Beyond Watching: Action Understanding by Humans and Implications for Motion Planning by Interacting Robots

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Abstract When you see an individual holding a baby in front of an elevator, you instinctively move to open the door for him. This seemingly obvious helping action is possible because you are able to immediately characterize, recognize and then *understand* his actions—that is, recognize the intention behind the observed individual's actions, estimate the outcome of his current actions, predict his future actions and infer his constraints due to the baby in his hands. Fast action recognition and action understanding abilities make humans adept at social interactions, and are fundamental requirements for future robots in order for them to interact with humans. While other chapters in this book focus on action characterization and recognition through the use of dance notations, in this chapter we will focus on the problem of understanding recognized actions. In particular, we aim to elucidate how ideas from action understanding research in primates can help robots formulate behavior plans when they interact with humans and other robots. We first briefly review the historical concepts, and psychological and neuro-scientific findings on action understanding by primates. Next, we detail the possible computational mechanisms underlying action understanding by humans. We then highlight the controversies regarding these beliefs and explain the results of our recent study that answers some of these controversies. Finally, utilizing results from our study, we propose and explain a conceptual bio-mimetic framework for action understanding by robots, in order to enable them to plan *helping* and *impeding* behaviors during interactions, similar to humans.

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1 Introduction

Humans and robots can navigate their physical world using their senses, vision being predominant for the majority. However, when it comes to 'navigation' of one's social environment, sensory observations are usually not enough because as famously written by Plato, "things are not always what they seem". Taking an example from sports, consider that you are a soccer defender who sees an opposition player approaching with the ball. This visual information of the opponent and his surroundings alone is not enough for you to decide your next action. To decide what you should do next, you need to analyze the visual information and predict if the opponent intends to go left or right and whether he intends to pass the ball or try to dribble his way around you. In either case you need to predict the outcome (of the pass or dribble) in terms of the rough ball trajectory so that you can intercept it. The opponent's behavior will depend on his physiological characteristics like his size, speed and whether he is left or right footed, and on his mental characteristics, whether he is anxious, scared or has the confidence to pass you. The situation is complicated by the fact that the opponent is making similar predictions about your behavior, which means that you need to consider his predictions about you when you make your predictions about him!

The choice of behaviors in social interactions requires action characterization and recognition, for example by utilizing dance notations, followed by *action understanding*; deciphering the emotion and intention leading to an observed action, detecting constraints associated with the action and the performing agent, predicting the outcomes of the observed actions, and predicting future actions. In this chapter we aim to introduce the robotics community to action understanding research in primates, elucidate the computational beliefs, and show how these can be useful for the development of automatic interaction behaviors in robots. We are interested particularly in scenarios like our elevator and soccer examples where the interacting agents need to plan their behaviors individually and without any explicit information exchanges. We believe that such *individualistic* interaction planning scenarios define the bench mark for future *intelligent* robot-human interaction research.

But how to enable robots to understand humans, and other robots? An obvious strategy is to examine human interactions and then try to implement the same in robots, a procedure that has yielded promising automatic robot behaviors previously [1–3] and what we will utilize here. On the other hand, the mechanisms underlying action understanding abilities in humans are still not completely clear and a subject of ongoing research. Therefore with this chapter, while we present a conceptual framework that allows formulation of interaction plans by robots, we also want to motivate the requirement for continued integrated research in robotics and behavioral neuroscience in the future.

The chapter is organized as follows. Sections 2, 3 and 4 first provide a brief historical account of action understanding research starting from the philosophical motivations to the recent neuroscientific findings that clarify the computational

mechanisms behind it. We conclude Sect. 4 by summarizing the controversy in regard to the previous findings. Section 5 discusses results from our recent study that answered some of these controversies. Finally, before going to the robotics discussions, in Sect. 6 we list the computational mechanisms in the neuroscience literature for action understanding. Section 7 summarizes previous action understanding research in robotics. Section 8 briefly defines some key concepts in *motion planning* and defines the planning problems during interaction. Section 9 then gives a description of our conceptual framework for planning robot behaviors during interactions with an example, before we conclude with Sect. 10.

2 Beyond Watching: The Philosophy Behind Action Understanding

Humans are adept at action understanding. Our social skills, from gestures for communication, sports, to driving a car safely, are critically dependent on our ability to understand observed actions performed by others and take appropriate actions ourselves [4]. Philosophers have questioned the mechanisms behind this human ability for a long time. The notion that actions are intrinsically linked to perception was first proposed by William James in his ideomotor principle. James claimed that "every mental representation of a movement awakens to some degree the actual movement which is its object" [5]. He also made similar observations between emotions and actions. He questioned the orthodox thinking that bodily expressions are the consequences of intrinsic emotions and proposed the converse, that in fact emotions were the consequences of bodily expressions. His proposal could, in principle, explain how a human can *feel* the emotions of a fellow individual, solely by observing his bodily expressions.

In order to explain aesthetic experience of an artwork by an observer, Theodor Lipps [6] borrowed the term *Einfühlung* (originally introduced by Robert Vischer and later translated in English as *empathy*) referring to the process by which the observer can imaginatively project himself into contemplated objects. Lipps later utilized *Einfühlung* to explain emotional perceptions of observed movements [6] suggesting that the feelings and intentions of a person can be perceived by projecting oneself inside him or 'walking in his shoes'. This concept was developed by Edmund Husserl who proposed that our ability to understand other agents stems from the belief that their bodily experiences are similar to our own experiences while acting on our bodies. The concept of empathy thus suggests how the perception of *self* and of others are coupled. Edith Stein extends this concept further in *On the Problem of Empathy* [7] (1912/1964, English translation), where she proposes the converse, that acts of empathy can help one to learn what type of person one is.

Similar closeness between perception of other's actions, and that of one's own were also expressed by the famous French philosopher Merleau-Ponty [8] when he

said, "The sense of the gestures is not given, but understood, that is, recaptured by an act on the spectator's part. The whole difficulty is to conceive this act clearly without confusing it with a cognitive operation. The communication or comprehension of gestures come about through the reciprocity of my intentions and the gestures of others, of my gestures and intentions discernible in the conduct of other people. It is as if the other person's intention inhabited my body and mine his", and by Herbert Mead (1912) [9] who wrote, "Any gesture by which the individual can himself be affected as others are affected, and which therefore tends to call out in him a response as it would call out in another, will serve as a mechanism for the construction of a self".

3 From Philosophy to Psychology

The recurring theme in all the philosophical works is the relationship between the *other* and the *self*. The sense of *ownership* (the perception that an observed limb is part of your body), *agency* (the perception that a limb movement is produced by you) and presence (the perception that you are at a particular location), are probably the fundamental features defining the *self* and consequently, the *other* by dissociating from the self. Though the perception of self is critically determined by multi-sensory congruencies and perceived causality between the intended actions (or motor commands) and sensory perceptions, it can be very plastic and change quickly, as demonstrated by studies on tool-use [10, 11] and the now famous rubber hand illusion [12]. In this illusion, synchronous touches, applied to a rubber hand in full view of the participant, and the real hand hidden behind a screen, produce the sensation that the touches felt originate from the rubber hand, leading to a feeling of ownership of the artificial rubber hand [13]. For more details on the sense of ownership and agency readers can refer to [14–17].

The core idea behind the philosophy of action understanding is that the other is NOT very different from the self and, extending on Stein's beliefs, the two can in fact be interchangeable in the brain. This idea of closeness between self and other was extended into the domain of action-perception in the *common coding theory* introduced by Prinz [18]. This theory hypothesized a shared representation for both perception and action; seeing an event activates the action associated with that event, and performing an action activates the associated perceptual event. This hypothesis was later verified by the discovery of the *Mirror Neurons* (see next section).

4 Action Understanding by the Brain

4.1 Discovery of the Mirror Neurons

While the philosophical and psychological concepts suggested the role of one's own action production system (or motor system) in the perception of actions observed in others, a concrete proof for the existence of such a mechanism did not come until 1992 when Giacomo Rizzolatti and his colleagues discovered, what they called *Mirror Neurons,* in the brain of a Macaca nemestrina monkey [19] (Fig. 1). These neurons, isolated in a region associated generally with motor activations (i.e. in the motor system), exhibited the unique feature that they activate during both, the execution of an action and the observation of the same action performed by others. Mirror neurons were first discovered in the ventral premotor area (F5) [19] and then in the inferior parietal lobule (PF/PFG) [20, 21]. The cortical network consisting of these areas were named as the mirror system or mirror neuron system [22].

While the mirror system was initially discovered in monkeys, human brain imaging studies using Magnetoencephalography (MEG) [23–25], functional Magnetic Resonance Imaging (fMRI) [26–28], brain stimulation studies using

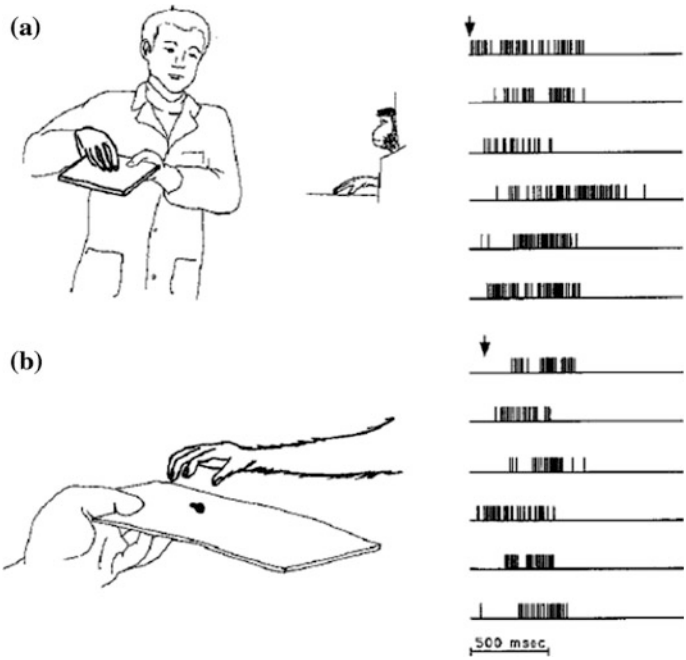

Fig. 1 In their seminal work [19], Giacomo Rizzolatti and colleagues discovered neurons in the ventral pre-motor cortex of a Macaca nemestrina monkey that activated both when, **a** the monkey observes a reach-grasp movement, and **b** when the monkey makes the same movement. Figure reprinted from [19] with permission

Transcranial Magnetic Stimulation (TMS) [29, 30], and a single unit recording study [31] have since provided sufficient evidence to show the presence of the mirror neuron system in the human brain. Interestingly, mirror neuron activity in the human brain has been observed to be modulated by the observer's own motor repertoire [32–35]. For example, the mirror system activities were observed to differ when viewing videos of classical ballet or capoeira depending on whether an observer was an expert in the observed task [33].

The discovery of the mirror neuron has exhibited a clear action specific coupling between the visual and the motor system that has motivated a series of debates, and controversies [36–39] regarding the functional significance of these neurons in regard to various social abilities in humans, including verbal communication, Theory of Mind and action understanding. We will concentrate on the investigations regarding the role of mirror neurons in action understanding. Readers can refer to [22, 40, 41, 42] for a discussion on the role of mirror neurons in other social functions.

4.2 Mirror Neurons, Motor System and Action Understanding

Does the brain utilize the motor system, namely the mirror neurons, to understand observed actions? Multiple reports from monkey and human studies suggest this to be true.

In their electrophysiological study, Umilta et al. [43] first isolated mirror neurons that activated both during the execution of a reach-grasp motion and the observation of the reach-grasp made by an experimenter. Next they exhibited that part of these mirror neurons activated only when the object, which was the goal of the task, was present and not when the same reach-grasp movement was mimed. Critically the neurons activated even when the grasped object was not visible (blocked with a screen) to the monkey but the monkey knew the object was present behind the screen. The authors claimed that this observation exhibits that the mirror neurons code not just the kinematics of the observed action, but the goal of the observed action. Other monkey electrophysiological studies have similarly exhibited motor activations related to action intention [20] and sounds [44] associated with actions.

In humans, fMRI [45, 46] and TMS studies [47–49] have shown that the mirror or motor system responding to the same observed action in terms of kinematics, are modulated by the contexts or prior information indicating what (goal) and why (intention) the agent is doing the action. For example, Iacoboni et al. had subjects observe pictures of an agent grasping a cup in different contexts reflecting different intention of the action. The "before tea" context suggested grasping the cup for drinking, while the "after tea" context suggested it is for washing the cup. They observed that frontal motor areas, that were previously associated with mirror neurons, exhibited significantly higher responses to the actions performed with context compared to actions without context, or to the presentation of static scenes suggesting the contexts [45].

Furthermore, behavioral studies have shown that the human ability to understand actions performed by others correlates with their ability to execute the same actions. In their study with developing infants, Kanakogi and Itakura observed a correlation between an infant's ability to make grasping movements and their ability to make predictive eye movements while observing reaching movements performed by others [50]. Other studies have reported the ability to predict action goals by infants [51] and action outcomes by professional sportman [35] to depend on their motor abilities.

4.3 Action Understanding by Association

Before moving on to the criticisms on the role of the motor system in action understanding, we note here that although in this chapter we motivate and concentrate on the role of the motor system in action understanding, this is not the only mechanism by which action understanding is enabled. There exists another, widely accepted mechanism of action understanding, *Associative learning* (also referred to as "understanding from outside" [42] or "understanding-by-association" [52]).

Associative learning refers to the process where an individual can understand actions, for example predict the outcome of an action, simply by learning (and remembering) the outcomes from when he previously observed the same actions [53]. Associative learning can explain how patients with lesions or damages in the motor areas and who are unable to make a repertoire of actions still can understand the same actions performed by others [36, 37] and why we can understand and predict the actions by non-human agents like pet animals or machines [54], even though obviously our motor system is very different from theirs. On the other hand, there is evidence to support that motor abilities in a task can additionally improve understanding developed through associative learning. In their experiment with professional basketball players, Agliotti and colleagues observed that athletes predicted the success of free shots at a basket earlier and more accurately than coaches or sports journalists, who can be considered to have comparable visual experience and hence comparative associative learning [35]. Therefore, arguably our ability to understand actions stems from the interactions of both the associative and motor mechanisms.

4.4 Criticism Against Motor Role in Action Understanding

However, in spite of a multitude of evidence supporting the role of the motor system in action understanding, this issue is still not popularly accepted and remains highly controversial [36, 37, 38, 39, 53, 55]. The controversy arises because the conclusions from the monkey electrophysiology [20, 43], human brain imaging [45] and child development studies [50, 51] in this regard (that we have presented in the last sections) are considered correlative and not causative in nature [37–39]. The issue is further complicated by the fact that it is very difficult to

quantify action understanding in monkeys. On the other hand, the results from lesion [56] and brain stimulation [29, 48, 49] studies have been criticized to be inconclusive because it is difficult to concretely access the functional extent of a lesion or electrical stimulation, which may include both motor and action understanding neurons [22]. Indeed no previous study has exhibited a causal relation between action understanding and action production, where a purposely induced change in the action understanding system affects action production, or vice versa.

In our recent study [57] we were able to present the first direct causal relationship between action production (by the motor system) and outcome prediction, a component of action understanding. We utilized a novel behavioral *outcome prediction learning* paradigm for this purpose, where the understanding of an individual is changed not through neural intervention but through learning. This paradigm enabled us to induce a focused change in the understanding system of individuals while avoiding the spatio-functional ambiguities (and the previous controversy) associated with neural and lesion studies, quantify the understanding change and then observe its effects on the individual's motor performance. We detail the results of this study in the next section.

5 Causation Between Action Production and Outcome Prediction of Observed Actions by Humans

5.1 Experiment Paradigm

Our study included 21 darts 'experts', three first time dart throwers (novice), and three novice ten-pin bowlers across three experiments. The experiments utilized the outcome prediction learning paradigm and examined the behavioral interaction between action production and outcome prediction [35, 50, 58], which is considered as a component of action understanding [59, 60]. Specifically, we asked expert dart throwers to predict the outcome of throws made by an unfamiliar darts novice by watching the novice darts player's throwing action. We regulated the relevant *prediction error* feedbacks available to the experts, controlled the improvement in their prediction ability [60, 61] and exhibit that this affects the accuracy of the expert's own dart throws.

Behavioral paradigms examining interference and transfer of learning between tasks have been previously utilized to investigate the neural processes behind human motor learning [62–68]. Here we use a similar procedure for *outcome prediction learning*. Behavioral paradigms cannot measure or identify where neural activity related to a behavioral function takes place in the brain. However their advantage lies in the fact that with proper control, they can ensure changes in neural processes specific to a behavioral function wherever they lie in the brain. For our purpose, the outcome prediction learning paradigm enabled us to induce targeted changes in the outcome prediction system of individuals while avoiding the

spatio-functional ambiguities characteristic of changes induced by lesions [56] and neural interventions [29, 48, 49]. We chose to use darts experts as subjects due to several reasons: (i) Experts in a sport are known to possess an excellent ability to predict the outcome of observed actions [35], (ii) Arguably, the observing expert will not explicitly imitate the novice and, (iii) an expert's motor performance is expected to be stable with time and resistant to fatigue. We could thus exclude any major contribution of explicit strategy changes [69] and fatigue in our results.

5.2 *Experiment-1: Watching Darts Versus Watching Bowling*

Experiment-1 extended over two days. 16 darts experts threw 70 darts (aimed for the center of the darts board) each day over two visual feedback (VF) blocks, where they could see where their darts landed on the board, and five blocks without visual feedback (nVF) where the room light was switched off when they threw their dart so they could not see where their darts landed (Fig. 2a). The nVF blocks were

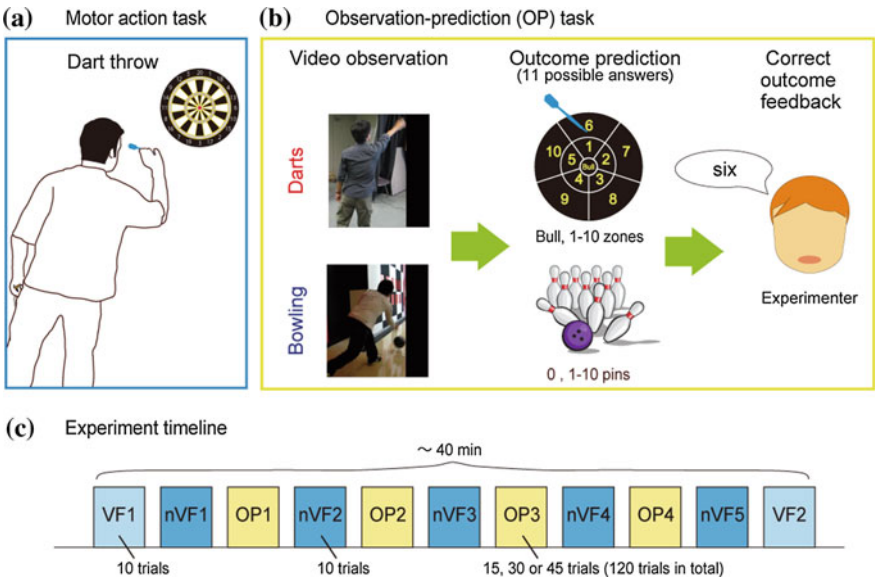

Fig. 2 Our experiment consisted of **a** two motor action tasks, one in which the subjects threw darts in the presence of visual feedback (*VF*) of where their darts land on the darts board and second, in the absence of visual feedback (*nVF*), and **b** observation-prediction (*OP*) tasks in which the subjects observed the video of either a novice darts thrower or a ten-pin bowler (snap shots shown), made a prediction of the outcome of each throw, and were given the feedback of the correct outcome orally by the experimenter. The chance level for both OP tasks was 9.09 % (=1/11 × 100). Each experiment session followed the sequence of blocks as shown in **c.**

interleaved with observation-prediction (OP) blocks, where the experts watched the video of a novice darts thrower (on one day) or a novice ten-pin bowler (another day) as control. Part of the videos in both cases were masked such that the dart flight trajectory and darts board, and the bowling ball trajectory and bowling pins were not visible to the viewers (Fig. 2b). Novice subjects were asked not to show any expressions after their throws and the recorded video was further checked and edited to remove any throws that still contained some expressions after. The experts were informed of the 'goal' of the novice actions (hitting the board center or 'bull' in case of dart throwers and felling all ten pins or a 'strike' for bowlers) and asked to predict the outcome of the throws (in terms of either the location on a lower resolution darts board or the number of bowling pins felled) by watching the action kinematics in the videos. They were informed of the correct outcome orally after each prediction. The experiment time line is presented in Fig. 2c. The nVF blocks were used to prevent visual correction by the experts and helped in magnifying the effects of the OP task on their darts performance.

The outcome prediction in the experts improved significantly through the OP task of Experiment-1 both, when they watched the video of a novice ten-pin bowler (abscissa of red plot in Fig. 3b; 8.57 ± 4.15 SD % correct predictions above chance, $t(15) = 8.25$, $p < 0.001$) and a dart thrower (abscissa of blue plot in Fig. 3b; 11.69 ± 7.15 SD, $t(15) = 6.54$, $p < 0.001$). Correspondingly, a two-way ANOVA revealed significant interaction ($F_{1,15} = 9.23$, $p < 0.01$) between the darts performance across VF block (VF1, VF2) and the observed video in the OP task (darts prediction, bowling prediction). Though the initial performance of experts was similar in the VF1 block ($F_{1,30} = 3.07$, $p > 0.05$), a significant increase in the performance error was observed in experts when they watched a darts novice ($F_{1,30} = 15.55$, $p < 0.001$) but not when they viewed a bowling novice. The darts performance deterioration, defined as the increase of performance error between VF1 and VF2, was therefore significantly positive in Experiment-1 (Ordinate of red plot in Fig. 3b; $t(15) = 5.10$, $p < 0.001$).

Experiment-1 thus exhibited two results. First, predicting a novice's action leads to a progressive increase in the performance error in the expert dart throwers. Second, the performance change is task specific: darts performance error increases on predicting outcomes of darts throws but not on predicting outcomes of ten-pin bowling, critically even when the improvement in outcome prediction was similar between darts and bowling OP task conditions ($t(15) = 1.22$, $p = 0.24$). The absence of performance changes in the bowling sessions (*blue plots*, Fig. 3b) shows that the increase in performance error is not due to fatigue, loss of attention or motivation or lack of visual feedback.

However, while Experiment-1 exhibits that watching novice dart throwers deteriorates the performance of experts, it does not conclusively exhibit that the deterioration is due to changes in the outcome prediction system. The outcome prediction did significantly improve in Experiment-1 but, the performance deterioration may have been unrelated to this prediction change and may have resulted simply due to unconscious mimicry (related to the so called Chameleon effect [70] of the observed novice's darts action which was different, both in style and

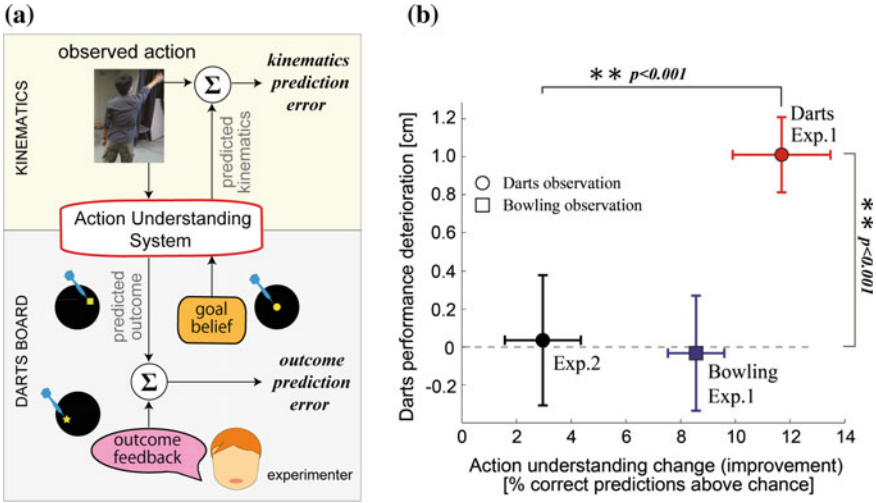

Fig. 3 **a** The experts could utilize two types of prediction errors to improve their outcome prediction in our task. First, the outcome prediction error between the expert predicted outcome and the correct *outcome feedback* from the experimenter. Second, the kinematic prediction error between the action kinematics predicted by the expert corresponding to his *goal belief* (of where the novice aims his throws for), and the kinematics the expert actually observes in the video. We modulated the outcome feedbacks and goal belief provided to the expert subjects across our experiments. **b** In the presence of both the prediction errors in Experiment-1 (*red plot*), the outcome prediction change (*abscissa* of *red plot*) was significant, leading to darts performance deterioration (*ordinate* of *red plot*). On the other hand when the experts watched the bowling videos, the outcome prediction change did not affect the darts performance (*blue plot*). When the outcome feedbacks and goal belief were both removed in Experiment-2, the outcome prediction change (abscissa of *black plot*) as well as the performance deterioration (ordinate of *black plot*) were prevented

variability, in comparison to the expert's. To exhibit that the improvement in the outcome prediction is indeed the cause of the performance deterioration, we conducted an additional experiment (Experiment-2) and examined how the performance deterioration is affected when the improvement in outcome prediction of the observed darts action is modulated by us.

5.3 Prediction Errors for Outcome Prediction Learning

The experts could utilize two *prediction errors* to improve their outcome prediction [60, 61, 71, 72] in the OP blocks of Experiment-1. The first is the outcome prediction error—the difference between the outcome predicted by the expert from the observed novice action, and the correct outcome provided to him orally by the experimenter (Fig. 3a). Second is the kinematics prediction error—the difference between the kinematics expected by the expert corresponding to the goal he

believed the novice aimed for (the center of the board), and the novice kinematics he actually observed (Fig. 3a).

5.4 Experiment-2: Watching Darts Without Prediction Errors

In Experiment-2, 16 experts (11 from Experiment-1 and 5 new recruits) were again asked to watch and predict dart videos (a different novice's video was used for experts who participated in Experiment-1) in the OP task. We removed the two types of prediction errors, expecting this to completely suppress the improvement of outcome prediction in the darts experts. The outcome prediction error was removed by removing the feedback of the correct outcome provided to the experts. On the other hand, the kinematics prediction error was suppressed by removing the expert's goal belief. We mis-informed the expert at the start of the experiment that "the novice does not always aim for the center but aims for unknown targets provided by us and that we display only those trials in which he was successful". We expected the mis-information to remove any prior goal belief that the expert may have. As expected, in the absence of prediction errors, the outcome prediction in Experiment-2 (black plot in Fig. 3b) was significantly lower than in Experiment-1 ($t(29) = 3.82$, $p < 0.001$) and not different from chance. The outcome prediction system was thus little affected in Experiment-2. Importantly, in contrast to Experiment-1, there was no evidence of performance deterioration in Experiment-2 (Fig. 3b, black plot; $t(15) = 0.11$, $p = 0.92$). Note that except for the removal of the prediction errors in the OP task, all other conditions, including the observed darts novice videos and the initial level of darts performance (evaluated as the darts error in VF1; $t(29) = 1.91$, $p = 0.19$), were same between Experiment-1 and Experiment-2. Therefore, clearly the improvement in outcome prediction was the cause of the performance deterioration in Experiment-1.

To summarize, across our experiments we observed that a focused change in the outcome prediction ability led to a modification in the motor performance in expert darts player. While, these behavioral results prevents us from making conclusions about the role of the mirror neuron system, they clearly demonstrate a causal relation between the action production and outcome prediction of observed actions by humans, and provide strong support that at least part of the motor system is involved in action understanding by humans.

6 Computational Mechanisms of Action Understanding

Up till now in this chapter, we have discussed how the concepts in action understanding, and specifically the role of the motor system in action understanding, were developed in philosophy, extended into the domain of action-perception in

psychology and are being supported by neuroscientific evidence from brain imaging, brain stimulation and behavioral studies. Before we can go on to discuss the implications of these concepts and results for robotics, we need to answer one key issue that will enable us to bridge the gap between neuroscience and robotics—How can the motor system, or what computations by the motor system, enable understanding of observed actions?

The prominent ideas in this regard can be categorized into three categories: Direct Matching mechanism (DMM), Hierarchical Predictive Coding (HPC) and Movement simulation (MS).

6.1 Direct Matching Mechanism (DMM)

The direct matching mechanism is reminiscent of the common coding theory and was proposed by Rizzolatti and his colleagues [22, 40]. In this framework, observing actions performed by others automatically triggers "resonated" activation of the observers' motor system which is required for the execution of the same action thus enabling imitation naturally. Furthermore, DMM proposes that due to the similarity between the action and perception activations, an observer can decode the intention, goals and outcomes associated with an action "from inside" (that is, based on one's own motor process). The closest robotics parallel of DMM is probably the application of affordance theory [73] in robotics [74].

6.2 Hierarchical Predictive Coding (HPC)

Other researchers have argued that DMM is not versatile enough to explain the understanding of many daily actions which are kinematically similar but lead to different outcomes. For example, a swinging arm can represent a person hailing a taxi or, swatting a wasp [60, 75]. In order to deal with such cases Friston and colleagues proposed a hierarchical action understanding schema which they referred to as the Hierarchical predictive coding framework (HPC) [76, 77]. In this schema, action understanding is achieved through hierarchically organized processes, each *understanding* the action at a different level- at the level of intention, goal, kinematics, and outcomes for example. The motor transformations between action commands and their consequences form the lowest level of this framework. Information processed at each upper level is transmitted as a prior for the predictions at a lower level while the prediction errors at each lower level are used for bottom-up update of information in the immediately upper level. An input to any level of the system thus leads to a cascade of self-organization until the prediction errors converge to zero, and consequently the observed action is *understood*. In this framework, taking the example of the swinging arm, higher level processing of the behavioral context (e.g. an agent is doing the action in his garden) can enables the

observer to infer the most probable intention behind the observed action (that is, swatting a wasp).

6.3 Movement Simulation

The *movement simulation* architecture is motivated from studies in human motor control where it is generally agreed that human movements are enabled by pairs of *internal forward* and *inverse* models [78–80] of the environment and self. These models are learnt through experience and store different features of the dynamics defining an environment or one's own physical system. The forward models predict the sensory consequence of motor outputs and are utilized for perception of self-action [81–84], for online motor control [85–87], motor learning [88, 89] and in the identification of behavioral context [90, 91]. On the other hand the inverse model is believed to develop motor commands given certain sensory state feedbacks [78, 79, 92].

In an inter-personal context, this theory believes that the observed actions can be understood by simulating them in one's own brain using the same (or similar) internal models [93–96]. Kinematic information of the observed action may be sent to an observers' inverse model which transforms it into a motor command which the observer would have generated to achieve the same observed kinematics. The generated motor command can then be sent to the observer's forward model to enable the observer to predict the consequence of the observed action. If the observer is considered to have multiple forward inverse model pairs, one for each of the many possible contexts like in the MOSAIC architecture [90, 96], then each module can make its own prediction of the consequence. The observer can make a final prediction by weighting the prediction from each module by his prior knowledge of the context, while a comparison of the individual module predictions with the actual consequence can enable him to update the understanding of the context to best explains the observed action (see Wolpert et al. [96]).

Though conceptually similar, note that this simulation is different from the simulation theory of empathy [97, 98] in the so called field of Theory of Mind which deals with mental states. Though, a hierarchical implementation of the MOSAIC model that is said to allow understanding of the intention and goal behind observed action [96, 99] brings the two concepts in motor control and social neuroscience close.

7 Action Understanding in Robotics: A Short Summary

The concept of action understanding is not new in robotics and has been previously explored in detail, particularly in the field of imitation learning by humanoid robots [100, 101]. Depending on the task, a robot may be required to imitate a motion,

action goal or action intention. Even when the aim of a robot is only to imitate the motion of a demonstrator (for example, a robot imitating a dance motion), a robot requires to first account for the viewpoint transformation of the observed motion, use the appropriate sensory-motor matching [101–103] and then solve the *body correspondence problem* [104, 105], to account for the differences in kinematics (and even dynamics) between the robot and the demonstrator. The requirement of action understanding is more intuitive when the aim of a robot is to imitate the goal or intention (e.g. [106, 107]). For example, imitating a hand reaching for a cup is a goal directed imitation that requires the robot to understand that the goal of the task is not to move the hand but pick up the cup. Imitation of a demonstrator's hand movements while he holds a big box with both his hand may be an example of an intention directed imitation where the robot needs to understand that the robot has to not just move the hands like the demonstrator but also keep a hold on the box while doing so.

Various mathematical strategies have been used for estimating the goal and/or intention for imitation. These can be summarized as methodologies that rely on a pre-learnt map (e.g. [108, 109]) that may be considered as an implementation of the direct matching mechanism, probabilistic models like in [110, 111] that may be considered to be close to hierarchical predictive coding, and probably the most popular, models utilizing Inverse optimization, inverse optimal control, inverse planning and inverse reinforcement learning [112–115] that can be considered to be movement simulation.

8 Motion Planning for Interacting Robots

Interestingly, except imitation learning, as far as we know, there is little implementation of action understanding in any other forms of interaction behavior by robots. Through the next two sections, we will present our conceptual idea with examples to show how action understanding, and specifically movement simulation, can play a key role in the planning of behavior in robots that intend to *help* or *impede* humans, and other robots.

8.1 Motion Planning in Robotics

Motion planning in a well-established and widely researched field, and interested readers are requested to refer to [116, 117] for an in depth discussion on it. Here we will not discuss motion planning in detail but only define some key concepts and definitions that will aid us in explaining our concepts and examples in the following sections.

In classical mechanics, the vector space required to define the states (or configuration) of a system are called its *configuration space,* while the set of actual configurations possible under real life constraints is called the system's

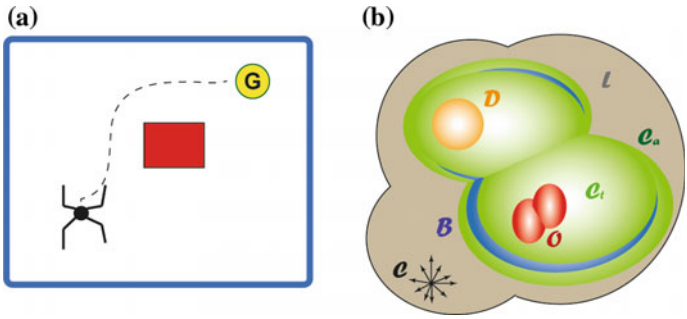

Fig. 4 **a** An example of an insect robot in constrained environment, and **b** the cartoon of the corresponding constraint representations in the configuration space

configuration manifold. Taking a concrete example, consider the two dimensional, quadrapedal robot insect in Fig. 4 that can move inside a given blue boundary. Suppose the robot has a spherical point body connected to four legs each with a hip and knee joint. Then the dimension of the robot's configuration space $\boldsymbol{\mathcal{C}}$ will be $\mathbb{R}^2 \times \mathbb{S}^8 = 10$ (2 translational for the body and 8 rotational for the legs) with S representing a unit circle. Now considering that the robot movement is restricted by the boundary $\boldsymbol{\mathcal{B}} = \mathbb{R}^2$ and suppose the knee joints are constrained by the joint limits $\boldsymbol{l} = \mathbb{S}^4$, the actual configuration space that the robot can traverse can be given by $\boldsymbol{\mathcal{C}_a} = \mathbb{R}^2 \times \mathbb{S}^8$ (in Fig. 4b). Furthermore, within this actual configuration space there may be constraints that limit the robot behavior. We can have *volume reducing constraints*, like obstacles $\boldsymbol{\mathcal{O}}$ which can usually be defined by inequalities $\mathrm{O}(\boldsymbol{c}) < 0, \boldsymbol{c} \in \boldsymbol{\mathcal{C}_a}$. We can have *dimension reducing constraints* $\boldsymbol{\mathcal{D}}$ like when the robot cannot use all its legs near the wall boundaries, and which can be represented by equalities of the form $\mathrm{D}(\boldsymbol{c}) = 0, \boldsymbol{c} \in \boldsymbol{\mathcal{C}_a}$. Then if the task of the robot is to move to goal *G,* the remaining task configuration manifold $\boldsymbol{\mathcal{C}_t}$ (Fig. 4b) defines the configurations that the robot can traverse while moving to goal *G*. Here we defined the task configuration space for a relatively simple case but a similar configuration space can be defined for any complex system and task. Given this mathematic space, the goal of a motion planner is usually to find the best path to particular goal configurations (or their functions) while minimizing a predefined criteria.

Popularly, two categories of methods have been employed to solve planning problems in robotics, and especially humanoid robotics [118]. First *Prioritized Inverse Kinematic* strategies, which try to take advantage of the redundancy in the robots to assign multiple tasks to completely or partially decoupled subsets of the configuration space of the system in a prioritized manner (e.g. [119–123]). And second, *Configuration Space Exploring* strategies that explore the task configuration manifold to find the *optimal solution* that minimizes a given criterion or *edge cost* [117]. In the case of high dimensional systems like a humanoid robot, these explorations may be sparsified utilizing algorithms such as *Probabilistic Roadmaps* [124] or *Rapidly exploring Random Trees* (RRT) [125]. See [117] for an extensive review.

8.2 Challenges to Planning Inter-Agent Interactions

Inter agent interaction and collaborative task planning has been extensively researched in the field of swarm robotics [126, 127]. However, here we are particularly interested in behavior planning of robots that will interact with humans. For example, in our soccer scenario from the beginning of the chapter, our interest would be to plan the behavior for a robotic soccer defender who requires to tackle a human opponent. This problem differs from most of the swarm robotics scenarios in two critical aspects:

1. Most swarm robotics algorithms utilize centralized or hybrid (a combination of centralized and de-centralized) control where there is a 'big boss' computer that can control and observe every individual interacting agent. On the other hand when interacting with a human, it is not possible to have a centralized controller or observer to help the robot. Robots that interact with humans require individual, de-centralized planners.
2. Even the algorithms that propose de-centralized control in swarm robotics, utilize communication channels where agents can explicitly communicate their *utility functions* (for example their capacity to do a particular task) to one another so that they can collectively make decisions. In case of human-robot interactions, explicit communication between agents is improbable in most scenarios, and the robot would require to *learn* and utilize subtle physical and haptic cues [128] to plan its actions.

So to repeat from the beginning of the chapter, in order to be a successful soccer defender our robot would require to decipher the intention (and maybe emotion) behind the human opponent's action, detect constraints associated with the human's action, predict the outcomes of his current actions, and predict future actions, and decipher all these issues without any communication with the human. In other words the robot would require action understanding.

9 Our Proposed Bio-mimetic Solution

9.1 An Example Interaction Task

In this section we propose a framework to enable action understanding by robots. We will utilize features of human action understanding, and particularly movement simulation to formulate and develop *helping* and *impeding* behaviors by robots during interactions with another agent. For sake of clarity, we will take a simple 2-dimensional, two robot example to explain our concept and discuss the extension of this concept to interaction with humans in the next section.

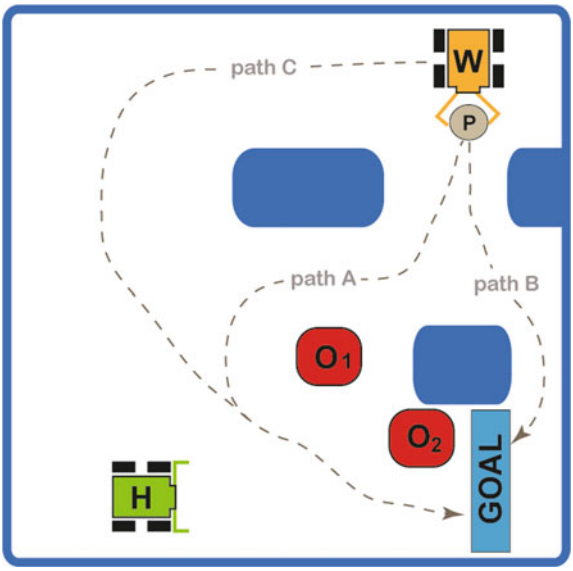

Fig. 5 Our 2-dimensional example involves two mobile robots that move inside a region bonded by blue non-movable walls. Robot *W* aims to bring peg *P* to the *GOAL* while robot *H* aims to *help* robot *W* in its task. O_1 and O_2 are manipulable obstacles that *W* is unable to move because it is holding the peg. The question we answer is how can *H* decide an action that would help *W*?

Let us consider a scenario with two interacting mobile robots, worker robot *W* and a helper robot *H* (Fig. 5), both with pincers with which they can hold and manipulate objects. We will assume that the robots can rotate arbitrarily and immediately about their base such that the robot's configuration space can be considered as $\boldsymbol{\mathcal{C}_a} = \mathbb{R}^2$ (and in fact will look very much like Fig. 5) and that they move at a constant speed. We also assume that the robots are aware that the red objects (O_1 and O_2) are manipulable while the blue walls are not. Finally, to disregard the effect of time on robot *H*'s behavior, we assume that robot *H* can move much faster than robot *W*.

The task of robot *W* is to get the peg *P* to the *GOAL* in the shortest possible time and the task of robot *H* is to *help* robot *W*. Our goal here is to identify and execute *help*. In order to help robot *W*, robot *H* has to achieve the following objectives:

1. It has to identify the task aim of robot *W*; that it wants to take *P* to *GOAL* as fast as possible.
2. It has to estimate the physical constraints of robot *W* that arise from its size and shape.
3. It has to estimate the task constraints of robot *W*; that *W* has to hold the peg and hence cannot manipulate other objects in the environment without wasting time.
4. It has to estimate what path robot *W* will take.
5. Considering 1–4, decide what manipulation in the environment can help robot *W*.
6. And finally, plan an action to execute the helping operation.

9.2 Concept and Algorithm

We will start by omitting (1) here because in most applications the general aim of an agent remains fairly constant (for example the aim of players throughout a soccer game is to score as many goals as possible). We assume the aim of robot *W* is known to Robot *H*. As mentioned before, our bio-mimetic solution to the problem is motivated by motor simulation. We propose that *at the start of the task robot H should assume that robot W is similar to itself and consider itself to be doing robot W's task*. By making this simple assumption, *H* can solve objectives (2), (3) and (4) by movement simulation. That is, robot *H* can assume robot *W's* physical constraints to be same as its own. It can define the constraints due to the peg by assuming the peg is being held by it (robot *H*). Robot *H* can then combine these constraint estimations with the environment information (volume constraints because of the walls and objects O_1, O_2 in our case) and perform *simulation planning;* develop a motion plan that *it* (robot *H*) would take to complete the task, and then assume that robot *W* would do the same. Robot *H* can thus estimate that robot *W* will take say *path A* (in Fig. 5) associated with a cost V_a (time or path length for our case). V_a at any path point gives the cost of moving from this point to the *GOAL* along *path A*.

Once robot *W*'s path is identified, we are left with the last question of identifying and planning the help. The generalized solution for the help identification and planning would be to simulate plans multiple times by *moving* each manipulable constraint (objects O_1 and O_2 in our case) within their configuration manifold in the environment and calculating the change in the cost in each case in order to identify the manipulation that would constitute the greatest cost reduction, and hence the best help.

The generalized solution can of course be computationally intensive. However, simpler algorithms can be defined for specific help behaviors. For example we propose a configuration space–distance based algorithm that can be useful for help planning in many common tasks. The algorithm involves two steps: help identification and help manipulation.

<u>*Help identification*</u>

Step 1 We start by first down sampling the configuration space path that we expect W to take (*path A*), and the associated cost, into n *path points*.

$$\boldsymbol{p}_{\mathrm{i}}, \boldsymbol{p} \in \boldsymbol{\mathcal{C}_a}. \wedge \mathrm{i} = [1, \mathrm{n}]$$
$$\boldsymbol{v}_{\mathrm{i}}, \boldsymbol{v} \in \boldsymbol{V}_{.} \wedge \mathrm{i} = [1, \mathrm{n}]$$

Step 2 Next we neglect all manipulable volume and (if any) dimensional constraints in our task and define the *unconstrained configuration space*. Then between each pair of path points, we find a difference of cost when moving from one point to the other traversing the planned path, and when traversing the shortest path in the unconstrained configuration space.

Set counter→0
For i=[1,n]
For k=[i+1,n]
counter→counter+1
Costdifference(counter) $= (\boldsymbol{v}_i - \boldsymbol{v}_{k)} - (\boldsymbol{v}_i - \boldsymbol{v}'_{ik})$
Loop k
Loop i

$\boldsymbol{v}'_{\mathrm{ik}}$ represents the cost at $\boldsymbol{p}_{\mathrm{k}}$ when $\boldsymbol{p}_{\mathrm{k}}$ is reached from $\boldsymbol{p}_{\mathrm{i}}$ in the unconstrained configuration space.

Step 3 We sort the cost differences in the decreasing order and starting from the top, consider the constraint associated with each difference and identify one (or more if allowed) as the *help constraint* to be manipulated during the helping action.

Help manipulation

If obstacle removal is the role the helper aims for, then the helper can move the identified obstacle utilizing the cost gradients near the object location in the (unconstrained) configuration space. The obstacle needs to be moved to a location where the cost is high because the robot will avoid this location.

Note that the same cost difference algorithm can be modified to not 'identify a constraint' but 'identify a point in the configuration space to be warped'. That is, once the help constraint is identified, the manipulation is not to move the constraint obstacle but move the two path points (between which the constraint exists) towards one another. If the *GOAL* is movable, this procedure will make the robot *H* help robot *W* by bringing the *GOAL* towards *robot W*.

9.3 Correcting for Estimation Errors

While the movement simulation by robot *H* serves as an initial estimate of robot *W*'s behavior, *H* can improve and correct these estimates by observing the actual behaviors by *W*. For example, if suppose robot *H* is half its present size in Fig. 5 then, while making the initial assumptions about the physical constraints, *H* will wrongly assume *W* to be as small as itself and expect *W* to take *path B* instead of *path A*. However, once robot *W* starts to move, *H* can notice that *W* (which follows *path A*) is not following *path B* and thus make corrections to its estimate of *robot W's* constraints. While in this simple example, this adjustment is trivial, in more complicated cases the mapping between these *estimation errors* and the planning constraints can be one to many. Depending on the nature of the agents, some situations may allow for simple scaling solutions while others may require priors or comparison of multiple models similar to the MOSAIC [90] architecture to enable corrections.

The concepts explained above have been represented graphically in Fig. 6.

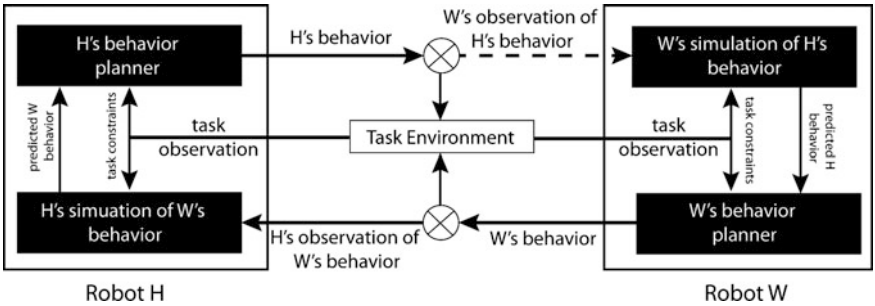

Fig. 6 A graphical representation of our proposed conceptual robot interaction planning framework (motivated from [129]). The dashed trace «W's observation of H's behavior» introduces inference looping between the agents

9.4 Challenges for Human-Robot Interactions

A big challenge for human interactions is the inference of the human intention during decision tasks. Motor simulation can help intention inference by letting a robot make an initial intention prediction from its own motor repotoire and then modify it (if it is wrong) with either the observed estimation errors or by observing responsive actions, which are relatively easier to understand. This procedure is similar to what humans do. For example, consider that you are sitting on a crowded train and see an old man approaching. You may first assume that he intends to sit and thus start to get up from your seat. However, you will change this assumption if you see him walking towards the door, or if he gestures you to keep sitting.

However human gestures and social behaviors can change extensively with different cultures and across individuals. Therefore in addition to action understanding by movement simulation, robots would also need to incorporate an associative learning-based action understanding (Sect. 4.3) procedure where behaviors experienced with a person (or in a particular culture) are stored in memory to be utilized for subsequent interactions, especially in regard to estimation error corrections. The memory requirement for this purpose can be large and movement notations, that can help store whole movements with minimal memory, will play an essential role in this aspect.

Once the intention is estimated, at least in the case of human-humanoid robot interactions where the physical dimensions of most humanoids are comparable or easily scalable to that of humans, simulation can quickly provide a robot with a good estimate of a human's configuration space and the volume reducing and dimension reducing constraints in a task. The robot can then predict the human behavior plan in most tasks by utilizing well established *human* cost functions [67, 130, 131], and thus plan how to help him. Online modifications (utilizing estimation error) may again be required in some cases at this stage to correct for errors in the assumed cost or due to the choice of sub optimal samples (as random sampling

is utilized for planning in high dimensional spaces, see Sect. 8.1) in the configuration space during the simulation planning.

Furthermore, while helping behaviors by a robot are relatively easier to handle, competitive behaviors can have additional complications. While in our example from Sect. 9.1, we considered the case when *H* simulates *W*, but as seen from Fig. 6, simultaneously *W* can simulate *H* as well. Such bilateral simulations can lead to interesting behaviors, especially in competitive scenarios. In our example, suppose robot *H's* goal is to not help robot *W* but instead to impede it. Then *H* would probably decide to move one of the manipulable objects into *path A* (optimally between the two blue walls where the corridor is narrow). However, if *W* can also simulate *H's* behavior, then *W* can predict this impedance and hence, avoid *path A* and choose *path C* instead. Note that such counter simulations can go on, where *H* can predict that *W* will predict its (*H's*) impedance and choose *path C*, and thus plan to impede *W* in a different way. Bilateral simulations can thus lead to infinite inference loops. This is the typical scenario, for example in chess, where players have to predict each other's plans over multiple moves. Addition of "W's Observation of H's behavior" (dashed line in Fig. 6) during robot-robot interactions should thus be done with additional constraints.

On the other hand simulation loops cannot be avoided in human-robot interactions because, as discussed in the earlier part of this chapter, humans always simulate their interacting agent's behaviors. Therefore, the authors believe that in order to achieve intelligent interactions, robots require to acquire at least the basic mathematical/logical understanding of the psychology and neuroscience behind human interaction behaviors. The robots then need to follow these same behaviors themselves. This will allow the robots to simulate and *understand* humans when they interact with them, and enable the humans to simulate and *understand* (or at least enable them to learn quickly to understand) the robots during the interaction. Providing humans with the ability to understand robots is crucial because like an old Indian saying goes, "what we (humans) don't understand, we fear", and are uncomfortable with.

10 Conclusion

Movement notations, like from dance are essential as they provide us with essential tools to characterize and quantify movements and describe them with concise notations. In this chapter we looked at the problem of utilizing the characterized actions during interactions for understanding the actions. We started this chapter with an introduction of action understanding by humans and presented a brief review of works in philosophy, psychology and neuroscience that evaluated the mechanisms by which humans perform action understanding. We then motivated the challenges faced by robots while interacting with humans, and exhibited how the ideas from human studies, especially movement simulation can go a long way into solving these challenges. In summary what we propose is: By considering another agent to be

similar to itself, a robot can utilize movement simulation in order to formulate the other agent's task, use its planners to solve the task, assume that the other agent would do the same, and then estimate which constraints impede the other agent's task the most. The agent can then plan to reduce or increase these impediments as per his required role while correcting for the estimation errors with actual observations.

The ideas we present are still conceptual where we left out many practical but essential issues like viewpoint transformations (addressed extensively in imitation studies) and especially, mechanisms to enable corrections of estimation errors. Furthermore, it is essential to develop a mechanism to integrate action understanding by movement simulation with associative learning-based understanding processes to enable a learning behavior in robots. Dance notations can play a major role in associative learning-based understanding by enabling efficient storage, characterization and retrieval of action experiences. Though some mechanisms to enable these are already available in literature, these topics need further research in the future by also incorporating knowledge of the human behavior, an issue which in itself is still far from being complete. Integrated research in robotics and neuroscience is thus required to improve future robot-human interactions.

We conclude the chapter with another interesting difference between interaction planning and the popular individual robot planning. From our discussions through this chapter, it is obvious that helping and impeding behaviors involve a larger computational work load than the task itself, because the helping agent has to first simulate the actions of the other agent inorder to understand the other agent, then plan his own task (though this may be done at a coarser resolution for some tasks), and then plan the help. This is consistent with observations in nature where the more *intelligent* animals show more complex interaction behaviors. On the other hand, it also means that agents should ideally utilize multiple plans for one task, a simpler plan for when they expect help and a complex (in terms of uncertainty and computation time) and even multiple plans (with switching) when they expect to be impeded. Thus when it comes to interaction scenarios, the optimal plan may not be a single fast solution, as is the norm with motion planning for individual robots.

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