Emergence of Altruistic Behavior Through the Minimization of Prediction Error

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***Abstract*—The emergence of altruistic behavior in infants fosters their social development and supports their involvement in our society. Altruistic tendencies, intended to benefit others with no apparent rewards, are also very useful for social robots that are designed to be used in our households. Yet, to make robots capable of learning how to help others as infants do, it is important to understand the mechanisms and motives responsible for the development of altruistic behavior. Further, understanding the mechanisms behind the early development of pro-social behavior would be a great contribution to the field of developmental psychology. To these ends, we hypothesize that infants from 14 months of age help others to minimize the differences between predicted actions and observations, that is, to minimize prediction errors. To evaluate our hypothesis, we created a computational model based on psychological studies and implemented it in real and simulated robots. Our system first acquires its own sensory-motor representation by interacting with its environment. Then, using its experience, the system recognizes and predicts others' actions and uses this prediction to estimate a prediction error. Our experiments demonstrated that our robots could spontaneously generate helping behaviors by being motivated by the minimization of prediction errors.**

***Index Terms*—Altruistic behavior, cognitive developmental robotics, helping behavior, prediction error.**

I. Introduction

INFANTS' tendencies to help others and to act altruistically have been observed and studied for decades, and young children were first considered not to be sufficiently socially and cognitively developed to generate extensive and efficient helping[1] behavior [2]. Scientists have recently proved that infants from around 14 months of age are in fact capable of helping others even without the expectation of future rewards [19], [23], [35]–[37]. In case of adult altruism, several researchers have reported theories on selfish altruism [7], kin altruism [1], [9], or reciprocal altruism [30] as potential mechanisms for them. However, only few theories have explained infants' motivations to act altruistically and described the mechanisms or the cognitive functions that foster the development of such comportment. To shed light on the origins of altruistic behavior, we reviewed different theories on neurocognitive motivations and the eventual mechanisms underlying prosocial behavior in infancy. In the following parts, we summarize two major theories proposed in [26] and highlight the main issues of these models (for a more general review of the different models, see [26]).

A. Emotion-Sharing Models

Emotion-sharing models suggest that an early form of empathy, in the form of emotional contagion, could be the primary behavioral motivation for infants to act altruistically [11], [12], [37]. Studies related to emotion-sharing models indeed posit that infants are primed to generate altruistic behavior in order to alleviate others' distress [14], [39]. This requires the ability to actually "feel" another person's distress, which is often called emotional contagion and represents "an automatic response resulting in a similar emotion being aroused in the observer as a direct result of perceiving the expressed emotion of another" (definition by Decety and Svetlova [12]). This ability is accepted as one of the lowest forms of empathy [11] and the cognitive requisite to altruism. Some scientists claimed that infants experience an empathy-based feeling toward individuals in need of help and that it serves as the primary motive for altruistic behavior [16], [31]. In practice, Warneken *et al.* [35] and Warneken and Tomasello [37] showed that infants helped others in achieving their goals and postulated that it substantiated the existence of an altruistic motivation in early infancy, closely related to empathy. It has been argued that empathetic concern is also independent from self-reflective abilities [10] and that empathy may be an innate capacity [15]. Studies have shown that very young children, before the age at which they develop self-other discrimination, attempted to alleviate the distress of others and showed empathetic concern [39], and that 12-month-old infants were concerned for others in distress and sometimes intervened by comforting them [14].

However, the cognitive abilities required by infants to feel empathetic concern for others, and thus to develop altruistic behavior on the basis of the alleviation of the shared distress remain very controversial. Some experiments have argued that self-other differentiation is required to acquire empathetic concern for others and to act altruistically, which implies that only infants that passed the self-recognition task would help others altruistically [5], [6], [18], [26]. Nevertheless, undeniable

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[1]The term helping is, according to Bar-Tal (1982), suggested to be "a term meaning an act that benefits others with no external rewards promised *a priori* in return."

proofs of the helping behavior have been shown during the first half of the second year of life, even though self-other differentiation and self-concept are immature. On the basis of these findings, we can assume that another source of motivation, more general in nature, may provide behavioral motivation to act altruistically.

B. Goal-Alignment Models

Unlike emotion-sharing models, which are based on emotional contagion and empathetic concern, the goal-alignment models propose that more general mechanisms, based on the understanding of others' goals, serve as behavioral motivations for infants to help others. In other words, inferring or feeling others' mental or emotional state is not required for acting altruistically, but the ability to understand others' goals is a sufficient prerequisite.

Goal understanding and goal inference have been widely studied and are known to appear very early in the cognitive development of infants. Sommerville and Woodward [33] proved that infants from three months of age could already detect the goal structure of an action after a time of habituation during which the infants could interact with their environment. Furthermore, Kanakogi and Itakura [17] showed that infants from six months of age could predict the goal of a grasping motion if it was performed by a human hand, whereas they could not do so if the reaching was performed with a mechanical claw or the back of the hand. Finally, Kuhlmeier *et al.* [20] showed that 12-month-old infants could recognize goal-directed actions and interpret future actions of an actor on the basis of the previously observed actions in another context. On the basis of these evidences, infants clearly possess the ability to understand others' goals. Therefore, researchers have argued that because of the immature self-other differentiation during early infancy, contagious processes might affect infants in such a manner that they unconsciously take others' goals as their own [3].

Even if it has been shown that infants are unconsciously affected by others' goals, the motivation to achieve these goals and help others in achieving their actions is not intuitive, which explains the popularity of emotion-sharing models. Nevertheless, studies showed that infants could help in situations where emotional contagion or empathetic concerns are unlikely. For instance, Kenward and Gredebäck [19] reported that 18-month-old infants could help spherical objects with no human-like body to reach their goals, which may imply that empathy elicited by direct body matching is not applicable. Further, they postulated that altruistic behavior may be "primed by an unfulfilled goal," which supports the possibility of a general mechanism, different from empathy and concern for others, that could motivate infants to exhibit altruistic behavior.

C. Our Hypothesis: Prediction Error Minimization

On the basis of previous evidences and the goal-alignment models, we try to shed light on a possible nonempathy-based motivation to altruistic behavior by hypothesizing that infants help others to minimize a prediction error (hereafter PE) that they estimate for others' action goals. Prediction errors are estimated as the differences between predicted actions and observations. Infants are supposed to first learn sensory-motor experiences by interacting with their environment. Then, using the past experiences, infants recognize and predict others' actions as if they are infants' own actions. PE estimated during this process finally triggers infants' actions to minimize it, which results in infants' helping behaviors. We suggest that the above process is closely related to the mirror neuron systems (hereafter MNS), which are groups of neurons firing both when executing and observing similar goal-directed actions [28]. It has been shown that infants', as well as adults' MNS activates for observed actions that they can perform by themselves [27], [29] (also discussed in [33]). The MNS theory therefore supports our hypothesis about infants' ability to recognize and predict others' actions as if they are infants' actions.

To test the plausibility of our hypothesis and determine to what extent it can explain infants' altruistic behavior, we present a computational model studying the effect of PE minimization on behavioral motivations. Our model is based on evidences describing infants abilities to understand and predict others' action goals. An important point is that it does not have any explicit intention to help others by design. Instead, altruistic behaviors emerge as by-products of goal-alignment, which suggests that infants always try to achieve predicted action plans. In our model, this motivation is implemented through the minimization of prediction-error. To identify what are the required cognitive abilities to estimate PE and determine whether its minimization is a possible motivation for altruistic behavior, we present two series of experiments: the first uses a simulated environment, and the second uses a humanoid robot iCub. The rest of this paper is organized as follows. First, we present our computational model and our experimental settings. Finally, results obtained from the two series of experiments are closely discussed, followed by future directions.

II. Model for the Minimization of Prediction Error

Our computational model is based on behavioral evidences of infant development and attempts to understand and reproduce the mechanisms of the emergence of altruistic behavior in 14-month-old infants. We then assume that our system has the cognitive and motor abilities of a 14-month-old infant, such as the ability to perform goal-directed actions, to detect and recognize action goals [17], [33], and to represent a behavior as relations between actions and objects [38]. Furthermore, as it has been shown to happen in the human brain [4], [32], our system can estimate PE signals when the actual outcome of an observed action is different from the predicted one.

Fig. 1 shows the overview of our model for the minimization of PE, which consists of four interdependent modules: 1) the scene recognition; 2) action prediction; 3) estimation of PE; and 4) minimization of PE. These modules are equipped with the abilities to recognize action primitives and the associated objects (conditions), to predict next action primitives, to

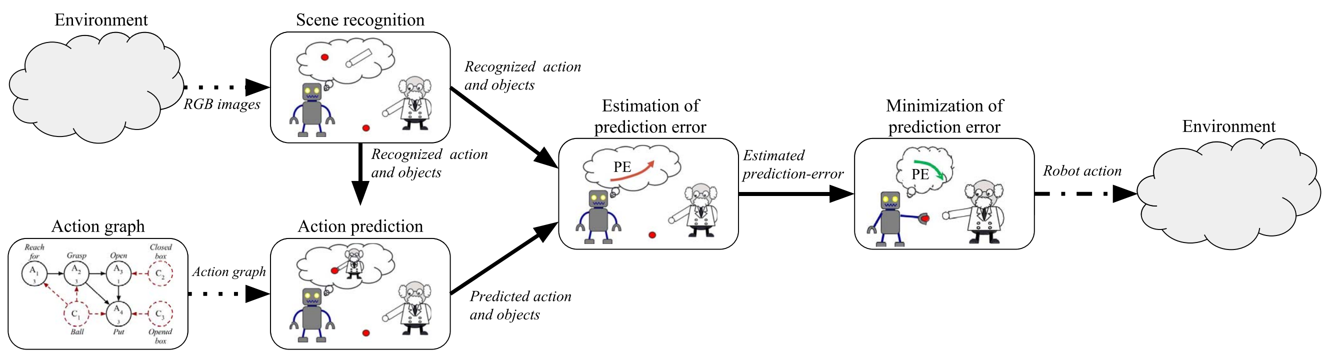

Fig. 1. Model for the minimization of PE. The four modules are used to recognize action primitives and the associated objects (conditions), to predict the next action primitives, to estimate PE and to generate the primitive to minimize PE.

estimate PE, and to generate actions to minimize PE, respectively. The action prediction module uses a directed graph, hereafter called an action graph, which represents the robot's "memory." The action graph is generated when the robot experiences actions with its environment. More details about the four aforementioned modules are presented in the following sections.

A. Scene Recognition Module

This module recognizes action primitives (noted A in the next sections) and objects contained in the scene (noted C in the next sections). Action primitives are simple motions that the robot can execute like reaching for a *Ball*, *Grasping* a *Mug*, covering a marker, etc. Hereafter, we call a sequence of action primitives "action." For instance, a "pushing" action contains the action primitives *Reach for* an object and *move* it. Objects are elements of the scene that can be interacted with like a *Ball*, a *Mug*, etc. Objects are called "conditions" hereafter as they are needed for executing actions. The result of the recognition is used by the action prediction module described in Section II-B.

B. Action Prediction Module

The action prediction module estimates the future action primitive based on the currently-observed primitive. This process is presented below as action prediction. The prediction is performed through the action graph, which memorizes the robot's past experience. In the following parts, we describe how the action graph is generated and how it is used for the action prediction.

1) Action Graph: The action graph (G) is made of two types of vertice, hereafter called nodes, representing the system's sensory-motor representation, namely the previously experienced action primitives and their associated objects.

1) The action nodes $\mathbf{A}$ that represent action primitives performed by the robot; The number of times an action node has been performed by the robot is noted NB_A.
2) The condition nodes $\mathbf{C}$ that represent the conditions for the action primitives, namely the object the robot interacted with while performing action primitives.

Action nodes are connected by directed edges $\mathbf{E_A}$ that encode the number of times a transition between two action nodes was experienced. The number of times a transition $\mathbf{E_A}$ has been activated is noted $\mathrm{NB}_{A_i \to A_j}$, where A_i and A_j are two different action nodes. The conditional relation of condition nodes to action nodes is represented by another type of edges noted $\mathbf{E_C}$. The graph is then represented by

$$\mathbf{G} = (\mathbf{A}, \mathbf{C}, \mathbf{E_A}, \mathbf{E_C}) \tag{1}$$

where all nodes are Boolean variables and can take a value of 1 (active) or 0 (inactive).

Fig. 2 shows an example of how an action graph is generated while experiencing three actions (action I twice and action II once). Action I: "*Reach for* a *Ball*, *Grasp* the *Ball*, and then *Put* the *Ball* in an *Opened Box*"; action II: "*Reach for* a *Ball*, *Grasp* the *Ball*, *Open* a *Closed Box*, and then *Put* the *Ball* in the *Opened Box*." Action I was experienced first, then action II and finally action I again. In this example, $\mathbf{A} = \{A_1, A_2, A_3, A_4\}$ and $\mathbf{C} = \{C_1, C_2, C_3\}$. A_2 is the child node of A_1, while A_1 is the parent node of A_2. The numerals inside the action nodes in Fig. 2 represent the number of times the primitives were successfully executed, noted NB_A. For instance, *Reach for* was executed during all actions, $\mathrm{NB}_{A_1} = 3$, while *Open* was executed once during action II, $\mathrm{NB}_{A_3} = 1$. The numerals by the directed edge in Fig. 2 represent the number of times the connected child and parent nodes were performed successively, noted $\mathrm{NB}_{A_i \to A_j}$. For instance, *Open* was performed one time after executing *Grasp*, thus $\mathrm{NB}_{A_2 \to A_3} = 1$.

The action node corresponding to the currently recognized action primitive is denoted as $A_{i(n)} \in \mathbf{A}$, and the condition nodes representing its conditions are contained in the subset $\mathbf{C}_{A_{i(n)}} \subset \mathbf{C}$. n represents the current discrete time step. In Fig. 2, for instance, the action primitive "*Put* a *Ball* inside an *Opened Box*" is described by the action node "*Put*" ($A_{4(n)}$) and the condition nodes "*Ball*" and "*Opened Box*," which are contained in $\mathbf{C}_{A_{4(n)}} = \{C_1, C_3\}$.

In practice, the action graph is constructed when the system executes actions with its environment. This process is ruled by the following mechanisms:

1) The system performs a primitive from its action repertoire involving objects in the scene.
2) For the executed primitive, the corresponding action node A_i and condition node(s) $\mathbf{C}_{A_i}$ are added to the

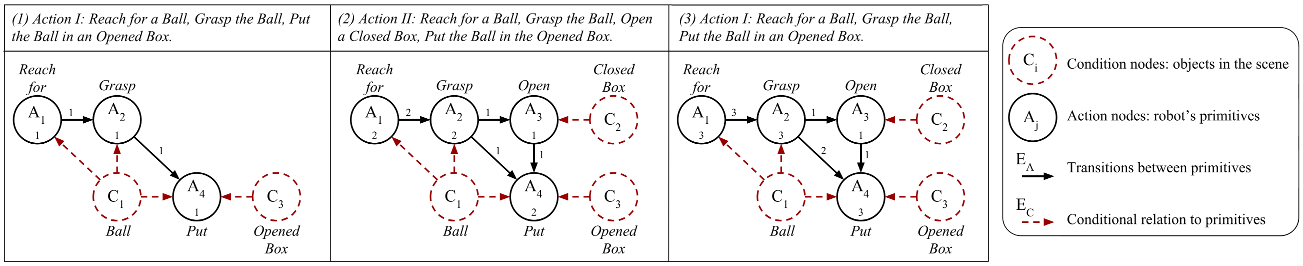

Fig. 2. Example of the different steps in the creation of an action graph after executing two different actions. action I: *Reach for* a *Ball*, *Grasp* the *Ball*, and then *Put* the *Ball* in an *Opened Box*; action II: *Reach for* a *Ball*, *Grasp* the *Ball*, *Open* a *Closed Box*, and then *Put* the *Ball* in the *Opened Box*. Action I was experienced first, then action II and finally action I again. The small numerals inside the action nodes represent the number of times the action primitive corresponding to the node was successfully executed, namely NB_A. The small numerals by the directed edge represent the number of times the connected child and parent nodes were performed successively, noted $\mathrm{NB}_{A_i \to A_j}$.

action graph. The condition nodes are connected to the action node by directed edge. If an action primitive is performed several times with different objects, multiple instances of the action nodes are created and connected to the corresponding subset of conditions. The delay between the onset and the completion of the action primitive is measured as T_{A_i}. The value NB_{A_i}, representing the number of times this primitive has been executed, is initialized at 1.

3) If the node corresponding to the performed primitive with the same subset of conditions is already contained in the graph (i.e., if the system has already experienced the primitive before), the delay T_{A_i} is averaged and the value NB_{A_i} is incremented.
4) If two action primitives are performed consecutively within a delay shorter than a value $T_{\max}$ (fixed at five seconds here), the corresponding action nodes $A_{h(n-1)}$ and $A_{i(n)}$ are connected by a directed edge $E_{Ah \to A_i}$. The value $\mathrm{NB}_{A_i \to A_j}$, representing the number of times A_j was executed after A_i, is initialized at 1 and incremented each time the same transition occurs. If the two action primitives are performed consecutively with a delay higher than $T_{\max}$, the newly performed primitive is considered as part of another action. Therefore, the action node is not connected by any edge.

By performing these learning operations multiple times with different objects and for all action primitives in the system's repertoire, the system becomes able to perform action prediction, which is explained in more details below.

2) Action Prediction: Based on the experience represented in the action graph, the system calculates the probability of observing a primitive $A_{j(n+1)}$ when a node $A_{i(n)}$ is activated. $A_{i(n)}$ can either be activated when the system is executing the action primitive or when it is observing another individual performing the same primitive. This probability is represented by the conditional probabilities $P(A_{j(n+1)} = 1|A_{i(n)})$, which is calculated as follows:

$$P(A_{j(n+1)} = 1|A_{i(n)}) = \frac{\mathrm{NB}_{A_i \to A_j}}{\mathrm{NB}_{A_i}} \quad (2)$$

where NB_{A_i} represents the number of times the primitive A_i was previously executed by the system, and $\mathrm{NB}_{A_i \to A_j}$ represents the number of times A_j was performed after A_i. The sum of the probabilities for a given current state $A_{i(n)}$ respects

$$\sum_j P(A_{j(n+1)} = 1|A_{i(n)}) = 1. \quad (3)$$

The system then tries to find the most likely future action node $\hat{A}_{(n+1)}$. To that end, the system detects the node $A_{j(n+1)}$ with the highest probability $P(A_{j(n+1)} = 1|A_{i(n)})$ and that can be activated. Indeed, if the value of at least one of its conditions $C_k \in \mathbf{C}_{A_{j(n+1)}}$ is 0, the corresponding primitive $A_{j(n+1)}$ cannot be activated. Therefore, the future primitive $\hat{A}_{(n+1)}$ is

$$\hat{A}_{(n+1)} = \arg\max_{A_{j(n+1)}} (\min(\mathbf{C}_{A_{j(n+1)}}) \cdot (P(A_{j(n+1)} = 1|A_{i(n)})); \forall j. \quad (4)$$

If two or more nodes have the same conditional probability and if all their corresponding condition nodes are activated, $\hat{A}_{(n+1)}$ is randomly selected among these nodes. If $\hat{A}_{(n+1)} = 0$, the system remains idle and no future action is selected.

C. Estimation of Prediction-Error Module

To estimate PE when $\hat{A}_{(n+1)}$ is predicted, two main components are taken into account:

1) the conditional probability of $\hat{A}_{(n+1)}$, which is hereafter noted P_{Max};
2) the difference between the delay T_{A_i} and the elapsed time (called t_e) since the current node $A_{i(n)}$ was activated.

PE is then measured as P_{Max} discounted by a time dependent function as follows:

$$\mathrm{PE} = P_{\mathrm{Max}} \cdot \beta \cdot (1 - e^{(T_{A_i} - t_e)}) \quad (5)$$

where $\beta = 0$ when $T_{A_i} \geq t_e$; else $\beta = 1$. β fixes $\mathrm{PE} = 0$ when the elapsed time is shorter than the average delay T_{A_i} of the observed action $A_{i(n)}$. Therefore PE starts to increase only as t_e becomes greater than $T_{A_{i(n)}}$. An example of PE estimation is depicted in Fig. 3 where a primitive is observed but not completed, leading to an increase of PE. PE is defined such as its value increases if a predicted action is not achieved within a certain amount of time. This definition is based on psychological and neuroscience observations, and is simplified to fit our experimental conditions.

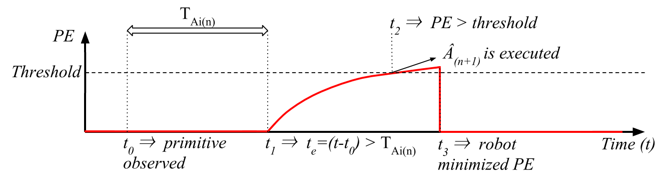

Fig. 3. Example of PE estimation. The system observes a primitive $A_{i(n)}$ and can predict the next action primitive $\hat{A}_{(n+1)}$. When the elapsed time becomes greater than T_{A_i}, PE starts increasing. Finally, when PE passes the threshold, the robot performs the predicted primitive to minimize PE.

D. Minimization of Prediction Error Module

The minimization of PE module generates actions to minimize PE. We hypothesize that observing others' failure in action execution would lead to the robot performing the predicted action primitive. If PE is greater than a threshold (empirically fixed at 60% of P_{Max} in our current experiments), the PE minimization module executes the predicted primitive $\hat{A}_{(n+1)}$ as an output of the system (see Fig. 3). For example, when the system observes another individual trying and subsequently failing to achieve an action (e.g., opening a Closed Box), the minimization of PE will lead to the robot executing the predicted action (e.g., the robot opening the Closed Box). From the point of view of the other individual, this process looks as if the robot helped the person even though it does not have such an intention. We suggest that primal altruistic behaviors emerge through the minimization of PE.

III. Experiment 1: Simulation

The first experiment aimed to validate our hypothesis and to show that the minimization of PE could be used as behavioral motivation to help others. Further, this experiment analyzed the effects of our system's experiences on the estimation of PE. We decided to use a fully simulated environment to remove any noise coming from the scene recognition module and focus on studying the relevance of the action prediction, PE estimation, and PE minimization modules. The scene recognition used instead symbolic representations of actions and conditions. In the following sections, we present the detailed procedure of our experiment, the results, and a short discussion.

A. Experimental Procedure

The experiment was separated in two phases: the training phase, during which the robot trained its sensory-motor representation by performing series of actions; and the observation phase, during which the robot observed others' actions and tried to minimize PE. The actions used during our experiment were inspired by the experiments performed by Warneken and Tomassello [36], [37] in which they showed that infants could help others trying to reach out-of-reach objects or overcome obstacles (e.g., out-of-reached cloth pins, and closed cabinet doors).

During the training phase, the system created an action graph, as presented in Section II-B1. We trained the system with several actions in a randomized order. During the observation phase, a series of nonaccomplished actions was presented to the system, during which PE was estimated. In order to study the effects of the system's action experiences on its ability to estimate PE, the amount of experience given to the system during the training was varied, from the execution of one action to that of all the possible actions. We describe the actions used in our experiment and the two phases of the experiment below.

TABLE I
Experiment 1: Six Actions the System Experienced

	Actions
Act1	Reach for a Ball and a Mug, Grasp the Ball, Open a Closed Box and Put the Ball in the Opened Box
Act2	Reach for a Ball and a Mug, Grasp the Ball and Put the Ball in an Opened Box
Act3	Reach for a Ball and a Mug, Grasp the Mug, Open the Closed Closet and Put the Mug in the Opened Closet
Act4	Reach for a Ball and a Mug, Grasp the Mug and Put the Mug in an Opened Closet
Act5	Reach for a Car and Move the Car
Act6	Reach for a Switch and Flip the Switch

TABLE II
Experiment 1: List of Others' Failed Actions. The Primitive Intended by Others Are Not Achieved

ID	Performed primitives	Other's intended primitive
F1	Reach for Ball	Grasp Ball
F2	Reach for Mug	Grasp Mug
F3	Reach for Ball and Mug	Grasp Ball
F4	Reach for Mug, Grasp Mug	Open Closed Closet
F5	Reach for Ball, Grasp Ball	Open Closed Box
F6	Reach for Car	Move Car
F7	Reach for Switch	Flip Switch

1) Actions: For this experiment, the system could experience six actions (Act1 to Act6) that are combinations of eight different objects (*Ball*, *Mug*, *Car, Switch, Opened Closet, Closed Closet, Opened Box*, and *Closed Box*) and six different action primitives (*Reach for, Grasp, Open, Put, Move*, and *Flip*). The actions the system experienced are described in Table I. Act1 to Act4 contain *Reach for* a *Ball* **and** a *Mug* because both objects are present in the environment. As we assume that our system cannot identify which of the *Ball* or the *Mug* is the target due to perception ambiguity caused by their close positions, both objects are conditions for the *Reach for* primitive.

2) Training and Observation Phases: During the training phase, the robot experienced up to six different actions. All action primitives were correctly performed. The actions were designed so that the number of children and parents for the different action nodes varies. In some cases, action nodes only had one child and parent node; for instance in Act5, *Reach for a Car* could only be followed by *Move the Car*. In contract, some action nodes had several parent or child nodes; for instance in Act1 to Act4, *Reach for a Ball and a Mug* could be followed by *Grasp the Ball* or *Grasp the Mug*. Fig. 4 shows an example of an action graph built after performing all the actions presented in Table I.

During the observation phase, other individuals performed seven uncompleted actions (F1–F7) listed in Table II. The action primitives and objects used in actions F1–F7 were the

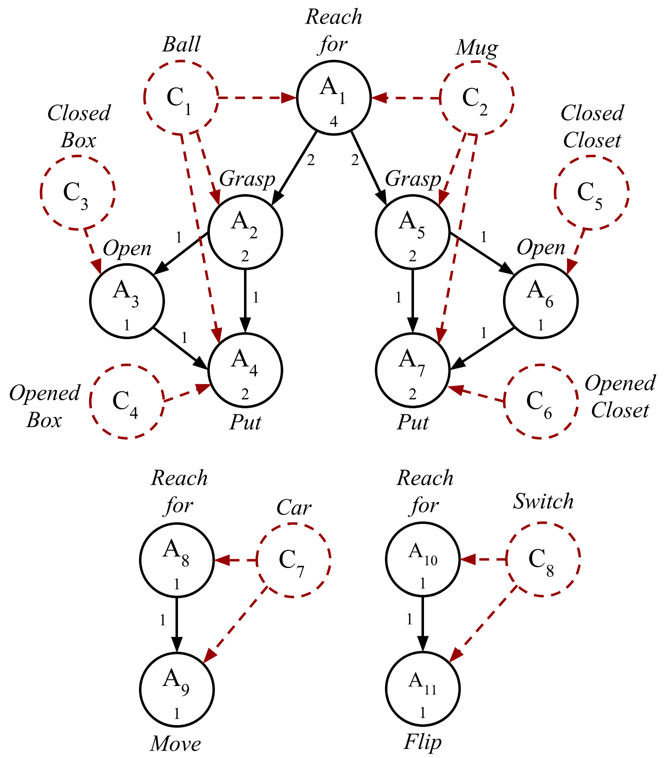

Fig. 4. Experiment 1: example of action graphs for all possible actions Act1 to Act6 executed once. The red nodes denote conditions, and the black nodes represent actions. The numbers inside the action nodes denote the number of times the primitives were executed.

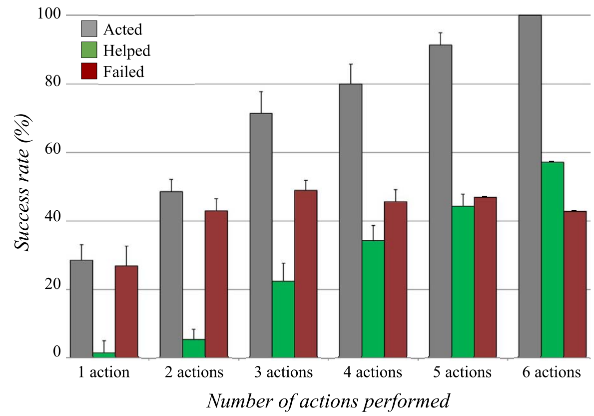

Fig. 5. Experiment 1: column plot representing our system's *Acted*, *Helped*, and *Failed* performances. The error bars represent the standard deviations.

same as those used during the training. These actions could be uncompleted for two reasons.

1) *Out-of-Reach:* Other individuals may fail to reach for an object if it is too far from them. In this case, the next primitives predicted after *Reach for* (e.g., *Grasp*) cannot be observed (activated).
2) *Physical Obstacle:* Other individuals may fail to use or interact with an object because of a physical constraint (e.g., cannot open a box if the hands are occupied with balls).

When observing others' actions, our system tried to predict the most likely next action primitives. Because some action nodes had several child nodes, the prediction could be ambiguous. For instance, if F3 was observed and if our system had previously experienced Act1 and Act3, both the primitive *Grasp the Ball* and *Grasp the Mug* could be predicted. This is later called prediction ambiguity.

B. Results

We trained our system for six different conditions, each with a different number of actions performed during the training. The number of actions performed was incremented from one in the first condition, to six in the last. During the training the order of action execution was randomized. We then tested our system for seven different tasks in which another individual performed uncompleted actions. For each trial, we observed whether the system could successfully produce an action to minimize PE (hereafter denoted as *Acted*). If the *Acted* primitive could help others in achieving their goals it was denoted as *Helped*. If it did not help achieving the goal, the action was categorized as *Failed*. In other words, a *Failed* primitive is a behavior that successfully minimized PE estimated by the system, but was not helpful from the other's point of view. The *Failed* cases were caused by different phenomena.

1) *Recognition Ambiguity:* If multiple objects are located close to each other and are associated with a same action primitive, which is currently activated, the system cannot identify the target object of the ongoing action.
2) *Prediction Ambiguity:* If multiple action primitives are experienced after a same action primitive (i.e., single parent node connected to multiple child nodes), the system cannot predict accurately which action primitive should be executed next.
3) *Perspective Difference:* The action primitive performed by the robot cannot always help others in accomplishing their intended behavior due to the perspective difference between the robot and others. For instance, when others intend to *Grasp a Mug*, the robot performs the action primitive *Grasp the Mug* after observing *Reach for the Mug* to minimize PE. This resulted in the *Mug* in the robot's hand, but not in others' hand.

Fig. 5 shows the *Acted*, *Helped*, and *Failed* performances of our system as a function of the number of actions experienced. The sum of *Helped* and *Failed* values represent 100% of the *Acted* value (*Acted* = *Helped* + *Failed*). The results show that the performance of our system improved as the number of actions experienced increases. The *Helped* value got higher than the chance level (16.67%) after experiencing three different actions. Some actions could be generalized better than others as shown by the *Acted* values and the standard deviations. Indeed, if only Act6 (see Table I) is experienced, only actions involving the Switch can be recognized, but if only Act1 is experienced, our system can make predictions for all actions involving the *Mug* or the *Ball*.

C. Discussion of Experiment 1

Our first experiment showed that the minimization of PE could possibly explain the motivation for infants to help others

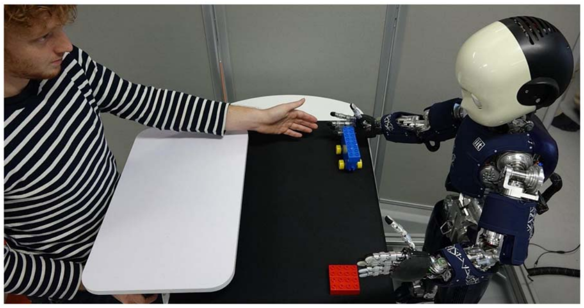

Fig. 6. Experiment 2: setting. The blue *Car* is shown on the right of the robot, and the red Marker is presented on the left of the robot.

achieve unsuccessful actions. Furthermore, we demonstrated that being able to recognize and to predict future action primitives is required to estimate PE, which is consistent with evidences presented in Section I.

In most cases, executing the predicted future action primitives could help others achieve their actions. However, it happened that even though PE was minimized, the robot's actions could not help others. As mentioned in Section III-B, we observed three scenarios that could explain why our system failed to help others: 1) recognition ambiguity; 2) prediction ambiguity; and 3) perspective difference. The ambiguity errors can be explained by the lack of training and generalization of our model. On the other hand, the perspective taking issues are more challenging to address and bring additional questions. Indeed, infants seem to rarely get affected by any sort of perspective between them and the individual they are helping [35]. The mechanism allowing infants to cope with perspective differences is not clear. Several possible solutions to this problem will be presented in the general discussion.

IV. Experiment 2: Humanoid Robot

The second experiment was designed to demonstrate whether our system could exhibit similar altruistic behavior in a more complex and noisy environment. Indeed, the experiment was conducted in a real environment with human participants who behave differently one to another and may cause perception errors. We additionally introduced and tested the scene recognition module using camera images, which was not implemented during the first experiment. The following sections present the system implementation, the experimental procedure followed by the results and a short discussion.

A. System Implementation

For this experiment, we used a humanoid iCub robot (see Fig. 6). This robot has 53 degrees of freedom, with seven in each arm and five in the head. The head, the right arm, and the left arm were used during our experiment.

The robotic system is presented in Fig. 6. The robot was placed 0.1 m away from a 1-m-high table on which a black mat was placed. Two objects (a toy *Car* and a Marker) were positioned on the black mat at a reachable distance from the robot's arms. The object positioned on the left was manipulated by the left arm, and conversely for the object on the

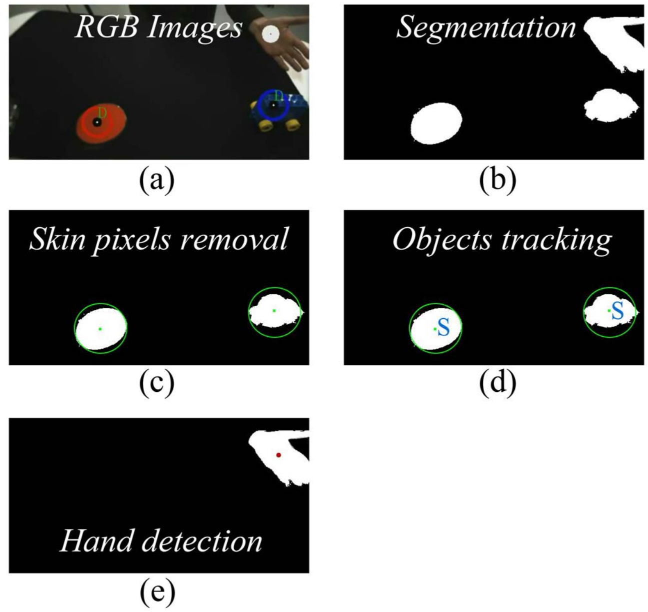

Fig. 7. Visual processing. (a) Raw image. (b) Extraction of all colors. (c) Color extraction without skin color. (d) Object tracking. (e) Hand recognition.

right. The objects had specific affordances: The car was move-able but not hide-able; the Marker was not move-able but hide-able. The robot was able to perform four action primitives: 1) *Reach From the Side*; 2) *Reach Straight*; 3) *Move*; and 4) *Hide*; the action primitives were executed using the YARP Cartesian interface [25]. The primitives were combined into two actions: 1) push (*Reach From the Side* and *Move*) and 2) cover (*Reach Straight* and *Hide*). Below, we detail the experiment specific definition of the scene recognition module and the action graph.

1) Scene Recognition Module: The scene recognition uses the RGB camera (640×480 pixels) placed in the robot left eye to detect the objects and a human hand. The objects are detected by combining pixels with similar color and (x, y) position [see Fig. 7(a) and (b)]. We use a set of predefined colors (e.g., blue or red) for the detection. The objects are then tracked based on their position and average hue [see Fig. 7 (c) and (d)] unless they are not visible for longer than two seconds. The objects are categorized into three states depending on their position history:

1) *stationary:* the object is stable in position;
2) *moving:* the distance traveled by the object during the ongoing action (no time limit) reached 50 pixels;
3) *occluded:* the object is not detected for more than 500 ms and less than 2 s.

Action primitives are recognized by looking at the relative position of the hand to the objects. The x and y coordinates of the hand in the image are detected using the predefined skin color like the object detection [see Fig. 7 (e)]. Our system can recognize two types of reaching, either *Reaching From the Side* if the hand is positioned on the side of the object in the x axis or *Reaching Straight* if the hand is aligned with the object.

2) Action Graph: For this experiment, the actions performed by the robot could result in no effect on the targeted

TABLE III
EXPERIMENT 2: LIST OF ACTION PRIMITIVES, OBJECTS, AND STATUS OF THEIR MEMORIZATION IN THE ACTION GRAPH

Action primitives	Objects	Status
"Reach from the side for" & "move"	Car	Memorized
"Reach from the side for" & "move"	Marker	Not memorized
"Reach straight for" & "hide"	Marker	Memorized
"Reach straight for" & "hide"	Car	Not memorized

objects due to their specific affordances. To cope with this issue, series of action primitives performed by the robot and the corresponding condition nodes (objects) are memorized in the graph if and only if the performed action modifies the state of at least one object in the scene. For instance, *Reach From the Side* for the *Car* and *Move* the *Car* would lead to the car's movement, and therefore the action is memorized. In contrast, *Reach From the Side* for the Marker and *Move* the Marker would have no effect on the Marker's state, and thus the action is not memorized.

B. Experimental Procedure

The experiment was divided into ten trials with five participants, each composed of two phases: a training phase and an observation phase. The participants were chosen from our laboratory and were not familiar with this paper. The two phases are further described below.

1) Training Phase: During the training phase, the robot interacted with the objects presented in front of it. The robot was instructed to either push or cover the objects on the left or right side on the table. During each trial, the robot performed all the four possible actions twice in a random order.

2) Observation Phase: During the observation phase, the robot was placed in front of an participant and observed his behavior. When the participant performed an action primitive with an object, the node corresponding to the primitive in the action graph was activated. The action prediction module then predicted the next primitive to be executed. If the participant failed in achieving the predicted action primitive within a certain time, PE started to increase. If PE exceeded a fixed threshold, a trigger signal was sent to the minimization of PE module, which executed the predicted action primitive in order to minimize PE.

C. Results

The results gathered during the training and the observation phases for the ten trials are presented below.

1) Training Phase: The *Car* and the Marker were randomly placed either on the left or the right side of the mat on the table. During each trial, the robot performed all the actions presented in Table III twice in a random order. Fig. 8 shows the robot performing two actions learned by our system: 1) *Reach From the Side for* the *Car* and *Move* the *Car* and 2) *Reach Straight for* the Marker and *Hide* the Marker. When moving the car, the state of the car switched from stationary to moving, and when hiding the Marker, the Marker's state switched from stationary to occluded. The action graph after performing all four actions is presented in Fig. 9.

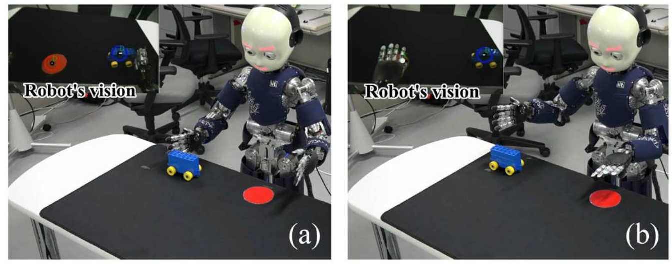

Fig. 8. Experiment 2: a scene from the robot's training. (a) Push the car. (b) Cover the marker.

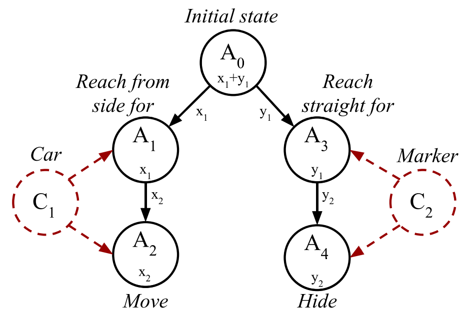

Fig. 9. Experiment 2: action graph after experiencing x times *Reach From the Side for* and *Move* the *Car*, and y times *Reach Straight for* and *Hide* the Marker.

2) Observation Phase: During the observation phase, the robot observed participants trying to push or cover either the *Car* or the Marker. All actions were performed once for each trial. Fig. 10 shows the robot's camera image capturing participants' actions and successfully estimating and minimizing PE by executing the predicted action primitives. This figure shows the following:

1) *(a1, b1):* The robot observes the participant and recognizes the action primitives: *Reach From the Side for* (a1) or *Reach Straight for* (b1). After observing these primitives, the robot predicts the future action primitives *Move* (a2) and *Hide* (b2).
2) *(a2, b2):* PE increases after our system predicts the future action primitives and the elapsed time is greater than the estimated delay.
3) *(a3, b3):* The robot performs the predicted action primitives to minimize PE, namely *Move* the *Car* (a3) and *Hide* (b3) the Marker.

After ten trials (training and observation), we measured the following:

1) *performed primitive:* the action that the participant was doing;
2) *success rate:* the amount of time the robot successfully achieved the participant's goal;
3) *PE:* the average PE at the moment of the robot's primitive onset (PE fixed threshold is 60% of the probability of the next primitive);
4) *delay:* the elapsed time between the first detection of the participant's primitive and the onset of the robot's action.

These results are summarized in Table IV.

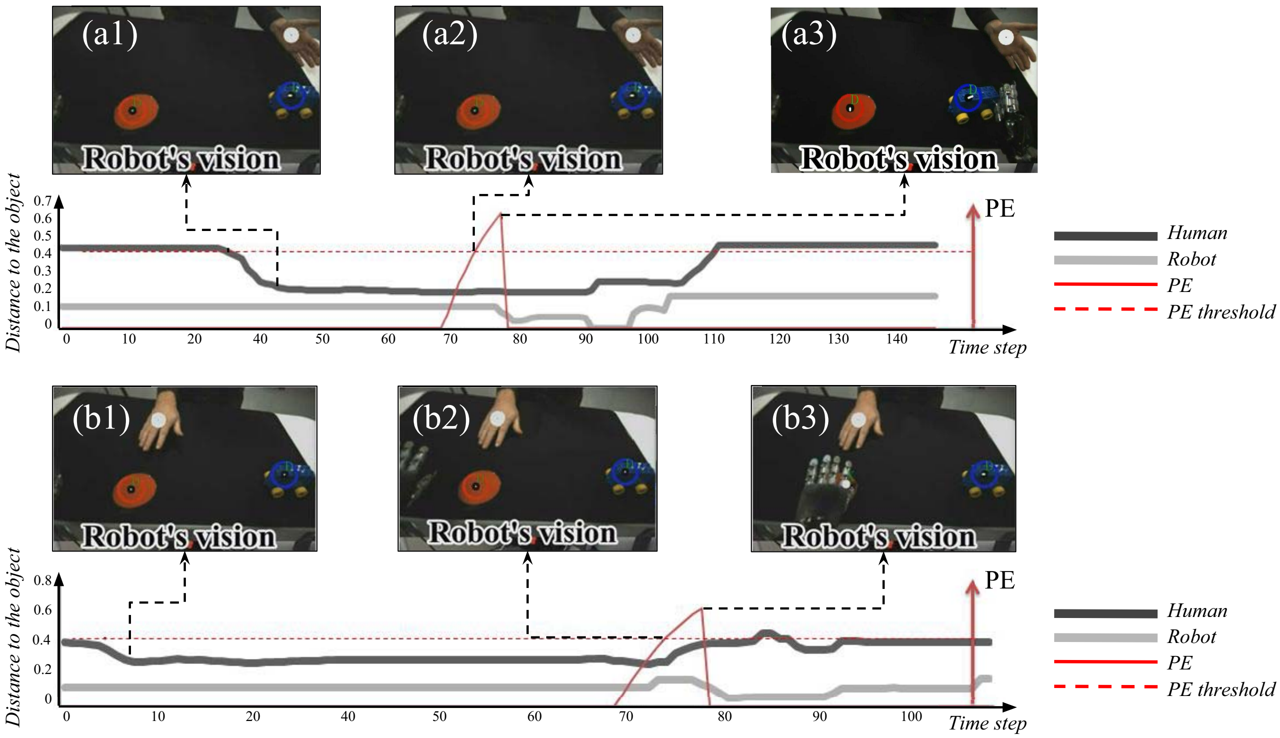

Fig. 10. Experiment 2: this figure depicts the successful cases during which the robot minimized PE after observing an unachieved action. The black and gray lines represent the distance between the human and the robot's hand to the targeted object, respectively. The red filled line denotes the estimated PE, and the dashed line indicates PE threshold above which the robot performs an action to minimize PE. Here, the robot successfully estimates and minimizes PE. (a1, b1) Participant reaches for the blue Car and the red Marker, respectively. (a2, b2) Estimated PE reaches the threshold, and the robot starts its action to try minimizing PE. (a3, b3) Robot's action successfully minimizes PE.

TABLE IV
EXPERIMENT 2: EXPERIMENTAL RESULTS. PERFORMED PRIMITIVE: PRIMITIVE PERFORMED BY THE PARTICIPANTS. SUCCESS RATE: PERCENTAGE OF TIMES THE ROBOT SUCCESSFULLY HELPED ACHIEVING AN ACTION. PE: AVERAGE MAXIMUM PREDICTION ERROR MEASURED BEFORE PE MINIMIZATION. DELAY: TIME BETWEEN THE RECOGNITION OF PARTICIPANT'S PRIMITIVE AND THE ONSET OF THE ROBOT'S ACTION. THE STANDARD DEVIATION IS CALCULATED FOR THE TEN TRIALS

Performed primitive	Success rate	PE	Delay(seconds)
"Reach from the side for" the Car	80%	0.265173 (SD: 0.00063)	5.12149 (SD: 0.25)
"Reach straight for" the Marker	100%	0.266002 (SD: 0.00127)	5.19768 (SD: 0.40)
"Reach from the side for" the Marker	0%	0.0 (SD: 0.0)	0.0 (SD: 0.0)
"Reach straight for" the Car	0%	0.0 (SD: 0.0)	0.0 (SD: 0.0)

The results show that the robot could reliably achieve the predicted goals of the participants (success rate: 80% and 100%) within a relatively short five seconds delay (SD = 0.25 and SD = 0.40). This was only true if the observed actions were previously experienced and had visible effects on the associated objects during the training. It shows that the system could cope with the noisy scene recognition and generate actions to minimize PE. In fact, the robot failed once because the participant removed his hand while PE was getting greater than the threshold and tried to performed another action, leading to the robot performing the previous action.

D. Discussion of Experiment 2

The second experiment intended to show if our system could also exhibit altruistic behavior in more complex and noisy environment while interacting with real participants. These new conditions led to variable interaction patterns with the robot. For instance, when asked to try reaching for an object, some participants repeated several times the same primitives to try enacting the robot's action. In contrast, other participants maintained their hand in the same position. These different behaviors generated multiple PE estimation dynamics throughout the experiment. Even with these new challenges, the robot succeeded in helping others achieve their actions by minimizing PE. The results support our hypothesis that the minimization of PE can be used as a behavioral motivation to help others. Finally, we believe that similar results can be expected even with more actions and more objects as long as the system can experience all the actions.

V. GENERAL DISCUSSION

The emergence of altruistic behavior in infants from 14 months of age is one of the key milestones of their prosocial development. In past decades, several theories, such as the emotional-sharing models and the goal-alignment models, have been proposed to explain the evolution of altruistic tendencies, but few of them clearly described the motivations and mechanisms allowing infants to help others. In this paper, we attempted to explain the emergence of altruistic behavior in infants by proposing PE minimization as a behavioral motivation. It can be argued that PE minimization is not the only possible motivation for early altruism, (see Sections I-A and I-B; [26]), but because of the generality and central role of PE in the brain (see [13], [22]), we chose to mainly focus on this mechanism. To then demonstrate our hypothesis, we conducted two experiments to examine to what extent PE minimization could provide a possible motivation for the helping behavior.

Our first experiment analyzed the effect of the system's own action experiences on the recognition and the prediction of others' actions. We showed that in order to recognize others' actions, the robot must experience similar behavior beforehand. Then, as our system was unable to clearly differentiate actions it performed and those performed by others, it executed an action to reach the predicted goal when observing others failing in achieving their goal. The behavior generated by our system was, in some aspects, similar to the comportment observed in infants in Warneken and Tomassello's [36], [37] experiments. Indeed, their experimental results showed that 14-month-old infants are good in helping "out-of-reach" actions, where the others' goals are easy to predict, whereas only older infants could help in more complex and nontransparent situations. Based on these evidences, our general claim is that the ability to help others is strongly dependent on the robot's (or infant) experience with the involved actions. Therefore, as the robot (or infant) acquires more experience through the interaction with its environment, more extensive helping behaviors will emerge.

In the second experiment, we integrated our model into the iCub robot and showed that the robot could also generate altruistic behavior. This result was not evident as the second experiment with human participants brought a whole new spectrum of challenges. Indeed, due to human variable interaction patterns with the robot, the estimated PE was not always stable and could have led to lower success rate. In addition, using the robot's camera images added noise to the detection of objects and others' action. Even with these new challenges, the robot succeeded in generating action to help others in achieving their actions. The results once more showed that the minimization of PE could explain the emergence of altruistic behavior.

Thanks to these two experiments, we confirmed our hypothesis and proved that minimizing PE is a possible behavior motivation to account for the emergence of altruistic behavior. Such results can greatly contribute to the understanding of the development of pro-social tendencies in infants, but also help the creation of more social robots that can be used in our household and in industry.

Despite these promising results, our experiments also showed that the actions performed by our system to minimize PE were not always able to efficiently help others in accomplishing their actions. Indeed, the prediction of the future action primitive was sometimes incorrect, leading to the robot's inappropriate responses, or the prediction was correct but the robot's action failed to help others achieving their goal. An issue is that, due to the lack of self-other differentiation in our system, the robot does not take others' perspective and executes the predicted action primitive to minimize PE and achieve its own goal, regardless of whether it helped the other achieving his goal. Some literatures show that infants at 14- or 18-month-old are actually able to help others even when the perspective difference should affect their behavior (i.e., handing over an out-of-reach object instead of keeping it) [35], [37]. In fact, infants may change their visual perspective while observing others performing actions. This cognitive ability is noted by Tomassello *et al.* [34] as a sociocognitive need for infants' altruistic behavior. Moll and Tomassello [21] showed that 24-month-old infants required the perspective-taking ability in order to help others achieve unsuccessful goal-directed actions. However, self-other differentiation, which is needed to perform such perspective-taking, is not yet acquired by 14-month-old infants [21]. Another possible solution, which does not need change in perspective, is to estimate PE in terms of states and not in terms of actions. Instead of predicting the future action primitive, our system will predict the impact of the observed action on the environment, and minimizing PE would mean achieving the predicted state. Some researches indeed showed that infants first perform actions that help in achieving the goal rather than imitating the means of an action with no predictable goal [8], [24]. Furthermore, it is strongly suggested that infants, from the age of 3–5 months, can represent actions in terms of goals, independent of the spatio-temporal properties of the target [33], which supports the idea of employing state prediction over action prediction.

To find out how infants can help others in perspective dependent situation, our future work will focus on demonstrating if and how the perception and the prediction of the environmental states instead of others' actions can improve the helping performances of our robotic system. Also, we will examine the effect of visual perspective taking, emerging in the second year of life in infants, on the emergence of altruistic behavior in our robot.

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