Animats and what they can tell us

Jeffrey Dean

Animats – autonomous robots or simulations of animals – and the animat approach represent the most recent attempt to comprehend the capacity of animals for autonomous generation of adaptive, intelligent behavior in complex, changing environments. Motivated by perceived limitations in classical artificial intelligence (AI), the animat approach promulgates an alternative, bottom-up route to understanding intelligent behavior. Important tenets include: (1) that adaptive behavior is best understood by focusing on the interaction between a behaving individual and its environment, hence the interest in 'embodied' physical robots 'situated' in natural environments; (2) that specific abilities, 'behaviors', are more natural units of analysis and design than general, information-processing functions and world models; and (3) that high-level behaviors will emerge as systems composed of simple behavioral competences become more complex. Thus, animat research often begins with low-level sensorimotor abilities and then moves up towards higher, cognitive functions. Both in analysis and in design, the animat approach borrows heavily from ethology, psychology, neurobiology and evolutionary biology, as well as from connectionism. For AI and robotics researchers, understanding the mechanisms behind adaptive behavior is secondary to creating them, but natural scientists can hope for tools and concepts to aid understanding of biological systems.

Animals have always fascinated natural scientists and inspired attempts at imitation[1]. Sometimes this fascination is tied to special abilities, such as flight or echolocation, but more generally it is evoked by animals' autonomous capacities for adaptive behavior – behavior promoting survival and reproduction – in complex environments and the development of this competence from a small set of genetic instructions.

The animat approach represents the most recent attempt to simulate the adaptive behavior characteristic of animals and the acquisition of this competence. 'Animat' refers to an autonomous robot or a simulation of an animal (see Box 1). An animat should capture more than a special competence; it should retain important aspects of the autonomy and the holism of an animal in its environment. Thus, the definitive animat would be a robot that could survive in a complex environment, as animals do. (Of course, if an animat's application is to benefit its human creator, it should not be entirely autonomous in its motivations[2].)

Although its major roots are in computer science, artificial intelligence and robotics, the animat community draws heavily from biological studies of animal behavior. From work carried out before the first formal conference in 1990 (reviewed in Ref. 3), it was realized that the study of autonomous robots was analogous to the study of animal behavior and that, therefore, ethological methods and neuroethological results were relevant. That conference can be considered to be an echo of the 1987 Santa Fe conference[2,4] marking the formal birth of the field of artificial life (a-life), in that both conferences represented a coalescence of researchers from diverse biological and technical fields considering phenomena common to animals and artificial agents (an agent refers generally to a self-contained entity autonomously processing inputs and carrying out a delimited task, e.g. Ref. 5).

Animat research can be considered as a subset of a-life[2], and agents in artificial life simulations can generally be regarded as animats. However, the a-life community includes many evolutionary biologists, and a-life studies as a whole are more likely to focus on evolutionary (i.e. the reproductive) aspects than on the proximate (i.e. survival) mechanisms of adaptive behavior. Many mainstream a-life researchers would agree with Maynard-Smith's statement that 'life should be defined by the possession of those properties which are needed to ensure evolution by natural selection'[6]. Animat researchers would see life in the adaptive behavior of the individual, while realizing that this can be both the product and the substrate of natural selection. Hence, evolutionary processes, such as genetic algorithms and developmental processes leading to adaptive behavior, play important roles in animat research.

J. Dean is at the Department of Biology, Vanderbilt University, PO Box 1812 Station B, Nashville, TN 37235, USA.

tel: +1 615 343 1781
fax: +1 615 343 0336
e-mail: deanrj@ctrvax.vanderbilt.edu

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Box 1. Animats

The term 'animat', short for artificial animal, was put forward by Wilson[a,b]. It became more widely known following a 1990 conference in Paris, entitled 'Simulation of adaptive behavior: from animals to animats (SAB90)', and the publication of the proceedings[c]. Organizers and conference participants represented a broad spectrum of disciplines from ecology, ethology and psychology to artificial intelligence, robotics and engineering. AI researchers disenchanted with classical approaches were an important contingent. The few participating neurobiologists studying real nervous systems typically represented small interdisciplinary groups studying invertebrates rather than humans or higher vertebrates.

The first conference successfully showed that these different disciplines were struggling with common problems and developing similar approaches. Three more conferences and books followed[d–f] and a society, the International Society for Adaptive Behavior, was formed. The conference volumes, together with *Adaptive Behavior*, a journal founded in 1992, are major sources for studies on animats.

Despite the obvious appeal of 'animat' – conjuring up visions of an artificial version of your favorite animal – a quick check of several databases in neuroscience and computer science revealed relatively few occurrences of this term in titles, key words or abstracts. In *Biological Abstracts*, for example, 'animat' turned up in fewer than ten entries from 1991 to 1997, many fewer than the 60 to 100 for 'artificial life', a term launched about the same time, and the over 300 for 'artificial intelligence'. Both 'animat' and 'artificial life' are sparsely represented in the PSYCHinfo databases apart from entries from *Adaptive Behavior*. Neither has 'animat' become widespread on the Internet, although it provides a useful distinction from 'animate' as in 'animation' or 'animate life forms'.

'Animat' research is more widespread than the occurrence of the term indicates. Some researchers apparently prefer the older 'automaton'[g] or 'animate agent' and many artificial life studies could equally well be considered studies of animats.

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The interdisciplinary nature of animat research leads to a disjunction in research goals that should be mentioned at the outset. Whereas biologists, as natural scientists, ultimately want to understand the behavior of a particular animal or, better still, general principles applicable to many animals, computer scientists and roboticists, as synthetic researchers, may be primarily interested in realizing particular competences and finding suitable design principles. For the latter, animals can provide inspiration for particular design features, but whether an animat resembles any biological model is of no concern[7,8]. Perhaps because synthetic researchers utilize biological principles, such as distributed processing, learning and self-organization, rather than logical design principles, they also accept that many of the new methods easily produce systems in which function is no more transparent than in biological systems[9]. In essence, the acquired understanding applies to how an appropriate system can be obtained, not to its function. Nevertheless, for natural scientists, the fact that animats are designed ought to provide an immense head start towards understanding their operation compared with the task faced by neuroethologists studying animals[3,10], and this is the ultimate basis for the hope that animat research will aid biologists.

Animat research as a reaction to classical AI

From the beginning, animat researchers have sought to define animat research as a coherent movement with an alternative approach to the study of adaptive – some would say intelligent[11,12] – behavior[3,9,13,14]. For a large contingent of AI researchers, a major impetus is a perceived inadequacy of classical AI techniques for controlling physical agents in natural environments[7,9,15]. Cast in extremes, classical knowledge-based systems are said to have the following characteristics: (1) a restricted domain with a single task; (2) a top-down design beginning with generalized problem-solvers based on logic and symbol manipulation; (3) a central world model, with a (declarative) knowledge-base representing detailed information about domain objects and relationships; (4) sequential processing through modules performing generalized functions, such as perception, planning and execution (Fig. 1A); (5) deliberative planning with respect to explicit, user-defined goals; (6) indirect access to the domain via the user acting as a symbol interpreter; and (7) a general neglect of learning and adaptation[7,9,15].

According to the critics, problems arise when classical AI systems are forced to interface directly with a natural environment. AI systems often show brittleness – catastrophic failure when the domain changes from that specified in the world model[9,15]. Processing delays appear to be wildly unnatural[2,15,16] and the amount of processing excessive[8,16]. Human perceptual response times of several hundred milliseconds allow only about 100 processing cycles in an individual neuron (the 100-step rule[8]). Of course, the total number of processor cycles is much larger due to the massively parallel network in the brain, but the computational power of computers approaches that of the human brain according to some estimates (e.g. comparing the number of transistors × clock cycles for a PC with the number of synapses × typical action potential rates; J.J. Hopfield, Porter Lectures, Nashville, 1997). If, as appears increasingly likely, differences in performance are not due to differences in raw computational power, the problem must lie in architectures,

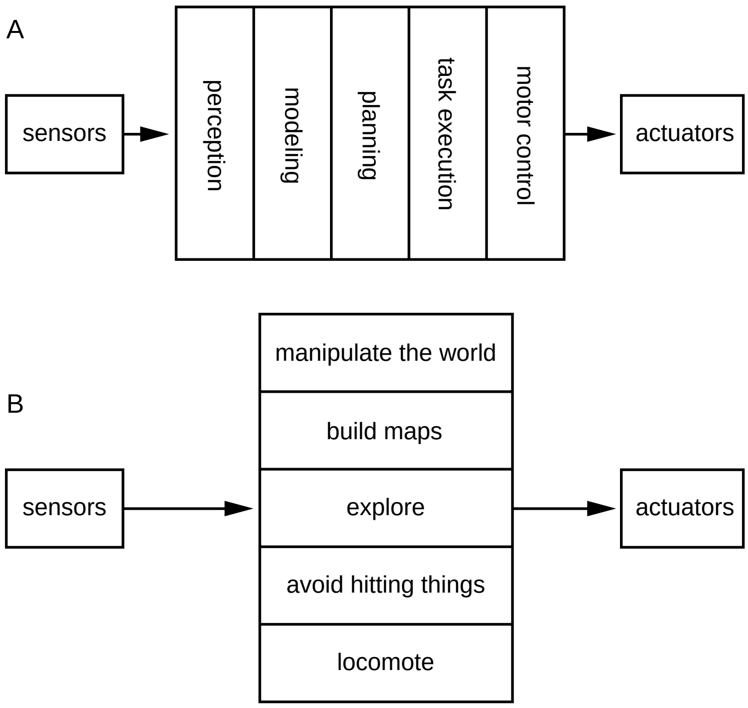

Fig. 1 Comparison of classical, knowledge-based architectures and behavior-based architectures. (A) Knowledge-based architectures use sequential processing through a single planner. **(B)** Behavior-based architectures have multiple parallel pathways – 'behavior' modules – connecting sensory and motor elements. (Modified from Ref. 15).

algorithms and implementations. For example, slow response speeds might be attributed to a cognitive bottleneck at the central planner[9].

In the critics' view, problems are particularly acute in apparently simple, low-level domains, such as processing natural sensory data to extract meaningful information – including the symbols that a knowledge-based system needs (the 'symbol grounding' problem[17]) – or controlling movement in an unpredictable environment (e.g. Ref. 18).

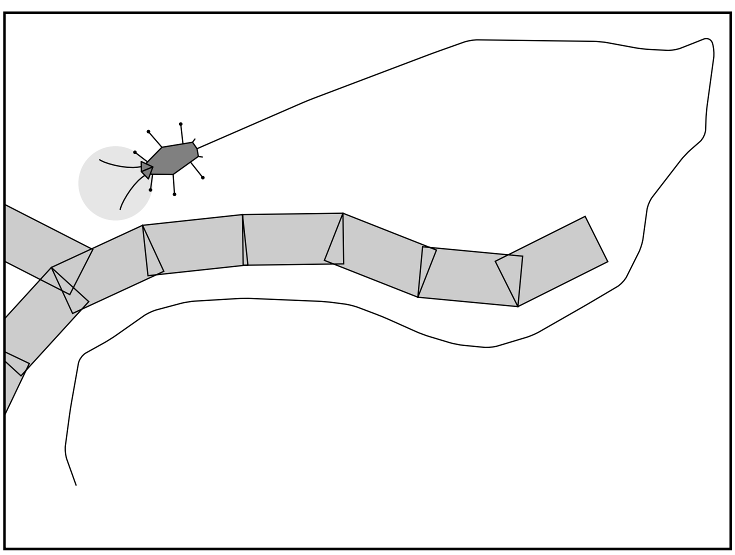

Fig. 2 A simulation of a roach-like animat in a simple environment with food (circle) and obstacles. Behavioral modules, implemented as neural networks, include obstacle avoidance, wall-following and attraction to food. The path is not planned but emerges from the behavioral repertoire and state of the animat. (Modified from Ref. 11).

In this respect, animals and humans clearly surpass even the best artificial systems. Humans effortlessly recognize pictures of people encountered briefly days earlier, a task done poorly and with enormous computation by AI systems. Similarly, dancers can imitate a colleague moving through a complex sequence of dynamically stable configurations, whereas most robots are poor at such imitations and are typically restricted to statically stable configurations that permit stopping at any instant to recompute planning and execution.

Many of these problems have been recognized within the AI community, leading to several alternative approaches sharing some features with the animat approach. These include 'animate vision'[16] or 'active vision'[19], 'situated action' and interactional interpretations of human–computer relations[20,21], and schema theory (e.g. Ref. 22). Defenders of 'good old-fashioned AI' (GOFAI)[23], still the dominant approach, remain unimpressed by animat systems[24], define symbols and symbol processing so as to include animats[25], deny that learning has been neglected[25], tout the advantages in explanatory power[26] or simply point to a number of successful systems[25]. Such systems typically involve heavily symbol-oriented tasks where planning time is not critical. Chess is a prominent example[27], but to many this success only highlights important differences from humans in terms of implementation, algorithms and computations.

The animat manifesto

Alternatives for real-time control in natural environments were inspired by researchers' reflections on animals. First, animals are confronted with a complex environment and multiple tasks to satisfy. Second, animals behave continuously and react to stimuli without significant delays for planning; often a less precise, speedy response is more adaptive than a precise, slow one. Sensory and motor systems in animals are connected by multiple parallel connections that vary in speed and complexity of response. Third, animals typically possess some basic behaviors from birth, and then develop more complex abilities, including many high-level cognitive abilities, but also motor skills (e.g. Ref. 28), in the course of interactions with the environment.

Thus, natural adaptive behavior is expressed in a particular context and depends essentially on that context. In other words, adaptive behavior in animals is 'situated', a term introduced in connection with human actions to emphasize their dependence on context, both material and social[21], and it is 'embodied', occurring in a physical agent[15]. These ideas have several corollaries. They require an investigator to adopt a holistic view of the agent and its environment, so general theories of agents and interactions will need to include a theory of environments[13] – characterizing the environment along lines of complexity, variability, frequency, and so on (e.g. Ref. 29). The theory of dynamic systems provides a start[30,31]. A behaving agent in an environment constitutes a dynamic system; one with a state (its condition at a given time) and regularities (dynamics) determining state changes, that one can try to capture mathematically. Placed in an appropriate context, even a purely reactive animat can produce complex behavior by acting in and on the environment and, thereby, changing its own input. Adding motivation, drives, learning or developmental plasticity, so that the animat has multiple states and therefore potentially diverse responses to identical inputs, further increases the complexity (see Fig. 2).

The notion of situated action further suggests that the (specific) action rather than the (abstract) plan is primary: an action is not an instantiation of a general plan, but rather a plan constitutes an abstract representation of the action performed[21]. If action rather than planning is fundamental, then architectures ought to be based on modules for specific behavioral competences rather than general modules for knowledge and planning.

Expanding the focus to include the agent and the environment imposes more demands on simulations, and increases the difficulty in creating an adequate world model for a knowledge-based system. In response, investigators have argued that the world is its own best model[2,7]. In fact, the world, and the interaction between agent and world, do make many (particularly local) regularities and constraints directly available; they do not have to be calculated and represented in an internal model. (Of course, some tasks, e.g. navigation, require representation of global relationships in some form.) Ballard's[16] formulation of 'animate vision' makes similar points. Psychologists will recognize notions of direct perception[32] and perception–action linkage[33]. A hexapod walker provides a motor example of the use of directly available information: the mechanical linkage of all legs in stance constrains the complete multi-joint system to change in the one physically possible way when a single joint moves[34].

For these reasons, many researchers feel that replacing computer simulations with physical models, or 'real robots', is a more valid way to study situated adaptive behavior[14,35,36]. Robots need not be high-tech; simple Lego™ robots, many modeled on Braitenberg's Gedanken experiments with simple sensorimotor vehicles[37], are an active field of research[38,39] (see Fig. 3). Advances in sensors and actuators should allow more biologically realistic animats, but, counter intuitively, improved technology can complicate control[35].

Animats, as products of all these observations, typically exhibit the following characteristics, which, as for those of classical systems, are cast in extremes[9,15]: (1) complex, natural environments with multiple tasks; (2) a bottom-up design built from modules controlling behaviors, hence a 'behavior-based' architecture (Fig. 1B); (3) implicit, procedural knowledge and minimal, module-dependent representations[7] (e.g. relational maps for navigation[40]) replacing the explicit, central world model of classical AI; (4) parallel, distributed processing with multiple behavioral modules; (5) real-time processing and autonomous selection of behaviors; (6) emergent behavior from competing behavioral modules[9,41] (e.g. Fig. 4), replacing explicit goals and deliberative planning; that is, the animat instead selects among alternative behaviors at each time; and (7) an emphasis on learning. Many of these features lend themselves to connectionist implementations, so artificial neural networks play a central role in many animats.

Not all of these ideas originated with animat research. Many were, in fact, considered by the founders of artificial

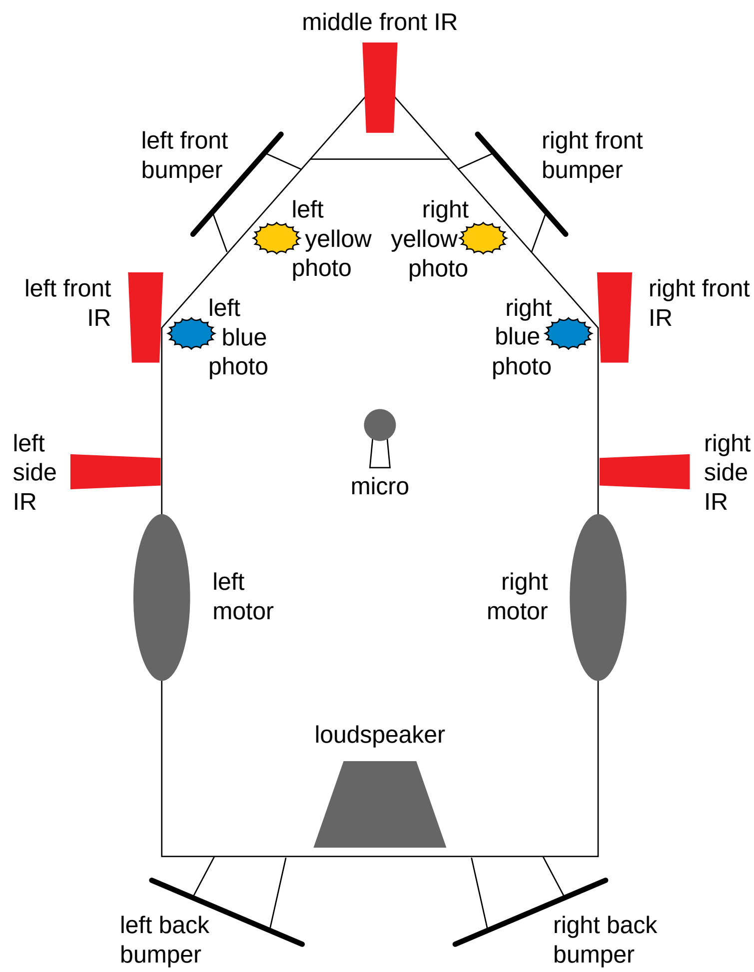

Fig. 3 Basic plan of an animat realized in Lego™ and used in experiments on navigation and cooperation. Separate motors power the left and right drive wheels. Sensors include photosensors (photo) mediating phototaxis, infrared (IR) rangefinders, mechanical bumpers, a microphone (micro) and a measure of battery charge. (Modified from Ref. 50).

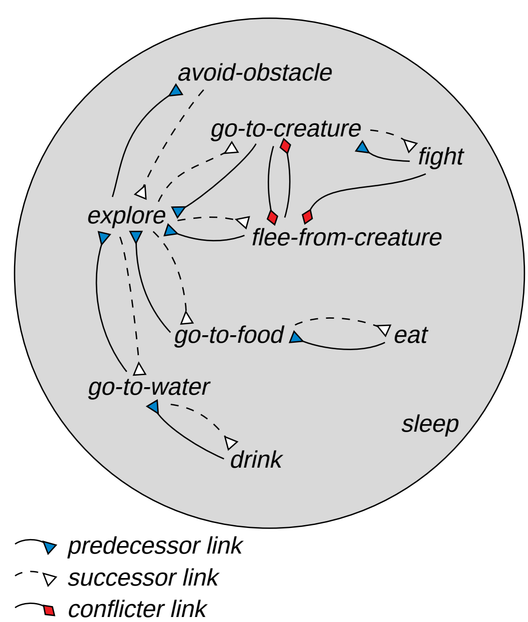

Fig. 4 A network for determining which behavioral module controls motor output. Each behavior inhibits conflicting behaviors and spreads activation to behaviors that functionally precede or succeed it. (Modified from Ref. 71).

intelligence research[2,13,42,43] and then neglected during the ascendancy of knowledge-based information processing systems.

The overall research goal, as in classical AI, is the production of adaptive (intelligent) behavior like that of animals and humans in real environments. This means that animat researchers also consider intelligence, adaptation and perception at high levels[13,44]. Categories addressed in conference proceedings[45–48] include perception and motor control, self-organizing cognitive maps and internal world models, motivation and emotion, action selection and behavioral sequences, ontogeny and learning, collective behaviors, cooperation and communication, evolution of behavior, as well as architectures and organizational principles.

The goal of animat research is to reproduce the high-level competence via a bottom-up approach beginning with simple competences. Rather than assume that agents exhibiting high-level, cognitive behavior are explicitly structured in accordance with introspective notions of rational function, the guiding belief is that high-level competence will emerge (either through design or under the aegis of learning or evolutionary mechanisms) from interactions among simple agents as system complexity increases. More modestly formulated, the goal is to explore the levels of behavioral complexity that systems based on simple behavioral competences can generate, adding complexity and explicit, higher-level functions only as necessary[7,49]. For example, one extreme approach, formulated in biological terms, begins with systems where the integration of different behaviors is limited to summation at the motor neurons[50].

A little over a decade of research has produced animats performing simple tasks, including navigation and cooperation, in natural environments, and showing quick response speed, graceful degradation, and self-organization of adaptive responses[9,14,15]. Initial design principles have been proposed[9,49–51] and an ambitious project to construct a humanoid animat is under way (called 'Cog', Ref. 44). Animats and a-life have attracted the interest of philosophers[26] and greatly expanded possibilities for experimental studies of intelligence and adaptive behavior[2,26,36]. Overall, however, the successes of the classical and animat approaches lie in high-level symbolic tasks and in low-level competences, respectively, so the two approaches are complementary rather than in direct competition[9,15,24,26].

Animats and other models of behavior

For a biologist, an animat is a version of a familiar tool, a model. The value of animat models seems to be clearest for collective behavior. For example, social insects, such as ants, perform many functions at the level of the colony. If similar behaviors emerge in models based on animats programmed with only simple behavioral competence, the necessity for explicit goals, or representations of the task to be performed, is disproved and the sufficiency of low-level behaviors supported[52].

Modeling the control of individual behavior, which is the province of the nervous system, is more problematical, basically because the number of parameters (neuron numbers, connections and characteristics) is much greater than the conceivable behaviors in functional descriptions.

If sufficient neurophysiological data are available, modeling at the level of the neural circuit ('realistic models'[53]) can be attempted. History shows several cautionary instances where initial models of the neural pattern generators for simple motor outputs provided misplaced faith in the completeness of the available data[54]. The increasingly evident complexity of real neurons[55] (which goes far beyond the original McCulloch–Pitts concept[56] or the units in most connectionist models using artificial neural networks), the numerous neuromodulators that adjust cellular and synaptic properties[57], the need to model neurons as multiple compartments, and the difficulty in acquiring all the necessary data[55], essentially restrict neural models to small systems. Nevertheless, such models have identified elements that were verified in subsequent physiological studies[58,59]; thus their value is clear. Coupling realistic neuronal models to natural sensorimotor systems, a direction suggested by animat research and labeled 'computational neuroethology'[11,60], is just beginning[61].

Most commonly, physiological data are insufficient, so models are constructed in terms of hypothetical functional modules, formulated so as to capture essential features ('simplifying models'[53]). Connectionist methods permit implementation of functional modules with neural-like architectures and facilitate simulations of biological data. A successful model constitutes a proof in principle, showing that a particular computational or algorithmic method can produce the observed behavior. This can be useful in applications, but rarely imposes significant constraints on possible neural realizations. By analogy, successful modeling as an animat, particularly as a real robot, also constitutes a proof in principle[34], which in this case can be considered to be stronger because such a closed model captures the physical context and the loop through the environment (i.e. any movement commanded by the control system on the basis of sensory inputs is subjected to the physical constraints of the body and of the environment, and the resulting actual movement can, in turn, change the environment, the robot and the relation between the two, changing the sensory inputs to the control system and completing the loop).

Such models can guide interpretations of biological data. For example, connectionist models showed the plausibility of an approximate algorithm for a sensorimotor network controlling interleg coordination in insects[62], a hypothesis later supported by physiological results[63] and implemented in an animat[34]. In another case[64], leech data indicated that the connectivity of interneurons participating in a tactile reflex did not strictly follow functional lines (e.g. some interneurons activated by a dorsal touch make connections to motoneurons for agonist and antagonist muscles that are apparently inconsistent with the observed movement). However, similar patterns occurred in networks trained by back-propagation to reproduce the behavior, lending support to the distributed-parallel-processing interpretation[64]. Significantly, back-propagation produced many network topologies that could duplicate the observed behavior. Thus, with respect to the withdrawal behavior, the biological circuit contains redundancy; it is not a unique control network, a minimal model. It might represent a minimal model with respect to the full spectrum of leech behaviors. More likely, though, the results indicate that there is little selective pressure for evolution of a minimal control system. This means that even if computational neuroethology does eventually create a general theory relating minimal control models to given tasks and environments, there is little likelihood that a particular animal will have evolved just this system.

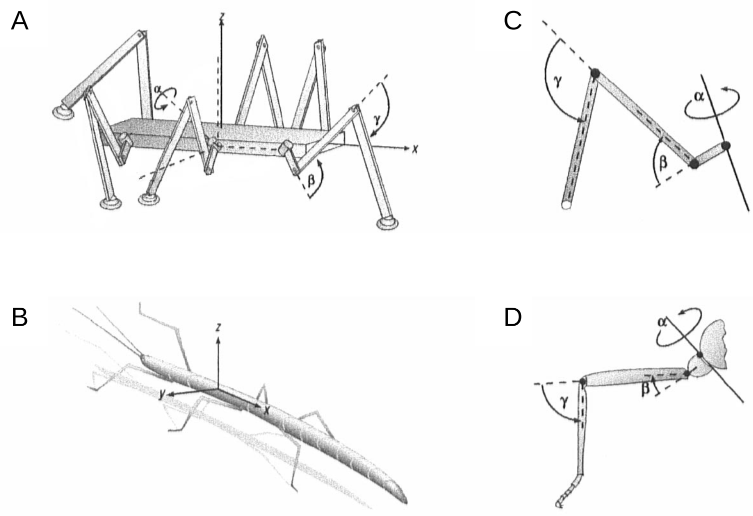

Fig. 5 A walking machine modeled on an insect. A hexapod walking machine **(A)** and the Indian stick insect **(B)** on which the geometry and control system of the machine is modeled. Scaled up in size by approximately 30 times, the machine retains the tilted joint axes of the insect, and an individual machine leg **(C)** has the proportions and joint axes of the insect's leg **(D)**. The control system implements the decentralized architecture and coordination mechanisms found in the insect. (Modified from Ref. 34).

Future directions and implications for neuroethologists

The results, to date, demonstrate the benefit of interdisciplinary animat research[14,36]. Past and future benefits for the synthetic, computational workers are easy to identify. Applying ethological methodology to the behavior of animats (one sense of 'computational ethology') should improve the analysis of animat behavior. Biological architectures and principles have been and will continue to be incorporated into animats[34,65] (Fig. 5). Most importantly, the adaptive behavior of animals, like the cognitive performance of humans, represents an existence proof for mechanisms allowing such functions to emerge in dynamic systems composed of simple elements. These animate models will continue to be, in the words of Brooks, 'a source of inspiration for researchers attempting to duplicate their performance in animats' (in Ref. 2, p. 281). However, it remains to be seen whether the initial successes of the animat approach with low-level competences can be scaled up to higher levels of performance and complexity[3,44] (see Outstanding questions). Proposals to substitute evolution for design[66] have been tempered by the realization that genetic algorithms will fail if a suitable fitness criterion cannot be found, which might be no easier than directly designing a given competence[67].

Biology does offer two cautionary notes. First, evolution is fickle. For example, one species of weak electric fish contains all the neural components (modules) used by other species to perform a simple adjustment of the frequency of their electric organ discharge (the 'jamming avoidance response'), and yet is not capable of this behavior because one connection has not evolved[68]. Thus, one should assume that desired complex phenomena might not emerge in animats in a reasonable time, at least until a general theory outlines conditions guaranteeing otherwise. Parenthetically, replacing computer simulations with real robots might actually slow the search for emergent behavior, but hybrid methods can provide some compensation[66].

Second, it is widely believed that biological evolution ensures optimization, but this need not hold in general, and certainly not for individual competences. Even the experimental support for optimal foraging theory, possibly the best studied case in ecology, is not conclusive[69].

For natural scientists, benefits of animat research are less tangible but significant. First, attempts to simulate an observed behavior are generally enlightening and often lead to new experiments. Second, and more important, is the shift of emphasis in animat research from the isolated organism to organism plus environment[61], which has added a dimension to the research of several biological groups previously focused largely on the neural function alone. Third, animat research has augmented biological findings demonstrating that approximations can often replace exact algorithms, and that studying the agent in the context of its interaction simplifies many computational problems.

Finally, computational neuroethology in the sense of computational neuroscience (a general consideration of neural computation and control of behavior) might some day elucidate general constraints and principles that can aid the interpretation of biological results in particular systems, and the understanding of links between behavior and neural function (see Outstanding questions). Potentially, animats and the theory of dynamic systems could substitute for traditional information-processing accounts of neural and cognitive function, replacing symbols and symbol processing with patterns of neural activity and their dynamics. Yet, as von Eckardt[70] argues with respect to neuroscience and cognitive explanations, it seems more likely that the former should merely constrain rather than supplant the latter and that information-processing accounts will remain an appropriate language for emergent, system-level phenomena. In other words, as systems become more complex, whether modeling at the neural level will translate into

Outstanding questions

- Animat research will have to move beyond simple demonstration and proof in principle, to contribute to a general theory of situated agents and environments. Will computational neuroethology uncover principles and constraints formulated at levels that connect to biological nervous systems, so that natural scientists can benefit from animat research?
- Can animats demonstrate the validity of the assumption that high-level competence will emerge naturally and in reasonable time when complexity is scaled up? For applied uses, a demonstration that the direction of emergent competence can be determined by design is required, that is, a general theory.
- Finally, for natural scientists, there is the question of the ultimate explanatory value of research with animats for understanding the function of biological nervous systems and connecting to information-processing accounts of higher, cognitive functions.

understanding or merely substitute one complex dynamic system for another, is unclear. Perhaps, successful animats will initially be no more understandable than biological nervous systems, although they certainly will be technically easier to dissect. For the moment, the wisest stance appears to be to welcome the additional opportunity for controlled, comparative study of adaptive behavior provided by animats.

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Capacities underlying word learning

Paul Bloom and Lori Markson

Children are strikingly good at learning the meanings of words. Current controversy focuses on the relative importance of different capacities in this learning process including principles of association, low-level attentional mechanisms, special word learning constraints, syntactic cues and theory of mind. We argue that children succeed at word learning because they possess certain conceptual biases about the external world, the ability to infer the referential intentions of others and an appreciation of syntactic cues to word meaning. Support for this view comes from studies exploring the phenomena of fast mapping, the whole object bias, the acquisition of names for entities belonging to different ontological kinds and the effect of lexical contrast. Word learning is not the result of a general associative learning process, nor does it involve specialized constraints. The ability to learn the meanings of words depends on a number of capacities, some of which are specific to language and unique to humans, others of which are potentially shared with other species.

Two- and three-year-old children have poor motor control and bad manners; they are unreflective artists and inept dance partners. However, they are strikingly good at learning the meanings of words. Children learn their first words by 12 months of age, are relatively proficient at word learning by 16–18 months, and eventually come to learn new words at a rate of over ten new words per day (see Box 1). Their early vocabularies include personal pronouns (me, you), proper names (Fido, Mommy), prepositions (in, on), adjectives (good, big), verbs (bite, want) and many classes of nouns including those referring to whole objects (dog, cup), substances (milk, water), parts (eye, finger), habitual activities (bath, nap), periods of time (minute, day) and abstract notions (story, game)[1,2]. While children sometimes get the precise meaning of a word wrong – for instance, sometimes calling a cat 'a dog' – serious mistakes are rare: children never call a chair 'a dog' or confuse proper names with common nouns, object names with substance names or adjectives with verbs[3].

One perspective on word learning is that parents do much of the work, carefully tailoring their speech to make the connection between words and what they describe particularly clear to their children. Such tutelage does occasionally occur in many cultures, including the middle-class Western culture that is the focus of most language acquisition research. But it is not universal; there are societies in which parents make no effort to teach words to children, leaving them to learn words on the basis of overheard speech[4]. Nevertheless, such children have no problem in developing a rich vocabulary. Furthermore, children raised in Western cultures learn at least some words, such as the personal pronouns[5], by overhearing them in the conversations of others, and even the most pampered child will learn many words that are used when the relevant object or event

P. Bloom and L. Markson are at the Department of Psychology, University of Arizona, Tucson, AZ 85721, USA.

tel: +1 520 621 7447
fax: +1 520 621 9306
e-mail: bloom@u.arizona.edu

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