

In the developmental robotics Modi Experiment, the humanoid robotic platform iCub was used. Although some initial iCub experiments were carried out in simulation through the open source iCub simulator (Tikhanoff *et al.* 2008, 2011) to calibrate the neural learning system, here the setup and data on the experiments with the physical robot are reported (Morse, Belpaeme, *et al.* 2010).

The robot's cognitive architecture is based on a hybrid neural/subsumption architecture (figure 7.4), and is based on the Epigenetic Robotics Architecture proposed by Morse and colleagues (Morse, de Greeff, *et al.* 2010). A set of interconnected, 2D self-organizing maps (SOMs) is used to learn associations between objects and words via the body posture hub. In particular, a visual SOM map is trained to classify objects according to their color, taking as input the data from one iCub's eye camera (the average RGB color of the fovea area). The SOM for the body-posture "hub" similarly uses as input the joint angles of the robot and is trained to produce a topological representation of body postures. Two DOFs from the head (up/down and left/right), and two DOFs from the eyes (up/down and left/right) were used. The auditory input map is abstracted as a collection of explicitly represented word nodes, each active only while hearing that word. These word units are artificially activated though a speech recognition system trained on a subset of ten words.

The neural model forms the upper tier of a two-layer subsumption architecture (Brooks 1986) where the lower tier continuously scans whole images for connected regions of change between temporally contiguous images (figure 7.4). The robot is directed to orient with fast eye saccades and slower head turns to position the largest region of change (above a threshold) in the center of the image. This motion saliency mechanism operates independently from the neural model, generating a motion saliency image driving the motor system. This motion saliency image can be replaced with a color-filtered image to provoke orientation to regions of the image best matching the color primed by the neural model.

The SOM maps are connected through Hebbian associative connections. The weights of the Hebbian connections are trained online during the experiment. Inhibitory competition between any simultaneously active nodes in the same map provides arbitration between multiple associated nodes resulting in dynamics similar to those expressed in Interactive Activation and Competition (IAC) model (McClelland and Rumelhart 1981). As the maps are linked together in real time based on the experiences of the robot, strong connections build up between objects typically encountered in particular spatial locations, and hence in similar body postures. Similarly, when the word “modi” is heard, it is also associated with the active body posture node at that time. The relative infrequency of activity in the word nodes compared with continuous activity in the color map is not a problem given competition is between nodes within each map and not between the maps themselves. Finally at the end of the experiment, when the robot is asked, “Where is the modi,” activity in the “modi” word node spreads to the associated posture and on to the color map node(s) associated with that posture. The result is to prime particular nodes in the color map. The primed color is then used to filter the whole input image and the robot adjusts its posture to center its vision on the region of the image most closely matching this color. This is achieved using the same mechanism that detects and moves to look at regions of change in the image, replacing the motion saliency image with a color-filtered image. The robot moves to look at the brightest region of the color-filtered image.

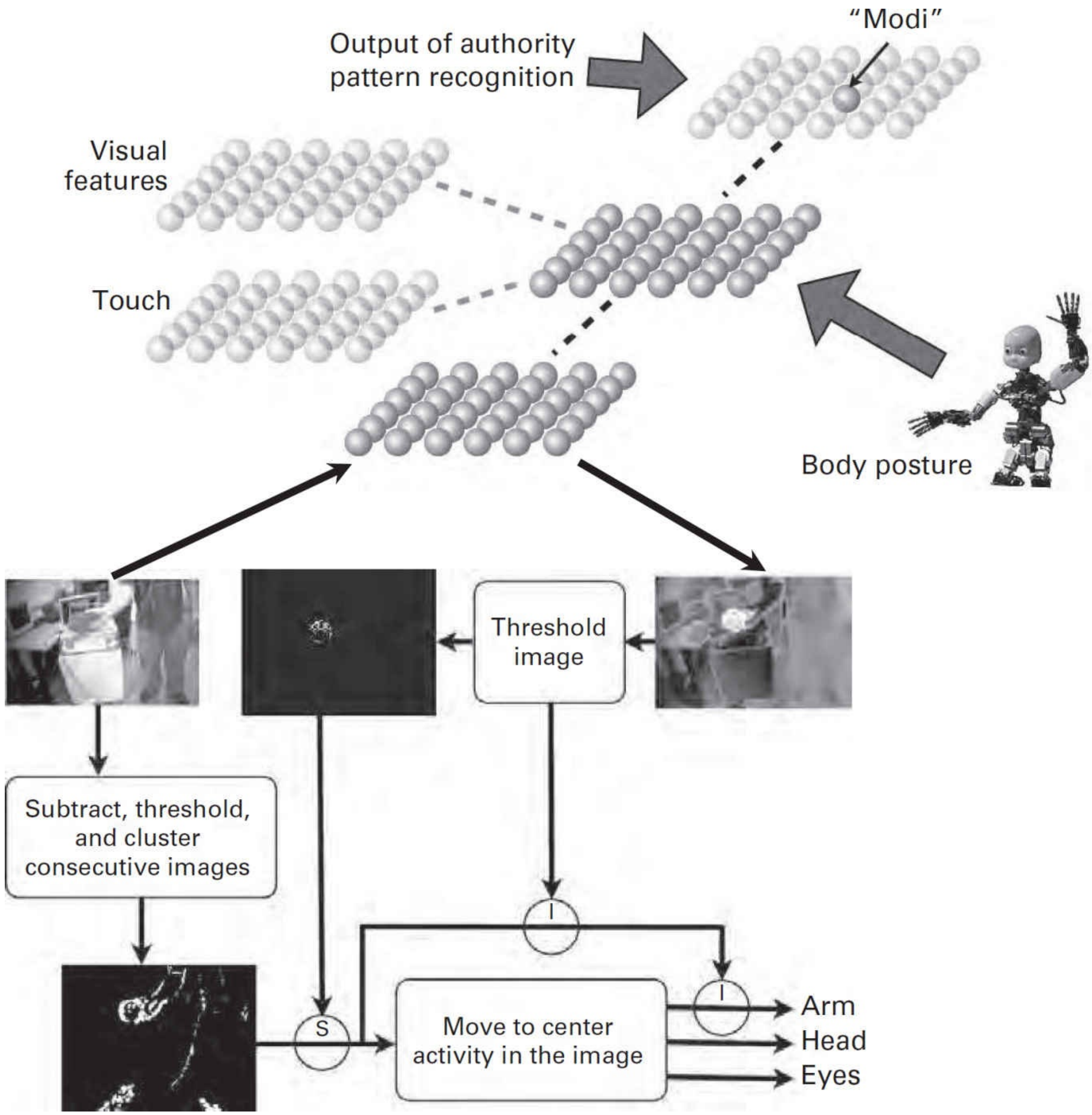


Figure 7.4

Architecture of the robot's cognitive system. The top part visualizes the neural network controller for the learning of word-object associations. The bottom part represents the subsumption architecture to switch behavior between the different stages of the experiment.

Given that the number of associations constructed will grow over time in the absence of negative Hebbian learning and in a changing environment, large changes in body posture are used to trigger a weakening of these associative connections consistent with the eradication of spatial biases in the psychology experiment following changes from sitting to standing. Additionally, external confirmation that the correct object has been selected leads to more permanent connections being constructed either directly between word and color maps or via a second pattern-recognition-based "hub." The Hebbian and the competitive SOM learning implements the Principle of Mutual Exclusivity, as discussed in table 7.2.

The model as described is then used to replicate each condition of Smith and Samuelson's (2010) four child psychology experiments described in section 7.1 (box 7.1). Figure 7.5 shows screenshots of the main stages of the default "No Switch" condition of the first Modi Experiment.

In each condition of each experiment, the results recorded which object, if any, was centered in the robot's view following the final step where the robot was asked to "find the modi." In the No-Switch condition of experiment 1, 83 percent of the trials resulted in the robot selecting the spatially linked object, while the remaining trials resulted in the robot selecting the nonspatially linked object. This is comparable to the reported result that 71 percent of children selected the spatially linked object in the human experiment in the same condition (Smith and Samuelson 2010).

Reducing the consistency of the object-location correlation in the switch condition resulted in a significant reduction in the spatial priming effect with a close to chance performance of 55 percent of the trials finishing with the spatially correlated object being centered in the view of the robot. The remaining trials resulted in the other object being selected. In experiments 3 and 4, when the object was labeled while being attended, the control group resulted in 95 percent of the trials selecting the labeled object, while in the switch condition only 45 percent of the trials resulted in the labeled object being selected. The remaining trials all selected the other object. These results are compared to the reported human child data in figure 7.6.

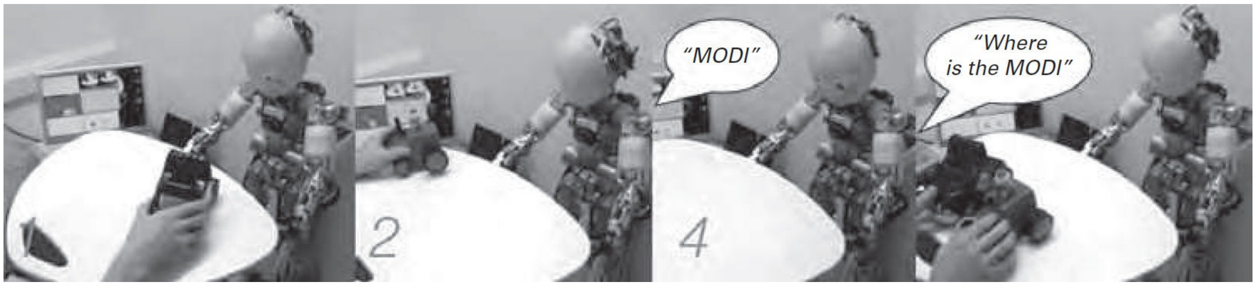


Figure 7.5

Sample images of the sequential steps of the Modi Experiment with the iCub robot (from Morse, Belpeame, *et al.* 2010).

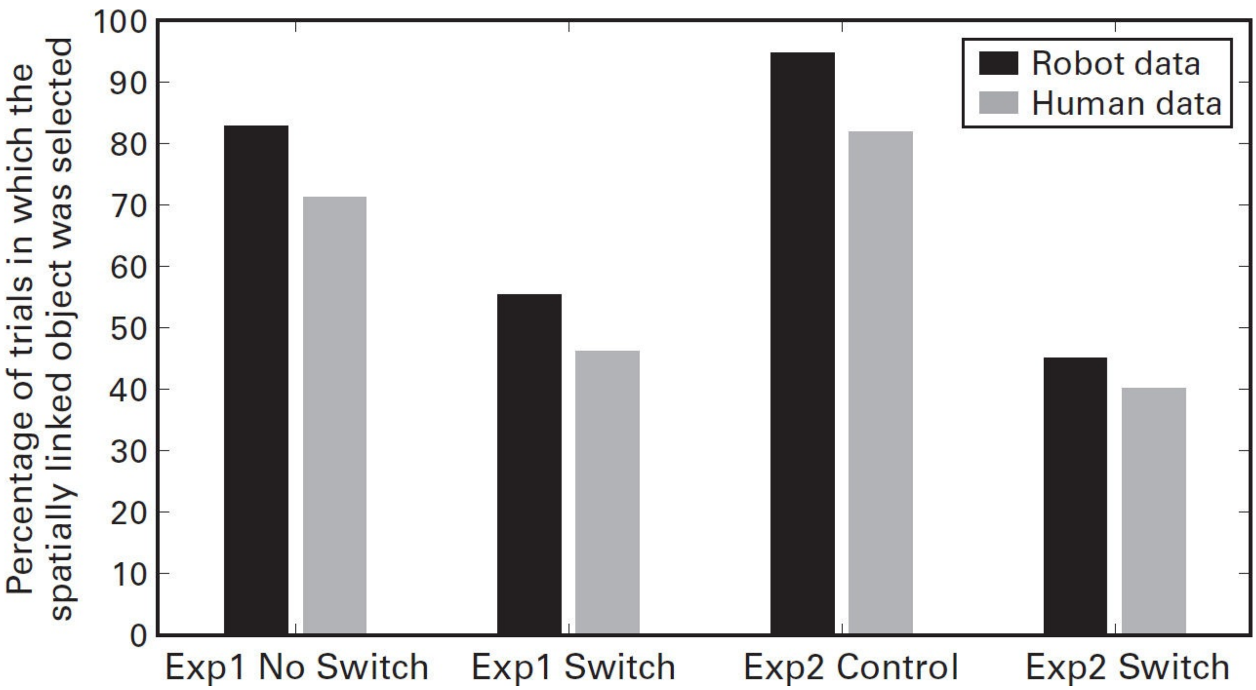


Figure 7.6

Results of the direct comparison between the robot's experiment and the benchmark empirical study of Smith and Samuelson 2010 (from Morse, Belpeame, *et al.* 2010).

The close match between the results from the robot experiments and the human child results reported by Smith and Samuelson (2010) supports the hypothesis that body posture is central to early linking of names and objects, and can account for the spatial biases exposed by these experiments. What is of relevance here is that the pattern of results, rather than the absolute percentages, in the various conditions of the experiments are consistent between the human and robot data. As can be seen from figure 7.6 the robot data consistently produced a slightly stronger bias toward the spatially linked objects than the human data, probably due to the fact that the robotic model is only trained on this task. Such a correspondence supports the validity of the cognitive architecture implemented in the robot to achieve the integration of body posture and word learning, proposing potential cognitive mechanisms on embodied language learning.

Moreover, this model has produced novel predictions on the relationship between the space embodiment bias and lexical acquisition. Variations of the posture configuration of the iCub during the different stages of the experiment (corresponding to the sit-down and upright position discussed by Smith and Samuelson) can be used by infants as a strategy to organize their learning tasks. For example, if a second interference task is added to that of the modi learning task, and a different sitting/upright position is separately used for each of the two tasks, then the two postures allows the robot (and the child) to separate the two cognitive tasks and avoid interference. This prediction, suggested by robot experiments, has been verified in new experiments with infants at the Indiana University BabyLab (Morse *et al.* in preparation).

7.3.3 Learning to Name Actions

The latest advances in developmental robotics models of language acquisition go beyond the naming of static objects and entities. This is because situated and embodiment learning is one of the basic principles of developmental robotics, and as such it must imply the active participation of the robot in the learning scenario, including the naming of actions and the manipulation of objects in response to linguistic interactions. The strict interaction between the language and sensorimotor systems has been extensively demonstrated in cognitive and neural sciences (e.g., Pulvermüller 2003; Pecher and Zwaan 2005) and informs ongoing developments in developmental robotics (Cangelosi *et al.* 2010; Cangelosi 2010).

A language learning model based on the simulation model of the iCub robot has focused on the development of a lexicon based on names of objects and of actions, and their basic combinations to understand simple commands such as "pick_up blue_ball" (Tikhanoff, Cangelosi and Metta 2011). This study will be described in detail to provide an example of the integration of various perceptual, motor, and language learning modules involved in developmental robotics.

Tikhanoff, Cangelosi, and Metta (2011) use a modular cognitive architecture, based on neural networks and vision/speech recognition systems, which controls the various cognitive and sensorimotor capabilities of the iCub and integrates them to learn the names of objects and actions (figure 7.7). The iCub's motor repertoire is based on two neural network controllers, for reaching toward objects in the peripersonal space of the robot and for grasping objects with one hand. The reaching module uses a feedforward neural network trained with the back propagation algorithm. The input to the network is a vector of the three spatial coordinates (x, y, and z) of the robot's hand, normalized from 0 to 1. These coordinates were determined by the vision system, by means of the template matching method, and depth estimation. The output of the network is a vector of angular positions of five joints that are located on the arm of the robot. For the training, the iCub generates 5,000 random sequences, while performing motor babbling within each joint's spatial configuration/limits. When the sequence is finished, the robot determines the coordinates of its hand and the joint configuration that was used to reach this position. Figure 7.8 (left) shows 150 positions of the endpoints of the robot hands, by representing them as green squares.

The grasping module consists of a Jordan recurrent neural network that simulates the grasping of diverse objects. The input layer is a vector of the states of the hand touch sensors (figure 7.8, right), and the output is a vector of normalized angular positions of the eight finger joints. The activation values of the output units are fed back to the input layer, through the Jordan context units. The training of the grasping neural network is achieved online, without the need for predefined, supervision training data. The Associative Reward Penalty algorithm was implemented in the network to adjust the connection weights to maximize the finger positions around the object. During training, a static object is placed under the hand of the iCub simulator and the network at first randomly initiates joint activations. When the finger motions have been achieved, or stopped by a sensor activation trigger, grasping is tested by allowing gravity to affect the behavior of the object. The longer the object stays in the hand (maximum 250 timesteps) the higher the reward becomes. If the object falls off the hand, then the grasping attempt was not achieved and therefore a negative reward is given to the network. Both the reaching and the grasping networks are successfully pretrained, before language is introduced, and are used to execute the reaching and manipulation instructions.

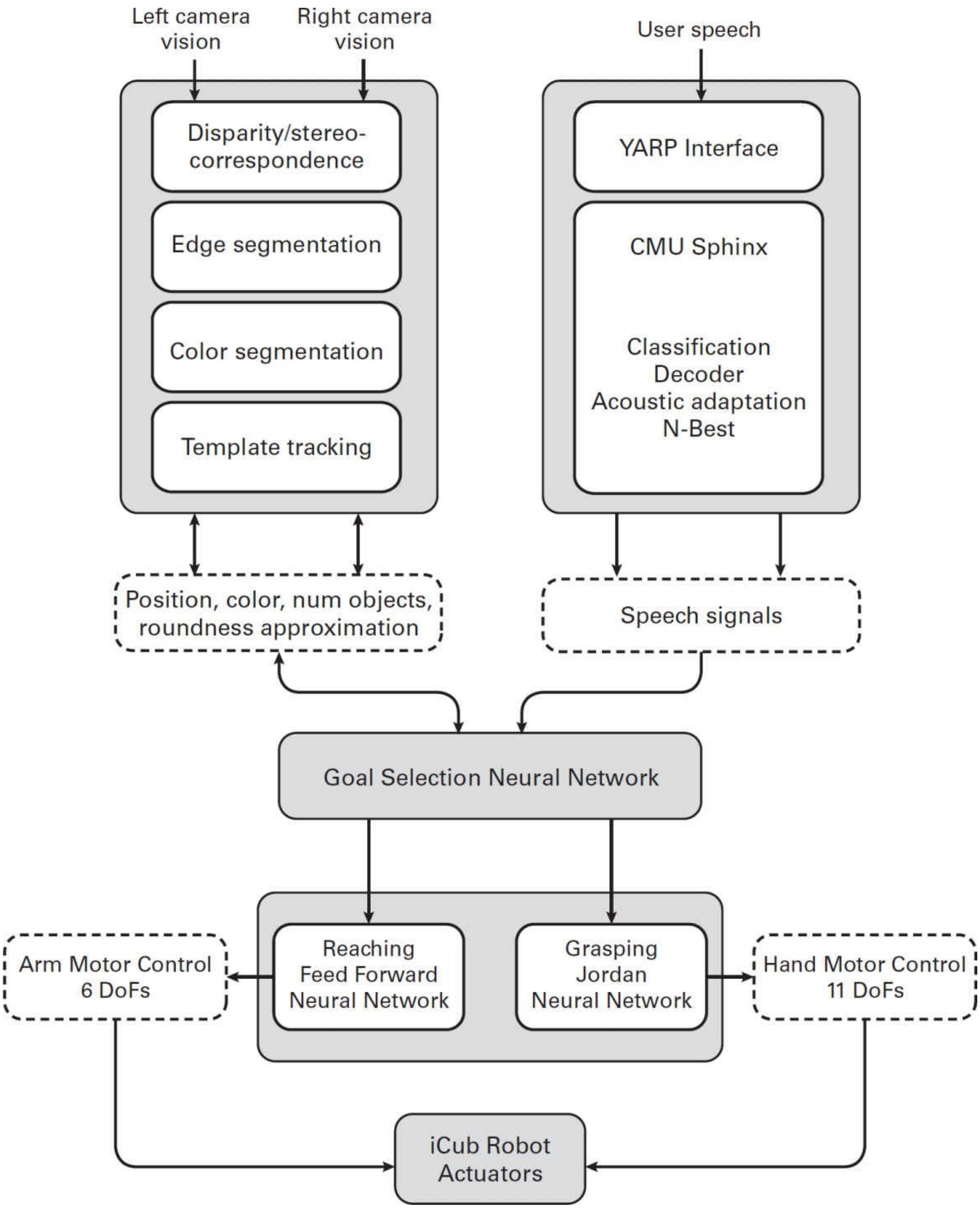


Figure 7.7

Cognitive architecture for the language learning experiment in Tikhanoff, Cangelosi, and Metta (2011).

Figure courtesy of Vadim Tikhanoff. Reprinted with permission from IEEE.

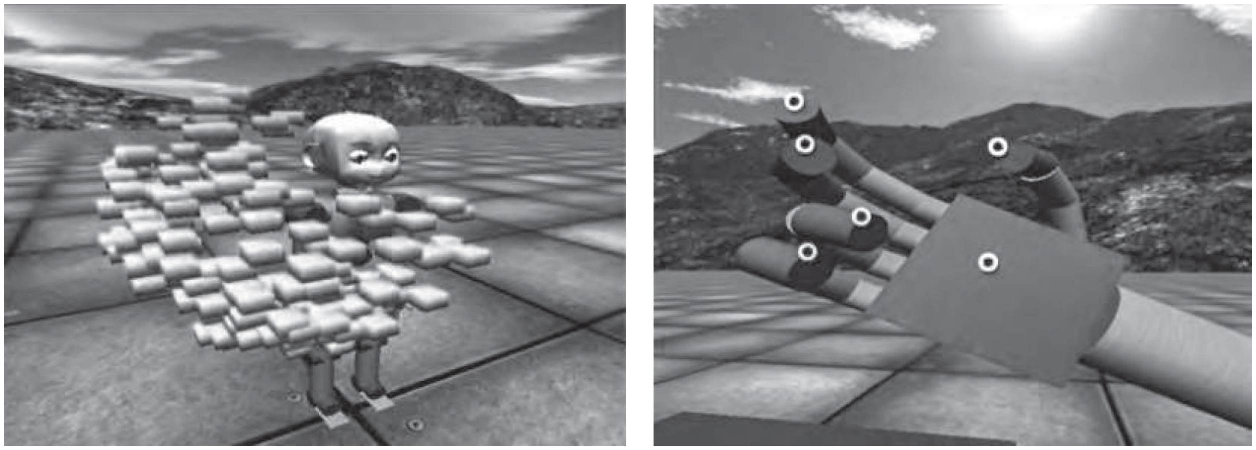


Figure 7.8

Images of the iCub simulator for the motor training. Left: example of 150 end positions of the robot arms during the motor babbling training. Right: location of the six touch sensors on the iCub's hand. Figure courtesy of Vadim Tikhanoff. Reprinted with permission from IEEE.

The visual input processing for the object centered in the robot's eye fovea is based on standard vision algorithms for object segmentation based on color filtering and for shape classification (roundness value). The language input is processed through the SPHINX speech recognition system, integrated with the iCub simulator.

The core module that integrates the various processing capabilities to respond to linguistic instructions is the Goal Selection Neural Network. This is an architecture similar to the feedforward networks used in connectionist object-naming experiments (e.g., Plunkett *et al.* 1992). The input to the network consists of seven visual features encoding object size and location, and the active language input units activated by the speech recognition system. The output layer has four units respectively selecting the four actions: idle, reach, grasp, and drop. The most active output action unit then activates the reaching and grasping modules, trained separately. During the training phase of the Goal Selection Network, the robot is shown an object along with a speech signal. Examples of sentences for handling a blue object are: "Blue_ball," "Reach blue_ball," "Grasp blue_ball," "Drop blue_ball into basket." This network is successfully trained though 5,000 cycles of sentence-object pairs. The final testing demonstrated that the iCub is able to correctly respond to all the combinations of the four action names and object names.

The Tikhanoff, Cangelosi and Metta (2011) model of language understanding in the humanoid robot iCub provides the validation of an integrated cognitive architecture for developmental experiments on vision, action, and language integration. The model also deals with the learning and use of simple sentences based on word combinations. However, these word combinations do not correspond to the full potential of syntactic languages, as the robots would need to be able to generalize behavior to novel combinations of words and the robot's neural controller is explicitly trained on all possible word combinations. Multiword sentences in these studies are more similar to the holophrases of a one-year-old child, than to proper two-word and multiword combinations that appear in later stages of child development, typically in the second year of life. In the next section we will look at developmental robotics models that specifically investigate the acquisition of syntactic capabilities.

Related models have proposed similar cognitive architectures for language grounding of action words. For example, Mangin and Oudeyer (2012) propose a model that specifically studies how the combinatorial structure of complex subsymbolic motor behaviors, paired with complex linguistic descriptions, can be learned and reused to recognize and understand novel, previously untrained combinations. In Cangelosi and Riga (2006), an epigenetic robotic model is proposed for the acquisition via linguistic imitation of complex actions (see section 8.3, this volume). Finally, Marocco *et al.* (2010) specifically aim at the modeling of the grounding of action words in sensorimotor representation for a developmental exploration of grammatical categories of verbs as names of dynamic actions. They use the simulated version of the iCub to teach the robot the meaning of action words representing dynamical events that happen in time (e.g., push a cube on a table, or hit a rolling ball). Tests on the generation of actions with novel objects with different shape and color properties show that the meaning of the action words depends on sensorimotor dynamics, and not on the visual features of the objects.

7.4 Robots Learning Grammar

The acquisition of grammar in children requires the development of basic phonetic and word learning skills. As shown in table 7.1, simple two-word combinations appear around eighteen months of age, near the period of vocabulary spurts that significantly increases the child lexicon. The developmental robotics models of lexical acquisition discussed previously have not fully reached the stage of reproducing the vocabulary spurt phenomenon, at least for the robotics studies that model the acquisition of the lexicon directly grounded in the robots' own sensorimotor experience. However, a few robotics models have been proposed that start to address the phenomenon of grammar development, though with smaller lexicons. Some of these grammar-learning models focus on the emergence of semantic compositionality that, in turn, supports syntactic compositionality for multiword combinations (Sugita and Tani 2005; Tuci *et al.* 2010; Cangelosi and Riga 2006). Others have directly targeted the modeling of complex syntactic mechanisms, as with the robotics experiments on Fluid Construction Grammar (Steels 2011, 2012), which permits the study of syntactic properties such as verb tense and morphology. Both approaches are consistent with cognitive linguistics and embodied approaches to language. Here we describe in detail some of the progress in these two fields of modeling grounded grammar acquisition.

7.4.1 Semantic Compositionality

Sugita and Tani (2005) were among the first to develop a robotic model of semantic compositionality, with cognitive robots capable of using the compositional structure of action repertoires to generalize novel word combinations. Compositionality refers to the isometric mapping between the structure (semantic topology) of meanings and the structure (syntax) of language. This mapping is used to produce combinations of words that reflect the underlying combination of meanings. Let us consider a very simple meaning space with three agents (JOHN, MARY, ROSE) and three actions (LOVE, HATE, LIKE). These meanings are isometrically mapped to three nouns ("John," "Mary," "Rose") and three verbs ("love," "hate," "like"). Through compositionality, a speaker can generate any possible combination of noun-verb-noun combinations, such as "John love(s) Mary," and "Rose hate(s) John," directly mapping sentences to agent-action-agent combinations.

The robotics experiments of Sugita and Tani (2005) specifically investigate the emergence of compositional meanings and lexicons with no a priori knowledge of any lexical or formal syntactic representations. A mobile robot similar to a Khepera was used. This was equipped with two wheels and an arm, a color vision sensor, and three torque sensors on both the wheels and the arm (figure 7.9). The environment consists of three colored objects (red, blue, and green) placed on the floor in three different locations (a red object on the left-hand side of its field of view, a blue object in the middle, and a green object on the right). The robot can respond with nine possible behaviors based on the combination of three actions (POINT, PUSH, HIT) with the three objects (RED, BLUE, GREEN) always in the same locations (LEFT, CENTER, RIGHT). The nine possible behavioral sequence categories resulting from the combination of actions, objects, and locations are shown in table 7.4 (uppercase text). The table also shows the possible linguistic combinations (lowercase).

Figure 7.9

Top-down view of the mobile robot with arm and the three objects in front, from the Sugita and Tani 2005 experiment. Figure courtesy of Jun Tani.

The robot's learning system is based on two coupled recurrent neural networks (Recurrent Neural Network with Parametric Bias [RNNPB]), one for the linguistic module and the other for the action motor module. RNNPB is a connectionist architecture based on a Jordan recurrent neural network that uses the parametric bias vectors (learned during training) as a compressed representation for the input state activating the behavioral sequence (Tani 2003). In this experiment, the network is taught, through direct supervision with the error backpropagation algorithm, to act on the three objects/location as per table 7.4. The linguistic and motor units respectively encode the sequences of words and actions to be learned. The two RNNPB modules are trained to produce the same parametric bias vectors for each action/word sequence.

The robot experiments are divided in two stages: training and generalization. In the training stage, the robot acquires associations between sentences and corresponding behavioral sequences. The testing stage tests the robot's ability to generate the correct behavior by recognizing (1) the sentences used during training; and (2), most important, the novel combinations of words. A subset of fourteen object/action/location combinations is used during training, with four left for the generalization stage.

After the successful training stage, in the generalization stage the four remaining, novel sentences are given to the robot: "point green," "point right," "push red," and "push left." Behavioral results show that the linguistic module has acquired the underlying compositional syntax correctly. The robot can generate grammatically correct sentences and understand them by giving a behavioral demonstration of the POINT-G and PUSH-R actions. This is achieved by selecting the correct parametric bias vector that produces the matching behavior. Moreover, detailed analyses of the robot's neural representations supporting the verb-noun compositional knowledge are possible by analyzing the space of parametric biases. Figure 7.10 shows the structure of representation for two sample parametric bias nodes for all the eighteen sentences, and separated substructure for the verbs and nouns. In particular, the congruence in the substructures for verbs and nouns indicates that the combinatorial semantic/syntactic structure has been successfully extracted by the robot’s neural network. In the diagram of figure 7.10a, the vectors for the four novel sentences are in the correct positions in the configuration of the compositional verb-noun space. For example, the parametric bias vector of “push green” is at the intersection between the substructures for “push” and “green.”

Table 7.4

Behaviors (capital letters) and linguistic descriptions (lowercase) in the Sugita and Tani (2005) experiment. The elements underlined are not used during the training and are presented to the network for the generalization stage testing.

	Point		Push		Hit	
	behavior	Language	behavior	Language	behavior	Language
RED LEFT	POINT-R	“point red” “point left	PUSH-R	“point red“ “point left“	HIT-R	“point red” “point left”
BLUE CENTER	POINT-B	“point blue” “point center”	PUSH-B	“point blue“ “point center“	HIT-B	“point blue” “point center”
GREEN RIGHT	POINT- G	“point green” “point right”	PUSH-G	“point green” “point right”	HIT-G	“point green” ”point right”

These analyses confirm that the sentences are generalized by extracting the possible compositional characteristics from the training sentences (see Sugita and Tani 2005 for further details and analyses). Overall, this robotic model supports the constructivist psychology hypothesis that syntax compositionality can emerge out of the compositional structure of behavioral and cognitive representations. In the next section we will see how an extended syntactic representation capability can support the developmental acquisition of more complex grammatical constructions.

7.4.2 Syntax Learning

An important framework for robot experiments on the development of syntactic knowledge is the Fluid Construction Grammar (FCG) developed by Steels (2011, 2012). The FCG is a linguistic formalism to adapt the cognitive construction grammar for the handling of open-ended grounded dialogues, as with robotic experiment on language learning. Although this formalism was originally developed for experiments on the cultural evolution of language (Steels 2012), it is also suitable for language development studies given its focus on the grounding of grammar concepts and relations in situated and embodied robotics interactions. Here we briefly present some properties of the FCG formalism, and a case study on FCG robotic experiments for the acquisition of the lexicon and grammar of German spatial terms (Spranger 2012a, 2012b).

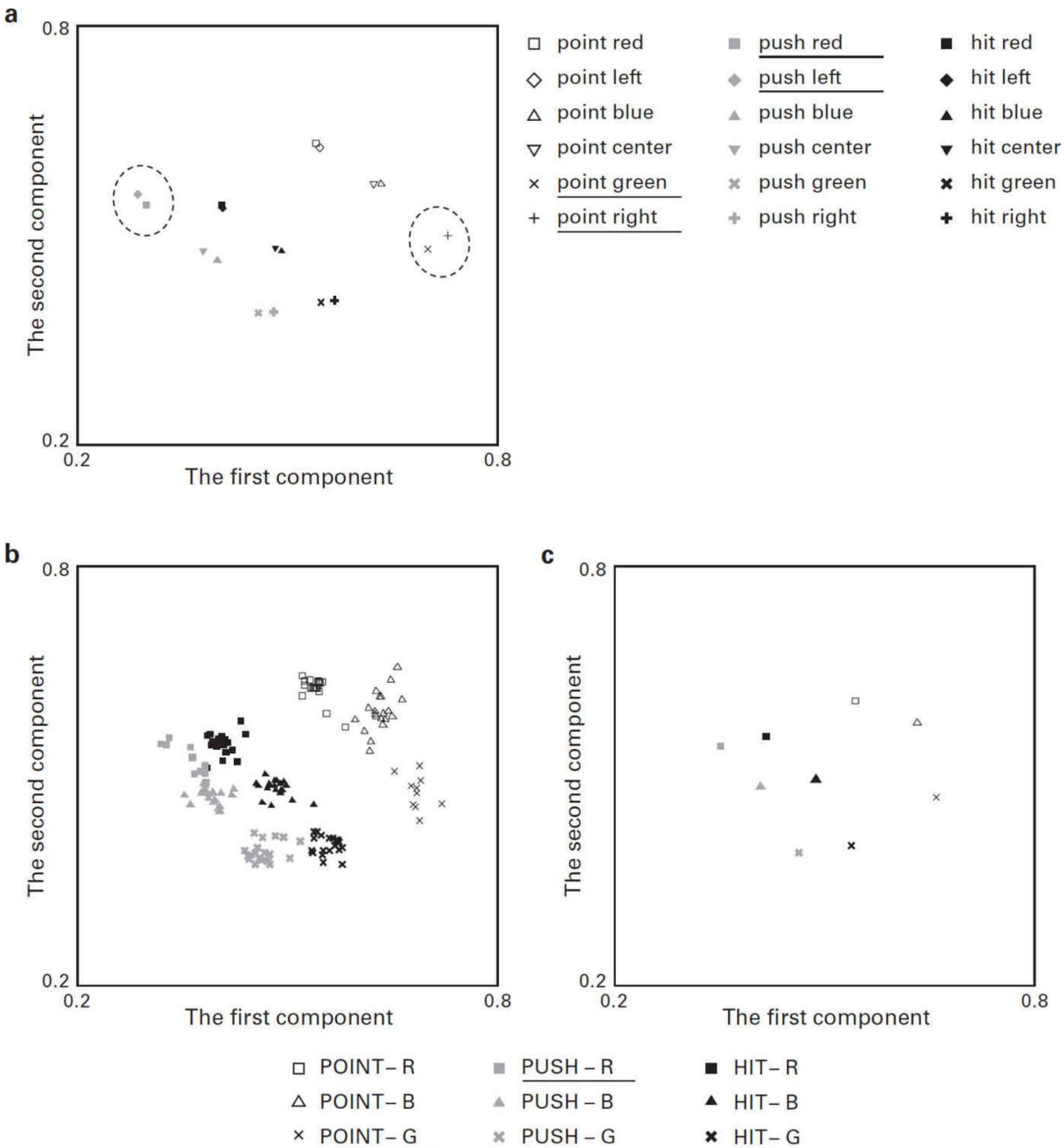


Figure 7.10

Results from the Sugita and Tani experiment. The plots show (a) the PB vectors for recognized sentences in the linguistic module where the vector points within dotted circles correspond to unlearned sentences; (b) the PB vectors for training behavioral sequences in the behavioral module; (c) the averaged PB vector for each behavioral category. Figure courtesy of Jun Tani.

For the overview of the FCG we will primarily follow Steels and de Beule

(2006), but refer to Steels (2011, 2012) for an extensive description of the FCG formalism. FCG uses a procedural semantics approach, that is, the meaning of an utterance corresponds to a program that the hearing agent can execute. For example, the phrase “the box” implies that the hearing agents can map the perceptual experience of the box object indicated by the speaker with the corresponding internal categorical (prototypical) representation. This procedural formalism is based on a constraint programming language called IRL (Incremental Recruitment Language) and implements the necessary planning, chunking, and execution mechanisms of constraint networks. The FCG also organizes the information about an utterance in feature structures. For the example “the box,” Steels and de Beule (2006) use the following IRL structure:

(equal-to-context ?s) (1)
(filter-set-prototype ?r ?s ?p) (2)
(prototype ?p [**BOX**]) (3)
(select-element ?o ?r ?d) (4)
(determiner ?d [**SINGLE-UNIQUE-THE**]) (5)

These elements are primitive constraints that implement fundamental cognitive operators. In (1), equal-to-context refers to elements in the current context and binds them to ?s. In (2), filter-set-prototype filters this set with a prototype ?p that is bound in (3) to [BOX]. In (4), select-element selects an element ?o from ?r according to the determiner article ?d that is bound to [SINGLE-UNIQUE-THE] in (5), meaning that ?r should be a unique element the speaker is referring to by using the article “the” (rather that the indefinite article “an,” which would be used to refer to a generic object).

Figure 7.11 shows the correspondence mapping between the semantic (left) and the syntactic (right) structure of the utterance “the ball.” In this feature-based representation system, a unit has a name and a set of features.

In FCG a rule (also called template) expresses the constraints on possible meaning-form mappings. A rule has two parts (poles). The left part refers to the semantic structure formulated as a feature structure with variables. The right part refers to the syntactic structure and is again formulated as a feature structure with variables. For example, among the various types of rules, the *con-rules* correspond to grammatical constructions that associate parts of semantic structure with parts of syntactic structure. These rules are used by Unify and Merge operators during linguistic production and parsing. In general, the unification phase is used to check whether a rule is triggered, and the merge phase represents the actual application of the rule. For example, in language production the left pole is unified with the semantic structure under construction, possibly yielding a set of bindings. The right pole is then merged (unified) with the syntactic structure under construction. During understanding and parsing, the right pole is unified with the syntactic structure and parts of the left part are added to the semantic structure. The con-rules are used to build higher-order structure encompassing all the level of complexity of full syntactic representation.

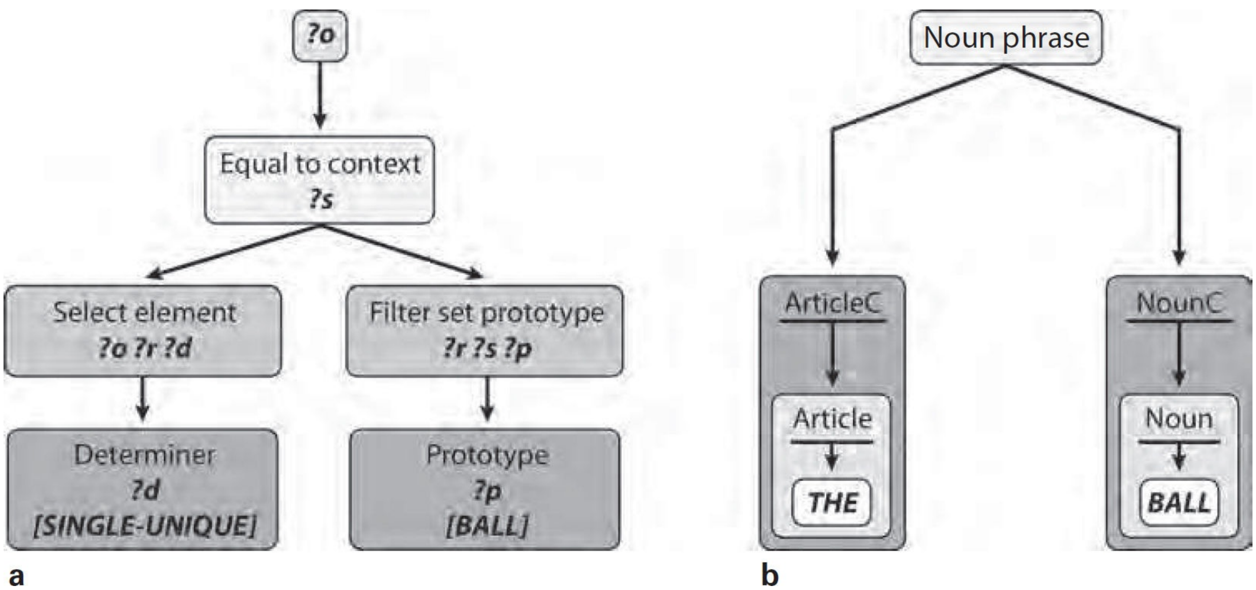


Figure 7.11

Simplified FGC decomposition of the constraint program for “the ball” in the semantic structure (a), and related syntactic structure in the Steels and de Beule (2006) study (b).

To demonstrate how FCG works in actual robotics language experiments, we will describe the case study on the acquisition of the grammar of German spatial terms (Spranger 2012a). This was carried through language experiments with the humanoid robot QRIO. The robotic agents play a spatial language game, in which they have to identify an object in a shared context. The environment has two robots, a number of blocks of equal size and color, a landmark on the wall, and a box with a visual tag pasted to its front (figure 7.12).

Although FCG was primarily developed for the modeling of the cultural evolution of language, we focus here on the experiments between a speaker and hearer when the meanings and words are predefined by the experimenter (in this case to match the German spatial terms). During each language game, the speaker first draws the attention of the listener to an object using a spatial description, and then the hearer points to the object it thinks the speaker is referring to. The robot's embodiment apparatus (i.e., perception of distance and angle) determines the main FCG cognitive semantics categories of "proximal-category" (subdivided into near/far subcategories) and "angular-category" (with front/back frontal dimension, left/right lateral dimension, up/down vertical dimension, and north/south absolute dimension). These dimensions are then mapped to the position of the landmark and of the referent object, as any sentence including a spatial term always implies the use of the landmark/referent pair.

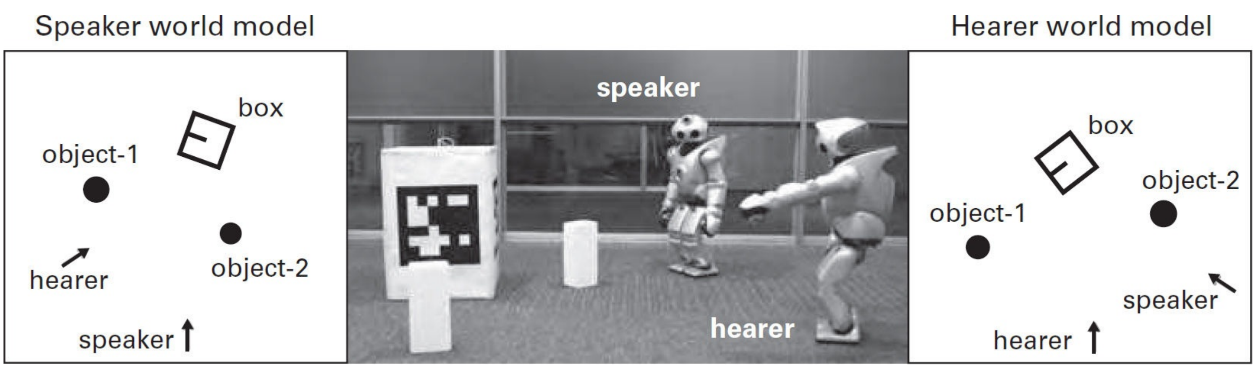


Figure 7.12

Setup for spatial language game with QRIO robots (center) and mental representations for the two robots (sides) from Spranger's (2012a) experiment. Figure courtesy of Michael Spranger. Reprinted with permission from John Benjamins.

All robots are equipped with predefined spatial ontologies and a lexicon for the following basic German spatial terms: *links* ("left"), *rechts* ("right"), *vorne* ("front"), *hinter* ("back"), *nahe* ("near"), *ferne* ("far"), *nördlich* ("north"), *westlich* ("west"), *östlich* ("east"), and *südlich* ("south"). During learning, depending on the success of each language game, the parameters of the FCG elements are refined, such as the width of a spatial category with respect to the central angle/distance. Different experiments are carried out for the learning of separate, or simultaneous, types of categories and spatial dimensions. Results show that the robots gradually learn to map (i.e., align) each spatial term to the target spatial perception configurations (Spranger 2012b).

Once the basic lexicon of spatial terms is acquired through language games, the robots undergo a grammar learning stage. The FCG formalism can help represent the constituent structure, word order, and morphology of the German spatial language.

In the study on grammar learning of Spranger (2012a), two groups of robots are compared: one equipped with the full German spatial grammar, and the second given only lexical constructions. The study compares the performance of the two groups with varying complexity of the scene, for example, with or without allocentric landmarks. Results show that the grammar greatly reduces the ambiguity in interpretation, especially when the context does not provide enough information to solve these ambiguities.

7.5 Conclusions

This chapter frames the current approaches and progress in developmental robotics models of language learning within the state of the art of child psychology studies of language acquisition and consistently with the framework of constructivist theories of language development.

We first gave a brief overview of the up-to-date understanding of the milestones and timescale of language development (table 7.1) and of the main principles used for infant's word learning (table 7.2). This overview shows that for most of the first year, the infant progresses on the development of phonetic competence through various babbling strategies. This leads to the acquisition of a language-like combinatorial phonetics system (e.g., canonical babbling for syllable-like sounds) and the acquisition of the very first words by the end of the first year (e.g., the child's own name). The second year of age is mostly dedicated to the acquisition of words in the lexicon, leading to the vocabulary spurt toward the end of year 2. In parallel, in both the second part of year 2, and in year 3 and subsequent years, the child develops grammatical skills, going from simple two-word combinations and verb islands (around the second birthday) to adultlike syntactic constructions.

The review of the developmental robotics models in sections 7.2–7.4 showed that most of the progress has been achieved for the models of vocal babbling and of early word learning, with some progress in grammar development modeling. Table 7.5 provides a syncretic mapping of child language development stages with the main robotics studies discussed in this chapter. As it can be seen, most robotics models assume that the robot starts with an intrinsic motivation to communicate (but see Oudeyer and Kaplan 2006, and Kaplan and Oudeyer 2007, for an approach specifically focused on intrinsic motivation for communication and imitation). Although robotics language models do not discuss how this intentional communication capability is acquired, some of the works presented in chapter 3 provide operational definitions and experimental testing of the emergence of such types of intrinsic motivations.

The phenomena of babbling and early word acquisition have been extensively covered by various models, though in most studies the focus is on either one or other of the mechanisms. Very few models, as in Brandl *et al.* (2008), have combined the learning of phonetic representation through babbling with word acquisition skills. As for the emergence of grammatical competence, a few studies have looked at the acquisition and use of two-word combinations, with just one explicitly addressing the learning of adultlike grammar constructs, as in Spranger's (2012a) FCG model of German locatives.

This tendency to produce models that focus on isolated language development phenomena is in part due to the early maturity stages of the developmental robotics discipline, and in part due to the inevitable complexity of an embodied, constructivist approach to language and the related technological implications. Given the early stages of developmental robotics research, the studies described in this chapter mostly consist of the presentation of a new methodological approach, rather than on the gradual build-up of incrementally complex experiments, and as such will specialize on one cognitive faculty. The exception of the Brandl *et al.* study, covering both phonetic and lexical development, is explained by the large-scale collaborative project on the ASIMO robot (and also the work by Driesen, ten Bosch, and van Hamme 2009, from the large European project ACORN, www.acorns-project.org). The other issue limiting the breadth of phenomena covered in a single study is the fact that developmental robotics experiments are by their own nature complex, so that the embodied and constructivist view of cognition and language necessitates the parallel implementation of control mechanisms for multiple cognitive capabilities. As this requires complex technological implementations, in most studies researchers tend to start with the assumption of preacquired capabilities, and investigate only one developmental mechanism. For example, in most of the word acquisition studies of section 7.3 the models assume a fixed, preacquired capability to segment speech, thus concentrating only on the modeling of lexico-semantic development (e.g., in Morse, Belpaame, *et al.* 2010).

Table 7.5

Mapping of child language development stages and the main robotics studies discussed in this chapter. Two (+) signs indicate the main focus of the work, and one (+) sign the general relevance to the language development stage.

AGE (months)	CAPABILITIES	Oudeyer 2006	Lyon, Nehaniv, and Saunders 2012	Brandl et al. 2008	Steels and Kaplan 2002	Seabra Lopes and Chauhan 2007	Morse, Belpeame, et al. 2010	Tikhanoff et al. 2011	Sugita and Tani 2005; uci et al. 2010	Steels 2012a; pranger 2012b
	(robot)	*Sim. head*	*iCub*	*Asimo*	*Aibo*	*Arm manip.*	*iCub*	*iCub*	*Mobile + arm*	*QRIO*
0–6	Marginal babbling	++								
6–9	Canonical babbling	++	++	++				+		
10–12	Intentional communication	+	+	+	+	+	+	+	+	+
	Gestures			+			+			
12	Single words (objects)			+	++		++	+	+	+
	Single words (actions)			+		++		+	+	
	Holophrases									
	Word-gesture combinations			+						
18	Reorganization of phonetics			++						
	Vocabulary spurt (50+ words)									
	Two-word combinations							++	++	
24	Longer sentences, verb islands									
36+	Adultlike grammar									++
	Narrative skills									

A further look at the language development stages that have not currently been modeled by developmental robotics studies (cf. bottom part of table 7.5) shows the areas needing attention in future research. For example, no developmental robotics models exist of the grounded acquisition of large lexicons (fifty-plus words, vocabulary spurt) in robot experiments. Although simulation models have looked at more extensive word repertoires (e.g., 144 words in Ogino, Kikuchi, and Asada 2006), and one long-term human-robot interaction experiment has investigated the learning of 200 object names (Araki, Nakamura, and Nagai 2013), overall the number of words learned in experiments with physical robots and objects has been limited to a few tens of lexical items. The same applies to the learning of incrementally complex grammatical constructions and of narrative skills. However, progress in these areas might benefit from the consideration of significant advancements in other areas of cognitive modeling, especially in the field of connectionist modeling of language (Christiansen and Chater 2001; Elman *et al.* 1996) and neuroconstructivist approaches (Mareschal *et al.* 2007). For example, connectionist models exist of construction grammar and the verb island hypothesis (Dominey and Boucher 2005a, 2005b) and of the vocabulary spurt (McMurray 2007; Mayor and Plunkett 2010). Moreover, work on artificial life systems (Cangelosi and Parisi 2002) and virtual agents can inform the development of developmental robotics studies, as in the work on narrative skills in virtual agents (Ho, Dautenhahn, and Nehaniv 2006). The integration of such findings and methodologies in future developmental robotics experiments can help create advances in language learning models.

Additional Reading

Barrett, M. *The Development of Language* (Studies in Developmental Psychology). New York: Psychology Press, 1999.

This edited volume, though not very recent, provides a clear overview of developmental theories and hypotheses on language acquisition. It ranges from a review of phonological acquisition research, to work on early lexical development, constructivist syntax acquisition, conversational skills and bilingualisms, and atypical language development. For a more focused account of usage-based constructivist theory of language development, also read Tomasello 2003.

Cangelosi, A., and D. Parisi, eds. *Simulating the Evolution of Language*. London: Springer, 2002.

This is a collection of review chapters on the simulation and robotics modeling approaches to the evolution of language. The chapters are written by the pioneers in the field, and include a review of the Iterated Learning Model (Kirby and Hurford), early robotic and simulated agent language games (Steels), the mirror system hypothesis for the evolution of the language-ready brain (Arbib), and mathematical modeling of grammar acquisition (Komarova and Nowak). The volume also has a useful introduction on the role of computer simulations for modeling language origins, a tutorial chapter on the main methods for simulating the evolution of language, and a conclusion written by Tomasello on the key facts of primate communication and social learning. A more recent overview of robotics and computer simulation models of language evolution is also available in some chapters in Tallerman and Gibson 2012.

Steels, L., ed. *Design Patterns in Fluid Construction Grammar*. Vol. 11. Amsterdam: John Benjamins, 2011.
Steels, L., ed. *Experiments in Cultural Language Evolution.* Vol. 3. Amsterdam: John Benjamins, 2012.

These two complementary volumes review the theoretical foundations (2011) and the experimental investigations (2012) of the Fluid Construction Grammar framework for the cultural evolution of language. The first volume provides the first extensive presentation of the framework, with the discussion of concrete examples on phrase structure, case grammar, and modality. The second volume includes computational and robotic experiments on the emergence of concepts and words for proper names, color terms, actions, and spatial terms, as well as case studies on the emergence of grammar.

9 Conclusions

This volume started with the introduction of the main theoretical principles underpinning developmental robotics. These included the view of development as a self-organizing dynamical system; the integration of phylogenetic, ontogenetic, and maturation phenomena; the strong emphasis on embodied, grounded, and situated development; the focus on intrinsic motivation and social learning; the nonlinearity of qualitative changes in development; and the importance of modeling online, open-ended cumulative learning. All these posit fundamental questions on the nature of development in both natural and artificial cognitive systems.

These principles have inspired past and current developmental robotics models, though with a varying degree of involvement and a primary focus on one or few of these design principles. Only a few studies have attempted to take into consideration all of these principles simultaneously and to embed their features in the developmental computational models and architectures. This is for example the case of the studies based on the iCub emergentist cognitive architecture (Vernon, van Hofsten, and Fadiga 2010) that we reviewed in chapter 8. Such an architecture included principles from self-organization and emergence, intrinsic motivation, social learning, embodied and enactive cognition, and online, cumulative learning. The architecture, however, only indirectly addresses the interaction among phylogenetic, ontogenetic and maturational phenomena.

Most of the existing developmental robotics models only focus on some of these principles, providing a clear operationalization of only one or few of these principles in specific developmental mechanisms. In this final chapter we will first reflect on the progress and achievements reached to date on each of the six principles presented in chapter 1. We will then look at other general achievements related to methodological and technological progress. This analysis will inform the identification and discussion of the open scientific and technological challenges for future research in developmental robotics.

9.1 Main Achievements on the Key Developmental Robotics

Principles

9.1.1 Development as a Dynamical System

The dynamical systems approach proposed by Thelen and Smith (1994) sees development as multicausal change within a complex dynamic system. The growing child can generate novel self-organizing behaviors through its interaction with the environment, and these behavioral states vary in their stability within the complex system. Such a principle is based on the mechanism of decentralized control, self-organization and emergence, multicausality, and nested timescales.

One study directly implementing and testing the dynamical systems hypothesis is the model of fetus and neonatal simulations by Kuniyoshi and Sangawa (2006). This model specifically instigates the hypothesis that partially ordered dynamical patterns emerge from the chaotic exploration of body-brain-environment interactions during gestation. This hypothesis is based on the observation of the spontaneous "general movements" reported in the two-month-old (eight to ten weeks) human fetus, and their role in the emergence of meaningful infant motor behaviors such as rolling over and crawling-like movements. The fetus's neural architecture consists of one Central Pattern Generator (CPG) per muscle. These dynamic CPGs are functionally coupled via the body's interaction with the physical environment and the muscle's response, rather than through direct connections. The behaviorally coupled CPGs produce periodic activity patterns for constant input, and chaotic patterns for nonuniform sensory input.

A similar dynamical system approach based on CPGs has been employed in various studies on the development of motor and locomotion skills (section 5.1.4). Righetti and Ijspeert (2006a; 2006b) used CPGs with the iCub to demonstrate the development of crawling strategies that correspond to the gait pattern produced by a human infant. Such a dynamical approach leads to the acquisition of the ability to combine periodic crawling movement with shorter, ballistic actions, such as reach-like hand movements (section 5.4). Li *et al.* (2011) extended this dynamic CPG approach to model crawling locomotion abilities in the NAO robot, Taga (2006) used similar CPG mechanisms to account for the stages of walking, by freezing and freeing DOFs, and Lungarella and Berthouze (2004) investigated the bouncing behavior. All these studies show the contribution of CPGs in modeling dynamical systems phenomena in development.

9.1.2 Phylogenetic and Ontogenetic Interaction

Progress on the modeling of the interaction of evolutionary (phylogenetic) and developmental (ontogenetic) phenomena in robotics has been limited, as most cognitive robotics models either focus on the evolutionary or the developmental learning timescale. For example, numerous models exist in evolutionary robotics (Nolfi and Floreano 2000), which investigate phylogenetic mechanisms and the evolutionary emergence of sensorimotor and cognitive capabilities. These tend to be separated from the developmental robotics models, which only emphasize the ontogenetic acquisition of behavioral and cognitive skills. However, some studies based on evolutionary robotics methods have been proposed that explore developmental issues. This is the case, for example, of the models of intrinsic motivation of Schembri, Mirolli, and Baldassarre (2007) on the evolution of a reinforcement-learning intrinsic reward mechanism in child and adult robotic agents. A set of evolutionary models have also been proposed that look at cultural-evolution phenomena, as with robotics and multiagent models of language origins (Cangelosi and Parisi 2002; Steels 2012). In this volume we analyzed Oudeyer's cultural evolution model of the emergence of shared phonetics repertoires.

Other pioneering work on phylogeny/ontogeny interaction phenomena, such as the Baldwin effects and heterochronic changes (e.g., Hinton and Nolan 1987; Cangelosi 1999), looks at general learning/evolution interaction, but not at developmental issues.

Some progress, instead, has been achieved in the field of modeling maturation changes in development. One key model that addresses both ontogenetic and maturational changes is the work by Kuniyoshi and colleagues on fetus and neonatal robots. The first model developed by Kuniyoshi and Sangawa (2006) consists of a minimally simple body model of fetal and neonatal development. The subsequent model by Mori and Kuniyoshi (2010) provides a more realistic rendering of the fetus's sensorimotor structure. Both models offer a useful developmental robotics research tool to investigate pre-birth sensorimotor development, as they are based on a realistic representation of the fetus's sensors (1,542 tactile sensors!) and actuators, and the reaction of the body to gravity and to the womb environment. The first model has one main parameter related to the developmental timescale, the gestational age that distinguishes the agent between a thirty-five-week old embryo and a 0-day old newborn.

Other developmental robotics models that implement some kind of maturational mechanism include the Schlesinger, Amso, and Johnson (2007) model of object perception, which provides an alternative explanation to Johnson's (1990) hypothesis on the role of cortical maturation of the frontal eye field for the acquisition of visual attention skills in early infancy.

9.1.3 Embodied and Situated Development

This is an area where significant achievements have been demonstrated in a variety of developmental robotics models and cognitive areas. Due to the intrinsically embodied nature of robotics, the validation of theories through experiments with robotic agents and their specific sensorimotor apparatus, it is natural that the great majority of developmental models emphasize the role of physical, embodied interaction with the environment.

Evidence of the role of embodiment in the very early (prenatal) stages of development comes from the fetus and neonatal model of Mori and Kuniyoshi (2010). Through their simulation model of fetuses and neonatal robots, they test the embodiment hypothesis that tactile sensation induces motions in the fetus. Using a fetus/ infant body model with a humanlike distribution of tactile sensors, they investigate the development of the two types of reactive movements following the embryo's general movements, in other words, the isolated arm/leg movements (i.e., jerky movements independent from other body parts observed in human fetuses from around ten weeks of gestation) and hand/face contacts (i.e., when the fetus's hands touch the face slowly, observed from the eleventh gestation week).

In the developmental robotics models of motor development, the simulation of reaching behavior in agents by Schlesinger, Parisi, and Langer (2000) demonstrated that the freezing strategy (i.e., the solving of redundant DOFs by locking [freezing] the shoulder joint and reaching by rotating the body axis and elbow joint) does not need to be programmed into the model. On the contrary, it can emerge for free as a result of the learning process, and as a mechanism of morphological computation coming from the coupling of the body's properties and the environmental constraints.

Developmental models of language learning also show the importance of the embodiment biases in early word learning. The Modi Experiment by Morse, Belpaeme, *et al.* (2010) provides a demonstration of the embodiment bases of language learning. Smith (2005) observed that children use their body relationship with the objects (e.g., spatial location, shape of the object) to learn new object-word associations and expand their lexicon. In the ERA cognitive architecture used by Morse to model Smith's embodiment bias (see boxes 7.1 and 7.2) the robot's neural controller uses information on the body posture as a "hub" connecting information from other sensory streams and modalities. This hub allows for the spreading of activation and the priming of information across modalities, thus facilitating the embodied acquisition of the names of objects and actions.

In the field of abstract knowledge, evidence for the role of embodiment has been reported both for numerical cognition and for abstract word experiments. Rucinski, Cangelosi, and Belpaeme (2011; 2012) has proposed two developmental models of number embodiment. One model simulates the SNARC effect, the space-number association that links the number cardinality with a left/right spatial map (see section 8.2 and box 8.2). The other model investigates the role of gestures in learning to count (Rucinski, Cangelosi, and Belpaeme 2012), when the iCub is trained to count by either looking at objects being counted (visual condition) or pointing at objects while counting them (gesture condition). The comparison of the visual vs. gesture performance shows an advantage of the gesture condition in the counting ability, mirroring the developmental psychology data (Alibali and DiRusso 1999) on gestures and counting experiments. As for the role of embodiment in the acquisition of words with an abstract meaning component, the two models by Cangelosi and Riga (2006) and by Stramandinoli, Marocco, and Cangelosi (2012) explore the role of the symbol-grounding transfer mechanism in the continuum between concrete and abstract concepts. In the first model, the robot is taught higher-order complex actions via linguistic demonstrations, where the grounding transfer mechanism combines a lower-level action concept with higher-level actions such as “grab” and “carry. In subsequent work by Stramandinoli *et al.* (Ibid.), these complex concepts gradually become less concrete, with the learning of more abstract words such as “accept,” “use” and “make.”

All these examples of the strict coupling between embodiment and various other cognitive skills show the importance of grounded and situated learning in development.

9.1.4 Intrinsic Motivation and Social Learning

One other area of developmental robotics that has achieved important results is that of intrinsic motivation and social learning.

In chapter 4 we reviewed a wide set of studies that highlight the progress on the modeling of intrinsic motivation and artificial curiosity. Such studies show that intrinsically motivated robots are not specialized for solving a particular problem or task, but rather are capable of focusing on the process of learning itself and on artificial curiosity leading to exploring the environment. A major result in developmental robotics has been the establishment of a taxonomy of algorithms for modeling intrinsic motivation along the two classes of knowledge-based and competence-based frameworks (Oudeyer and Kaplan 2007; section 3.1.2). The knowledge-based view focuses on the properties of the environment, and how the organism gradually comes to know and understand these properties, objects, and events. Such a view includes novelty-based intrinsic motivation (i.e., when novel situations produce a mismatch or incongruity between an ongoing experience and stored knowledge) and prediction-based motivation (i.e., when the organism implicitly predicts how objects or events will respond to its actions). The competence-based view of intrinsic motivation focuses instead on the organism and the particular abilities or skills it possesses. Competence-based motivation promotes skill development by leading the agent to seek out challenging experiences and to discover what it can do. An example of this is Piaget’s functional assimilation mechanism, that is, the tendency for infants and young children to systematically practice or repeat a newly emerging skill.

A significant achievement in the modeling of intrinsic motivation has come from the use of reinforcement learning (Sutton and Barto 1998; Oudeyer and Kaplan 2007). This learning approach is particularly suitable on the modeling of internal or intrinsic reward factors that influence behavior and their interaction with the environment's external reward.

This volume reviewed examples of knowledge-based novelty intrinsic motivation (section 3.3.2), as with the Vieira-Neto and Nehmzow (2007) model of visual exploration and habituation in a mobile robot, and the integration of both exploration and novelty-detection behaviors. Huang and Weng (2002) investigate novelty and habituation with the SAIL (Self-organizing, Autonomous, Incremental Learner) architecture and mobile-robot platform. This model combines sensory signals across several modalities (i.e., visual, auditory, and tactile) and implements novelty detection and habituation using the reinforcement learning framework.

In the field of knowledge-based prediction intrinsic motivation (section 3.3.3), we have seen the "Formal Theory of Creativity" proposed by Schmidhuber (1991). In this framework, the intrinsic reward is based on changes in the prediction error over time, in other words, on the learning progress. In a similar fashion, the prediction-based approach by Oudeyer, Kaplan and Hafner (2007), called intelligent adaptive curiosity (IAC), is centered on prediction learning and the mechanisms by which the "Meta Machine learner" module learns to predict the error and circumstances under which the "Classic Machine learner" forward model predictions are more or less accurate. The IAC framework has been successfully tested in the Playground Experiments with the AIBO mobile robot.

Examples of developmental models directly implementing the competence-based framework of intrinsic motivations are those based on the contingency perception phenomenon in early infancy with the child's ability to detect the influence that their actions have on events (section 3.3.4). This has been linked to neuroscientific investigations on dopamine burst in the superior colliculus for intrinsic motivation and contingency detection (Redgrave and Gurney 2006; Mirolli and Baldassarre 2013). These dopamine bursts have been proposed to serve as a contingency signal and intrinsic reinforcement signal that rewards the corresponding action. Computational models implementing such mechanisms include the study by Fiore *et al.* (2008), on the role of perceptually salient events in a simulated robot rat experiment on conditioning learning, and the model by Schembri, Mirolli, and Baldassarre (2007) on mobile robots with a childhood phase, when the reward signal is internally generated, and an adult phase with externally generated reward during adulthood.

Overall, such a variety of models has provided a series of computational algorithms and mechanisms for the operationalization of the key concepts of habituation, exploration, novelty-detection, and prediction in developmental robotics models of intrinsic motivation.

Significant progress has also been achieved in the field of social learning and the imitation "instinct," as seen in chapter 6. In developmental psychology, newborn babies show from the very first day of life the instinct to imitate the behavior of others and complex facial expressions (Meltzoff and Moore 1983). In comparative psychology studies with human infants and primates, evidence exists that eighteen-to twenty-four-month-old children have a tendency to cooperate altruistically, a capacity not observed in chimpanzees (Warneken, Chen, and Tomasello 2006). These empirical findings have directly inspired developmental robotics models of social learning, imitation, and cooperation. For example, imitation skills are acquired in robots via the implementation of the HAMMER architecture, directly based on the AIM child psychology imitation model of Demiris and Meltzoff (2008). The HAMMER architecture includes a top-down attentional system and bottom-up attentional processes, such as those depending on the salience properties of the stimulus itself. It also consists of a set of paired inverse/forward models, where the acquisition of forward models is similar to the motor babbling stage of infant development (association between random movements and their visual, proprioceptive, or environmental consequences). These learned forward associations can then be inverted to create approximations to the basic inverse models by observing and imitating others. This allows the robot to learn how certain goals correspond to input states.

The modeling of the social skills of cooperation and shared intention is demonstrated in the work of Dominey and Warneken (2011). They carry out experiments in which a robotic arm with a gripper jointly constructs a shared plan with a human participant to play a game with goals such as "Put the dog next to the rose" or "the horse chases the dog." These cooperative skills are implemented through a cognitive architecture based on the Action Sequence Storage and Retrieval System. This is used to represent the steps of the joint game as a sequential shared plan, where each action is associated with either the human or the robot agent. Such an ability to store a sequence of actions as a shared plan constitutes the core of collaborative cognitive representations, which Warneken and colleagues claim is a unique ability of human primates (Warneken, Chen, and Tomasello; see also box 6.1).

Finally, the experiment of the acquisition of the concept of negation and of the word "no" shows the importance of social interaction between the caregiver and the child, as with the negative intent interpretation of rejection where the adult caregiver provides the child with a linguistic interpretation of her negative motivational state.

9.1.5 Nonlinear, Stage-Like Development

The existence of developmental stages in cognitive development permeates child psychology, starting from Piaget's sensorimotor stage theory. Developmental stages are typically characterized by qualitative changes in the strategy and skills used by the child, and in nonlinear progression between stages. The (inverted) U-shaped phenomenon is an example of such nonlinearity, as a stage of good performance and low errors is followed by an unexpected decrease in performance, which is subsequently recovered to show high performance.

One of the main examples of developmental robotics studies demonstrating the emergence of nonlinear, qualitative changes from situated developmental interactions is Nagai et al.'s (2003) experiment on gaze and joint attention. Results from the human-robot experiments with a robotic head showed the emergence and transition of the three qualitative joint attention stages described by Butterworth (1991): ecological (stage I), geometrical (stage II), and representational (stage III). In the initial ecological stage, the robot can only look at the objects visible within its own view, thus only achieving joint attention at a chance level. In the second stage, the robot head can also achieve joint attention by gazing at a location outside its view. In the final stage, the robot shows joint attention in practically all trials and positions (see figure 6.6). The transition between stages is the result of developmental changes in the robot's neural and learning architecture and the history of interaction with the user, rather than top-down manipulations of the robot's attention strategies.

Another developmental robotics model replicating the stage-like development of social skills is the one based on Demiris's imitation experiments. In his experiments, the HAMMER model of imitation learning follows the developmental stages of imitation behavior in infants, such as the initial imitation of the surface behavior of the demonstrator, followed by the later understanding of the underlying intentions and goal-imitation skill using different behavioral strategies. Similarly, in Scassellatti's (2002) model of the theory of mind in robots, this implements Leslie's and Baron-Cohen's stages of the theory of mind in infants.

Other models have also directly addressed the modeling of nonlinear, U-shaped phenomena. This is the case for example of the Morse *et al.* (2011) model of error patterns in phonetic processing, built on the ERA architecture for early word learning, and Mayor and Plunkett's (2010) vocabulary spurt simulation.

9.1.6 Online, Open-Ended, Cumulative Learning

The principle that focuses on the simultaneous and cumulative learning of cognitive skills from the online, open-ended interaction with the world is the one where progress has been more limited. The great majority of models reviewed in this volume typically focus on the simulation, or experiment, of single, isolated sensorimotor or cognitive skills. For example in chapter 5, we have reviewed numerous models on motor development that look at the four key motor skills of reaching, grasping, crawling, and walking. Unfortunately, the full integrated spectrum of locomotion and manipulation behaviors has not yet been captured by existing studies.

Some models simulate the use of multiple cognitive capabilities to contribute to the acquisition of a specific skill (e.g., frequent integration of visual skills with motor knowledge), though there is no real accumulation, over time, of different skills leading to cognitive bootstrapping and the further development of complex skills. In this book, however, we have seen some attempts to look at the cumulative role of acquiring multiple skills for the subsequent learning of higher-order cognitive skills. For example, in their model of reaching Caligiore *et al.* (2008) propose that motor babbling provides a bootstrap for learning to grasp (section 5.3). Fitzpatrick *et al.* (2008), Natale *et al.* (2005a; 2007), and Nori *et al.* (2007) use motor skill development (reaching, grasping, and object exploration) as a bootstrap for the development of object perception and object segmentation. Moreover, in the experiments on the embodied nature of number learning and the SNARC effect, the previous training of the robot on simple motor babbling tasks allows its neural control system to develop a later association between left/ right spatial representations and numbers of different size (section 8.2).

Specifically for the property of open-ended learning, some significant progress has been achieved in the field of intrinsic motivation. In the numerous studies in chapter 3 we have seen that once an intrinsically motivated robot achieves mastery in one area, it can subsequently shift its focus toward new features of the environment or new skills that it has not yet learned. This is possible through the robot’s own general-purpose exploration, novelty-detection, and prediction capabilities.

The major potential contribution to the modeling of online, open-ended, continuous learning comes from the proposal of emergentist cognitive architectures (section 8.5). As cognitive architectures aim at the design of a broadly scoped, general-purpose computational model capable of capturing the essential structure and process of cognition, they offer a tool to model the simultaneous and cumulative acquisition of sensorimotor and cognitive skills. This constitutes, however, a potential contribution, as most of the existing developmental robotics cognitive architectures are specialized for a subset of cognitive skills. On the one hand, we have specialized architectures as the ERA (Morse, de Greeff, *et al.* 2010) and LESA (Lyon, Nehaniv, and Saunders 2012) architectures focusing on language learning tasks, though they permit the simultaneous consideration of sensorimotor, speech, semantic, and pragmatic phenomena. The shared gaze (Nagai *et al.* 2003), the HAMMER (Demiris and Meltzoff 2008), and the cooperation (Dominey and Warneken 2011) architectures focus on the integration of skills related to social learning. On the other hand, some general developmental cognitive architectures, including work on the iCub (Vernon, von Hofsten, and Fadiga 2010), aim at a more comprehensive consideration of most functional capabilities (see table 8.4 and figure 8.10) and therefore offer the most promising approach to the modeling of online, open-ended, cumulative learning in robots.

9.2 Additional Achievements

Further achievements related to methodological and technological issues have been achieved, in addition to the progress on the preceding developmental robotics principles. Specifically, we will look at attainments in (1) the direct modeling of child development data, (2) the development and access to benchmarking robot platforms and simulators, and (3) applications of developmental robotics to assistive robotics.

9.2.1 Modeling of Child Development Data

One of the key aims of developmental robotics is to take explicit inspiration from human developmental mechanisms to design cognitive skills in robots. In this volume we have seen numerous examples of how child psychology experiments and data have directly inspired developmental robotics. Specifically, we can distinguish two main types of relations between developmental psychology and developmental robotics. In the first case, the robot experiments are directly constructed to replicate specific child psychology experiments, even allowing a direct qualitative and quantitative comparison of empirical and modeling results. The other type of relation concerns a more generic, higher-level bio-inspired link between the broad developmental mechanism studied in child experiments and the general developmental aspects of the robotic algorithm.

While most of the studies reviewed in this book employ a general, higher-level bio-inspired approach, a few allow a direct comparison between empirical and modeling experiments. For example, in chapter 7 on visual development, Schlesinger, Amso, and Johnson (2007) propose a model of perceptual completion directly simulating Amso and Johnson's (2006) experiments with infants on the unity perception task. This computational investigation permits the comparison of the performance of the simulation model results (simulated distribution of scans) with three-month-olds infants' eye tracking data (figure 4.13). The computational model provides further evidence, and an operational hypothesis on the neural and developmental mechanisms, in support of Amso and Johnson's (ibid.) hypothesis that the development of perceptual completion is due to progressive improvements in oculomotor skill and visual selective attention. In the same chapter, the developmental robotics study by Hiraki, Sashima, and Phillips (1998) investigates the performance of a mobile robot on the search task described by Acredolo, Adams, and Goodwyn (1984). This is the experiment in which a participant is asked to find a hidden object, after being moved to a new location. In addition to using the experimental paradigm comparable to the task studied by Acredolo and colleagues, Hiraki's work also proposes a model specifically designed to test Acredolo's hypothesis that self-produced locomotion facilitates the transition from egocentric to allocentric spatial perception.

Dominey and Warneken (2011) used a direct comparison of robotics and child psychology studies in their investigation of social cooperation and shared plans. This is detailed in the comparison between the Warneken, Chen, and Tomasello (2006) child/ animal psychology experiments in box 6.1 and the Dominey and Warneken (2011) model setup in box 6.2. In this case, the developmental robotics study comprises seven experimental conditions that extend in various ways the original 2 × 2 experimental design of the psychology study (two conditions for complimentary/parallel collaboration roles, and two for the problem solving and social game tasks).

In language acquisition models, the Morse, Belpaeme, *et al.* (2010) simulation of Smith and Samuelson's (2010) "Modi Experiment" is another clear example of the direct comparison between child psychology and robot experimental conditions and results. Specifically in boxes 7.1 and 7.2 we provide details on the child psychology and robot experiments. Moreover, figure 7.6 directly compares quantitative data from the four conditions of the children's and the robot's experiments. The close match between the empirical and modeling results is used to support the hypothesis that body posture and embodiment bias are central to early word learning.

A similar approach is shown in chapter 8 with the work by Rucinski, Cangelosi, and Belpaeme (2011; 2012) on the embodiment biases in numerical cognition. Section 8.2 details the direct comparison between robots' and human participants' data on the SNARC effect. Figures 8.3 and 8.4 demonstrate that the iCub's reaction time increases with larger numbers and for smaller distances between numbers, thus showing a space-number response code association similar to that shown with human participants reported in Chen and Verguts (2010). Moreover, Rucinski's developmental robot simulation on the role of gestures in the acquisition of numbers (two experimental conditions with/without the use of the pointing gestures when counting) provides quantitative evidence that there is a statistical increase in the number set size when the pointing gesture accompanies the number recitation. This directly models the observed advantage of the gesture condition in the child psychology study by Alibali and DiRusso (1999).

The great majority of developmental robotics studies, however, take on a more general, higher-level inspiration strategy from child psychology experiments. A typical example of a developmental robotics study that follows such a general inspiration approach is the work on negation by Förster (2013). In this case, two general hypotheses on the emergence of negation are considered as a starting point to investigate the acquisition of the use of the word "no" in human-robot interaction experiments: (1) the negative intent interpretation of rejection hypothesis by Pea (1980), and (2) the physical and linguistic prohibition hypothesis by Spitz (1957). As a consequence, two different experiments were designed. The first experiment used a rejection scenario, where the iCub robot elicits the participant's rejection interpretation with nonverbal behavior, as frowning and head turning, toward a disliked object. The second experiment used the prohibition scenario, where two of the objects are declared as forbidden and the human participant is instructed to restrain the robot from touching these two prohibited objects. This approach does not permit a direct comparison between experimental data and modeling results, but rather a higher-level validation of the two hypotheses. This is what Förster (2013) does when he uses numerous analyses of the human participants' and the robot's utterances and behavior to demonstrate that both the rejection and the prohibition strategies play a role in the development of negation capabilities.

Similarly, Demiris and Meltzoff's (2008) HAMMER model provides a higher-level computational implementation of the Active Intermodal Matching (AIM) theoretical model (figure 6.2). This computational architecture then inspired various robotic experiments by Demiris and collaborators (Demiris and Hayes 2002, Demiris and Johnson 2003; Demiris and Khadhouri 2006) to test different cognitive mechanisms involved in imitation behavior as top-down and bottom-up attention and limited memory capabilities.

Both the direct empirical-robotic comparison studies and the higher-level developmental-inspired works show the benefits of modeling the gradual acquisition of cognitive skills, which is a key tenet of developmental robotics. Moreover, both approaches benefit from the direct collaboration between roboticists and developmental psychologists. This is the case for most of the examples described above. For example, Schlesinger provided complementary computational expertise to the psychology work by Amso and Johnson on object perception in infants, Morse collaborates with the child psychologist Smith on the embodied bias in word learning, and the roboticist Demiris collaborates with Meltzoff to propose and test the robot computational architecture of the AIM model. The direct roboticist-psychologist collaboration has the significant advantage to make sure that the robotic-computational version of the model is robustly grounded on child psychology theories, experimental methodologies and data. Moreover, such a close collaboration allows a two-way interaction between the two communities. For example, in both the Schlesinger, Amso, and Johnson (1997) and the Morse, Belpaeme, *et al.* (2010) computational studies we have seen situations in which the robotics experiment can provides predictions and insights for human development mechanisms, leading to further experimental investigations in child psychology. Specifically, the embodiment and early word learning robot experiments of Morse and colleagues predicted novel phenomena on the change of full body posture during the "modi" experiments, which have been verified and confirmed in subsequent experiments at Smith's Babylab (Morse *et al.* in preparation).

9.2.2 Access to Benchmark Robot Platforms and Software Simulation Tools

Another important methodological and technological achievement in developmental robotics has been the design and dissemination of benchmark robot platforms and simulators. Some use the open source approach, while others are based on commercial platforms and software simulation suites.

In chapter 2, we looked at over ten "baby robot" platforms and three main software simulators used in this field. Of these robot platforms, three have had a significant impact in developmental robotics, contributing to its origins and subsequent growth: the AIBO mobile robot, as well as the iCub and the NAO humanoid platforms.

The mobile platform AIBO robot (see full details in section 2.4) was one of the very first platforms used in the pioneering developmental robotics studies. This was a commercial platform (now out of production) widely available in late 1990 in robotics and computer science labs, due to its standard use in the RoboCup league and its affordability. Seminal studies using the AIBO for developmental robot models are Oudeyer *et al.* (Oudeyer, Kaplan, and Hafner 2007; Oudeyer and Kaplan 2006, 2007) on artificial curiosity and intrinsic motivation, Kaplan and Hafner (2006a, 2006b) on joint attention, and Steels and Kaplan (2002) on word learning.

The NAO robot (cf. section 2.3.2) has more recently become one of the two main benchmark humanoid platforms for developmental modeling. This is again due to its affordability and wide availability in research labs, as this robot has become the new standard in the RoboCup competition (directly replacing the AIBO). The NAO in particular is suitable for studies on intrinsic motivation, navigation, and locomotion, and on social interaction involving action imitation given its robust motor capabilities. In this volume we have for example seen the use of the NAO for crawling and walking development (Li *et al.* 2011) and pointing gestures in social interaction (Hafner and Schillaci 2011).

The iCub robot (cf. section 2.3.1) is the most recent success story in developmental robotics. More than twenty-five laboratories worldwide have access to this open source platform (2013 data). This extensive dissemination is the result of the European Union Framework Programme investment in cognitive systems and robotics, and the Italian Institute of Technology’s support for this open source platform. This volume has seen numerous developmental robotics studies with the iCub as in studies on motor development (Savastano and Nolfi 2012; Caligiore *et al.* 2008; Righetti and Ijspeert 2006a; Lu *et al.* 2012), social interaction and cooperation (Lallée *et al.* 2010), language acquisition (Morse, Belpaeme, *et al.* 2010; Lyon, Nehaniv, and Saunders 2012), number learning (Rucinski, Cangelosi, and Belpaeme 2011, 2012), negation (Förster 2013), and cognitive architecture (Vernon, von Hofsten, and Fadiga 2010).

The success and widespread use of platforms like the iCub and NAO have also been supported by robot software simulators that further facilitate research on the platforms. For example, the open-source iCub simulation software (section 2.4) has allowed hundreds of students and staff to participate in the yearly "Veni Vidi Vici" iCub Summer School (running from 2006) to learn to use the simulator robot, extending its use to labs with no access to the physical platform. As for the NAO simulator, its default availability in the Webots simulator has also facilitated wider use of this platform.

The enhanced access to developmental robot benchmark platforms (both hardware and simulators), accompanied by the continuous development of specialized platforms such as the ones reviewed in chapter 2, are key factors in the uptake and success of developmental robotics.

9.2.3 Applications in Assistive Robotics and Child Human-Robot Interaction (cHRI)

A further and important achievement of developmental robotics has been the translation of robot modeling research, especially the studies on social interaction, into applications of social assistive robotics for children. This started with the extension of the pioneering developmental robotics work on modeling social interaction and theory of mind to experiments on children with social skill disabilities, as in the autism spectrum disorders (Weir and Emanuel 1976; Dautenhahn 1999; Scassellati 2002; Kozima *et al.* 2004; Kozima, Nakagawa, and Yano 2005; Dautenhahn and Werry 2004; Thill *et al.* 2012). These applications have more recently encompassed other assistive robot areas, such as with children with Down syndrome and hospitalized child patients.

Autism spectrum disorders (ASDs; also referred to as the autism spectrum continuum) include a variety of chronic, life-long disabilities that affect children's capacities to communicate and interact with peers and adults and to understand social cues. Two of the most common types of ASDs are autistic disorder and Asperger's syndrome, which in addition to the social communication and social interaction deficits include symptoms such as restricted, repetitive patterns of behavior (Scassellati, Admoni, and Matarić 2012).

Dautenhahn (1999) was the first researcher to propose the use of physical robots as assistive social companions for ASD children, with the experiments of the AURORA project (AUtonomous RObotic platform as a Remedial tool for children with Autism; Dautenhahn and Werry 2004; www.aurora-project.com). The AURORA team has used various mobile and humanoid robots in different interaction studies with children with autism, including a study showing that the AIBO robot can adapt in real-time to the ways autistic children play with the robot (Francois, Dautenhahn, and Polani 2009a). In one of their pioneering studies, Wainer *et al.* (2013) investigated the effects of a session on autistic children's play interaction with the KASPAR humanoid robot on the subsequent improvement of social interaction with human adults. Comparison of the children's social behavior before and after the robot play session showed that autistic children were more invested in the game and collaborated better with the human partners after playing with KASPAR. The AURORA project led to numerous experimental investigations on autism and social robots by Dautenhahn and colleagues (e.g., Robins *et al.* 2012b; Dickerson, Robins, and Dautenhahn 2013), including a study by Wood *et al.* (2013) that shows the suitability of KASPAR as a tool for conducting robot-mediated interviews with children.

Another pioneering study on autistic children and robot interaction was presented in section 2.3.7, when we described the upper-torso humanoid platform Infanoid. Kozima *et al.* (2004; Kozima, Nakagawa, and Yano 2005) carried out child-robot interaction experiments with five-and six-year-olds, which compared typically developing children with autistic children. Their main interest was the children's perception of the robot and the demonstration of the robot's three stages of "ontological understanding": the neophobia stage marked by embarrassment and staring; the exploration stage featuring poking at the robot and showing toys; and finally, the interaction stage for reciprocal social exchanges. The comparison between autistic children and a control group showed similar responses in all three phases, with the only difference that autistic children enjoyed longer interactions, without losing interest as typically developing participants. Kozima has used both the Infanoid humanoid robot and the Keepon toy-like creature robot (Kozima, Nakagawa, and Yano 2005) to further explore these issues.

Scassellati (2005, 2007) also contributed to early studies on robot therapy for ASD children, given his interest in social development and theory of mind (section 6.5). His main contribution has been the use of social robots as diagnostic tools of ASD, in addition to their treatment role. For example he used the commercial robot face ESRA in two experimental conditions: (1) pre-scripted, noncontingent one-way dialogue with children, and (2) contingent play through Wizard of Oz control of the triggering of the robot's behavior in response to the child's reaction. Results show that autistic children are not sensitive to the differences in the two conditions, and did not show any reduction of interest in the last part of the interaction sessions (typically developing children's interest weaned during the last parts of the interactions). The manipulation of conditions that discriminate between children with different social behavior deficits can contribute to the definition of quantitative, objective measurements of social response and ASD symptom assessment. Scassellati proposes the implementation of structured interactions between ASD children and robots to create standardized social manipulation tasks designed to elicit particular social responses. The responses to monitor and quantify include gaze direction, focus of attention, position tracking, and vocal prosody.

A recent review of work on assistive social robots and ASD by Scassellati, Admoni, and Matarić (2012) gives an overview of the achievements in this field. This review for example points at consistent evidence that the use of these robots as autism therapy tools provides: (1) increased social engagement, (2) boosted levels of attention, (3) joint attention, (4) spontaneous imitation, (5) turn taking with another child, (6) manifestations of empathy, and (7) initiation of physical contact with the experimenter. Scassellati and colleagues claim that these improved social skills and behaviors are the consequences of the fact that robots provide novel sensory stimuli to the ASD child. Moreover, these social robots play an intermediate, novel role that sits between interactions with inanimate toys and animate social beings. On the one hand, inanimate toys do not elicit novel social behaviors, while people can be a source of confusion and distress for children with autism. Animated social robots, on the other hand, create new sensory situations facilitating novel behaviors as joint attention and empathy with the experimenters.

A similar approach to the use of social robots as therapy for ASD children has been applied to other disabilities. Lehmann *et al.* (2014) report an exploratory case study concerning a child with Down syndrome. These children have quite good nonverbal communication and social interaction skills, in contrast with the much more limited social interaction skills associated with ASDs. This study used two different robot platforms, the humanoid, doll-like KASPAR robot and the mobile IROMEC robot, for educational interactive games such as the “Move the robot” game and an “Imitation.” The case study results showed that the child was more interactive with the human experimenter and the robot in the games with the humanoid platform KASPAR for most behaviors such as looking at experimenter, pointing at the robot, vocalization, imitation of robot and prompted imitation of experimenter. The IROMEC mobile platform only showed advantages for the behavior of touching the robot. The advantage of the KASPAR platform is explained by the fact that its humanoid, robotic, and childlike appearance stimulates social behavior, in which Down syndrome children excel.

All these studies with varying developmental disorders like ASD and Down syndrome demonstrate the utility of the use of social assistive robots for different social and cognitive deficits. Moreover, other application areas of social robotics have been extended to their use as companions for children in the hospital (Belpaeme *et al.* 2012; Carlson and Demiris 2012; Sarabia and Demiris 2013). For example, Belpaeme *et al.* (2012) in the ALIZ-e project use the NAO humanoid platform as a long-term social companion for children with chronic disease such as diabetes. Specifically, the NAO robot has been used both in hospital environments and summer camps to support children to cope with the long term issues of diabetes and to help children understand dietary restrictions, medication and physical exercise requirements. This project includes action and dance imitation games, to encourage children to do regular physical exercises and help improve their self-image, and interactive tutoring and quiz sessions, to support the patient’s learning about dietary restrictions and identify (and avoid) foods with high carbohydrate and sugar levels. The work on diabetes has also led to the extension of the NAO hospital companion role for different pathologies. A clinical case study involving an eight-year-old cerebral stroke patient specifically investigated the advantages of using a social robot to assist in physiotherapy for stroke recovery (Belpaeme *et al.* 2013).

The growing trend on studies on robots interacting with healthy, ill, and disabled children more generally contributes to the field of child human-robot interaction (cHRI) (Belpaeme *et al.* 2013). cHRI has distinctive features when compared with standard, adult HRI. This is due to the fact that because the child's neural, cognitive, and social development has not reached full maturity, they will thus respond to different interaction strategies employed by the robot. For example, in cHRI with two-to three-year-old children, the interaction will be facilitated with the use of nonverbal communication strategies and error-tolerant linguistic communication as the toddlers' linguistic skills have not fully developed. Moreover, cHRI benefits from the fact that young children readily engage in social play and pretend play, and have a tendency to anthropomorphize and attribute lifelike qualities or personalities to toys (and robots). Therefore, the design of cHRI studies will benefit from the utilization of play interaction strategies and the exploitation of the child's attribution of empathy and lifelike characteristics to the robot (Turkle *et al.* 2004; Rosenthal-von der Pütten *et al.* 2013). Given the joint interests and overlapping research issues between developmental robotics and cHRI, these two approaches will benefit from the sharing of methodologies on human-child interaction experiments and the general investigation of sociocognitive developmental mechanisms.

9.3 Open Challenges

We have analyzed in the previous sections a broad set of theoretical and technological achievements, which demonstrate the significant advances in the first ten to fifteen years since the beginning of developmental robotics. However, the aim of understanding developmental mechanisms in natural cognitive systems and their operationalization and implementation in artificial robotic cognitive systems is implicitly a very complex task, with a long-term timescale spanning well beyond the "infant" stage of this discipline. This leaves open a wide set of scientific and technological challenges. In this concluding section we are going to highlight some of the key open challenges, specifically future work on the cumulative, long-term learning of integrated skills, on the evolutionary and developmental changes in body and brain morphology, and on cHCI and child-robot interaction ethics.

9.3.1 Cumulative Learning and Skills Integration

As we saw in the previous section on achievements in the general developmental robotics principle of open-ended cumulative learning, this is an area where the level of scientific advances has been limited. Although we have seen the design and testing of an impressive number of models of the developmental learning of isolated sensory, motor, social, linguistic, and reasoning skills, in only a very few cases have we seen these integrated into a single cognitive agent.

One way to address this issue is the incremental training of a robot controller to learn skills of increasing complexity. For example in language development models, the same robot controller should be used for cumulative adding of phonetic skills and single-word learning, followed by two-word acquisition and the acquisition of simple grammar constructs, further followed by the gradual development of complex adultlike syntactic skills. In parallel, the same robot should be able to integrate lexical, semantic, and constructivist grammar skills with sensorimotor representations, along the lines of the embodied view of language development. A specific example of a research roadmap for language and action learning has been proposed by Cangelosi *et al.* (2010). Following a twenty-year research perspective, this roadmap proposes the following six milestones in linguistic skill acquisition research: (1) grounded acquisition, decomposition, and generalization of simple transitive holophrases in learning by demonstration tasks; (2) grounded acquisition, decomposition, and generalization of the five basic argument constructions of English from holophrastic instances and the event types that are associated with their prototypical uses; (3) grounded interactive language-learning games in simple joint attention scenarios based on the implementation of elementary sociocognitive/pragmatic capabilities; (4) learning from increasingly complex and diversified linguistic input within progressively less restricted learner-tutor interactions; (5) progressively more humanlike cooperative ostensive-inferential communication based on the implementation of more advanced sociocognitive and pragmatic capabilities; and (6) learning progressively more complex grammars from quantitatively naturalistic input. These language-specific milestones are accompanied by three parallel sets of research milestones respectively in action learning, social development, and actionlanguage integration. Vernon, von Hofsten, and Fadiga (2010) have proposed similar exercises for a research plan covering all areas in a robot's cognitive development.

Another approach to the issue of cumulative learning is the use of developmental cognitive architectures. Such architectures encompass the integration of multiple skills and behaviors, and as such allow the modeling of cumulative skill development. In section 8.5 we discussed extensively the different types of emergentist cognitive architectures and their consideration of multiple cognitive mechanisms and behavior.

Recall also that one of the primary long-term goals of research on intrinsic motivation is to demonstrate hierarchical, cumulative learning. While work on this goal is still at an early stage, the conceptual framework for skill transfer across contexts and domains is relatively well established. In particular, the competence-based approach to IM that we discussed in chapter 3 proposes that many important skills are initially acquired "simply for fun or play," or in the service of "exploring the environment," but that these same skills are later recruited and reused as components within more complex, survival-related behaviors (Baldassarre 2011; Oudeyer and Kaplan 2007). Preliminary support for this approach is provided by studies such as the Fiore *et al.* (2008) model, which demonstrates an important element of the competence-based approach, that is, how contingency perception can provide an essential learning signal for the organism when there is no external reinforcement to drive behavior.

A further approach to open-ended, cumulative development and learning comes from long-term human-robot interaction experiments. Accumulating "life-long" experience means raising an infant robot into early childhood, if not longer, in an artificial "robot kindergarten." A recent contribution to this is the study by Araki, Nakamura, and Nagai (2013) on the interactive learning framework for long-term acquisition of concepts and words by robots. In this experiment a learning robot interacts for a full week with an experimenter, who teaches the robot the names of 200 objects during numerous online learning sessions. The analyses of the experiment revealed that the teacher produced 1,055 utterances, with the robot acquiring 924 words in total. Of these only a small set of 58 words are meaningful: 4 functional words, 10 adjectives, 40 nouns, and 4 verbs.

The approach of a ”virtual school student” in a robot kindergarten/school scenario has been proposed by Adams *et al.* (2012) within the field of Artificial General Intelligence. This method foresees the implementation of a virtual student robot growing in both “preschool learning” and “school learning” environments. The preschool learning scenario involves continuous, long-term HRI experiments for the practice and development of sensorimotor skills and basic cognitive capabilities. The School Learning scenario continues the virtual preschool scenario, but with a focus on the long-term practice of higher cognitive (symbolic) abilities. The design of methodologies for long-term robot learning and interaction experiments will be a key step in addressing the challenge of integrating ever more complex skills and the resulting bootstrapping of the cognitive system.

9.3.2 Evolutionary and Developmental Changes in Body and Brain Morphology

The interaction between evolutionary and ontogenetic mechanisms is another area where limited efforts have been dedicated to date, and that remains a key challenge in this field. The combination of both evolutionary and developmental algorithms permits the investigation of coevolutionary adaptation of brain-body systems, and the modeling of morphological changes in ontogenesis. As we saw in section 1.3.2, this includes maturational changes in the anatomy and physiology of both the infant robot’s body and neural control system.

Evolutionary computation and modeling approaches such as the fields of evolutionary robotics (Nolfi and Floreano 2000) and of evo-devo models (Stanley and Miikkulainen 2003) can already directly address the interaction between brain and body and between phylogenetic and ontogenetic changes. Future research combining both evolutionary and developmental robotics models can further our understanding of the adaptive value of maturational changes. Simulation approaches like the fetus models by Kuniyoshi (see section 2.5.3) can already provide a methodology to investigate body-brain coadaptation. Another area of potential advances in this field can come from the recent development of modular, reconfigurable robots. Specifically, modular, self-reconfigurable robots are able to change their own shape by rearranging the connectivity of their body parts to respond to environmental changes and requirements (Yim *et al.* 2007). Such robots typically have a neural control system to deal with the nonlinearity and complexity of behavioral control, and strategies for dynamically varying body configurations. This type of robot could be used to model maturational changes in the baby robot's morphology, modeling anatomical maturational changes. Other advantages of reconfigurable robot research are the modeling of self-repair (Christensen 2006).

Another area of research that can contribute to the understanding of the complex and dynamic nature of body/brain adaptation and morphological changes is that of soft robots. As discussed in the conclusions of chapter 2, on baby robot platforms, recent advances in the field of material sciences (e.g., pneumatic artificial muscle actuators, rigid materials with soft dynamics as with the electromagnetic, piezoactive, or thermal actuators) have facilitated the production of new soft materials that can be used as robot sensors and effectors, and that are contributing to the production of soft robots prototypes (Pfeifer, Lungarella, and Iida 2012; Albu-Schaffer *et al.* 2008). Moreover, anthropomimetic robot platforms based on compliant musculoskeletal material and effectors, such as the ECCE robot platform (Holland and Knight 2006), provide a research tool to look at self-organization and emergent principles in robot control, and morphological computation strategies, which can be used to model the early stages of sensorimotor development in epigenetic robots.

9.3.3 cHRI, Robot Appearance, and Ethics

The scientific and technological progress in designing developmental robots has important implications for the design of intelligent interactive robots in a variety of domains. In particular, as we saw in the previous section on methodological and technological achievements, developmental robot studies have led to the design and testing of assistive robotics applications for children's use, and the general area of cHRI (Belpaeme *et al.* 2013). Increasing use of assistive and companion robots has important implications for robot platforms types and their level of autonomy and assistive capabilities. This raises critical issues on ethics principles in the use of robots, especially with children.

In the introductory chapter we discussed the uncanny valley phenomenon. This applies to the cases when users interact with android robots with appearances increasingly similar to the human body and face. If there is a mismatch between a humanlike robot whose appearance is indistinguishable from that of humans, but whose limited behavior capabilities do not correspond to the expected full capability of a person, the user can have a sense of revulsion and eeriness. The correct handling of the uncanny valley phenomenon is particularly important in cHRI. In addition to the general discussion on the uncanny valley (MacDorman and Ishiguro 2006), various researchers have looked at the role of the robot's appearance in HRI. Specifically, experimental investigations have considered the comparison between interactions with physical vs. simulated robots (Bainbridge *et al.* 2008) and with remote/present robots (Kiesler *et al.* 2008), the issue of proximity between the robot and the user (Walters *et al.* 2009), and the role of appearance (Walters *et al.* 2008). Such studies have however focused on adult participants, with little focus on the reaction of child users. Future work in cHRI should therefore look at children's expectations and reactions to the robot's appearance and physical and behavioral attributes. A direct open question is whether the humanoid design should focus on robot-like platforms, like the iCub and the NAO, or instead move toward a more humanlike appearance, as in the doll-like KASPAR robot.

In more general terms, research and practical applications of human-robot interaction, especially with child users or disabled and ill users, raise wider issues related to ethics and robotics. This has recently led to a more careful consideration of the legal, medical, and social-ethical rules and principles in robot use (van Wynsberghe 2012; Gunkel, Bryson, and Torrance 2012; Lin, Abney, and Bekey 2011; Wallach and Allenn 2008; Veruggio and Operto 2008). For example, van Wynsberghe (2012) has looked specifically at ethical implications in assistive care robots. She proposes a framework where the assistive robot designers must be explicit about values, uses, and contexts throughout the whole design process. This should be achieved through a direct dialogue with all stakeholders, throughout the whole process from the conceptual design of the robot platform and its application, right to the point of implementation and testing. Specifically, in the context of assistive robot applications, the recommendation is to empower all users (doctors, caretakers, patients, as well as roboticists) to maintain full responsibility for the human-care providers, rather than the technology. Given the specific requirement of cHRI, and the additional constraints of the use of robots with disabled and child patients, fundamental questions regarding the ethical principles of developmental assistive robots remain open for future research.

Robot ethics implications go beyond the specific needs of child assistive robotics. For example, the ongoing progress in the design of increasingly complex motivational, behavioral, cognitive, and social skills in (baby) robots paves the way to research ethics considerations related to the issue of autonomy. In particular, the modeling of intrinsic motivation in robots, as seen in chapter 3, is a first step toward the design of fully autonomous robots with their own motivational and curiosity system. This, together with the implementation of developmental-inspired mechanisms allowing the autonomous learning of sensorimotor, cognitive, and reasoning capabilities, can result in the design of robots that no longer require continuous control by the human user and can apply their own decision making. Furthermore, research on increasingly complex and autonomous robots could lead to the potential design of self-awareness and consciousness capabilities in robots and machines (Aleksander 2005; Chella and Manzotti 2007). While progress on robot autonomy has reached advanced technological stages, the design of conscious machines and robots is a longer-term research issue. However, both have important ethical implications. Therefore, scientific and technological advances in autonomous developmental robotics necessitate the investigation, understanding, and definition of ethics principles constraining robot research and development.

The three open research issues discussed in this chapter constitute the key general scientific, technological, and ethical challenges that span the integration of a wide set of behavioral and cognitive skills. More specific open challenges and directions for future research on individual cognitive mechanisms have been discussed in the various central chapters (chapters 3–8) of this book. Through the review of the seminal models and experiments respectively covering motivational, perceptual, motor, social, linguistic, and reasoning capabilities, we have analyzed the achievements and limitations of current research, and identified the need for more work in these key areas of developmental robotics. The highly interdisciplinary nature of developmental robotics, ranging from robotics and computer science to cognitive and neural sciences, and reaching philosophical and ethics disciplines, can together contribute to the understanding of developmental principles and mechanisms in children and their operationalization for the autonomous design of behavioral and cognitive capabilities in artificial agents and robots.

To conclude, we can confidently state that developmental robotics has reached the end of its infancy, and now begins the years of early childhood! Therefore we expect in the next ten to fifteen years we will see child robots that can go completely from crawling to walking, that can speak in two-and three-word sentences, that can engage in pretend play and deceive others through their own theory of mind, that are beginning to develop a sense of gender and a sense of morality.

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