Prediction Error Minimization for Emergence of Altruistic Behavior

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***Abstract*—Young infants have been shown to help others even in novel situations where no rewards are given or expected. One interpretation is that this altruistic behavior is motivated by an early form of empathy. On the other hand, infants have also been demonstrated to help nonhuman entities, which implies that another source of motivation may trigger an infant's altruism. In both cases, understanding others' intentions and predicting their future goals appear to be necessary for the infant to perform such behavior. In this study, we attempted to find the minimal cognitive abilities and possible behavioral motivations for infants to behave altruistically. Our hypothesis was that infants understand and predict others' behavior and then help them to minimize the prediction error (PE) they estimate for others' action goals. To verify this hypothesis, we designed a computational model for the emergence of altruistic behavior and performed two experiments in order to determine the minimal cognitive abilities required to estimate the PE and demonstrate that PE minimization is a possible motivation for altruistic behavior. Our experimental results showed that the ability to recognize and predict others' actions is indeed required to generate a PE and that its minimization can motivate altruistic behavior without any given or expected rewards.**

I. INTRODUCTION

Why do we help each other? What is the motivation that makes us help others in various situations? These questions have been debated by scientists in different disciplines, and hypotheses have been made. Three of the main theories are as follows (for a more detailed review, see [1]):

1) Selfish altruism: We help others to get an immediate benefit [2]. For instance, if a fruit is inaccessible to an individual alone, helping each other and sharing the fruit will procure a direct food reward for both individuals.
2) Kin (familial group, relatives) altruism: This theory was first been established by Darwin [3] and updated by Hamilton et al. [4]. According to them, "natural selection could encourage altruistic behavior among kin so as to improve the reproductive potential of the family."
3) Reciprocal altruism: Trivers et al. [5] hypothesized that we help others at an immediate cost but for a predicted higher reward in the future.

These three theories account for the origin of human adults' altruism. However, to find the underlying mechanisms for the emergence of altruistic behavior, evidence of infant altruism should be analyzed as well.

A. *Evidence in young infants*

Like adults, infants may help others in an altruistic manner when others fail to achieve their goals, even in novel situations where no rewards are received or expected by the infants [8]. Such behavior, which benefit others without any evident rewards to the infants, have been widely observed in human and non-human animals. Darwin [3] and Robert et al. [4] postulated that these altruistic behavior could have been acquired through natural selection. However, the above theories and current knowledge do not fully explain the emergence of such altruistic behavior. To unravel the underlying mechanisms of these early helping tendencies, studies on infants' altruistic behavior must be carefully reviewed, and a more general theory must be formulated.

Even though infants' altruistic behavior has been scientifically observed for several decades and is a well-addressed topic in developmental science, the underlying mechanisms for their emergence are still not well understood. For instance, Warneken and Tomassello [6]–[8] performed a series of experiments on 14-month-old and 18–24-month-old children in order to demonstrate the infants' tendency to help others in novel situations where no rewards are given or expected. Their results showed that even infants from 14 months of age were able to altruistically help others in simple cases (e.g., "out-of-reach objects" but not "wrong mean, wrong end"). Warneken and Tomassello postulated that, from 14 months of age, infants can help others by predicting their goals and understanding their directed motion (e.g., stretching the arm toward an object to grasp it). However, the motivation behind the emergence of such behavior remains unclear.

Tomassello et al. [9] suggested that, in order to help others in novel situations, infants must "acquire socio-cognitive abilities to represent others' goal, visual perspective-taking and imitation." Indeed, infants from 14 months of age already have the ability to predict reaching actions [10], [11] and detect anomalies in action sequences [12]. These studies theorized that infants help others thanks to an early form of empathy toward their adult conspecifics [7], [8], but this hypothesis cannot explain all aspects of altruism. Recent experiments have shown that 18-month-old infants can help spherical objects with no human-like body to achieve their goal, which may imply that empathy elicited by direct body matching does not apply here [14]. The authors postulated that altruistic behavior may be "primed by the unfulfilled goal." These findings seem to imply that other motivation mechanisms apart from empathy are involved in the emergence of infants' altruistic behavior. Furthermore, some autistic children, who are known to have varying deficits in forming empathetic connections with others, have also been shown to help others (e.g., out-of-reach situations) almost as effectively as normally developed children [13].

B. Our hypothesis: prediction error minimization

Our hypothesis is that young infants help others to minimize the prediction error (PE) they estimate for others' action goals. This assumption is based on studies showing that the PE is triggered in the brain as a teaching signal [15] and that the PE produces "strong motivation urges that are not justified by any memories of previous reward values" [16].

To verify this original idea and determine the motivation behind infants' altruistic behavior, we first studied the role of PE minimization as a behavioral motivation in young infants. Then, we designed a simple system that mimics the development of behavior in infants and is based on well-established studies and computational models of the brain (e.g., [17]–[19]). The system tries to reproduce the mechanisms for the emergence of altruistic behavior in young infants by reproducing infants' known cognitive abilities and motor skills and minimizing the PE to generate a motivation signal. We attempted to verify our hypothesis by identifying the cognitive abilities required by young infants to estimate the PE and by showing that PE minimization is a possible motivation for altruistic behavior. The rest of this article is organized as follows. First, we present our model for the emergence of altruistic behavior. Then, we discuss our experiments and the obtained results before concluding with the implications of our results toward the understanding of the emergence of altruistic behavior.

II. Model for emergence of altruistic behavior

Fig. 1 shows the design of our model for the emergence of altruistic behavior, which consists of four interdependent modules: recognition, prediction, PE, and action. These modules represent the ability to recognize others' action primitives and their context (e.g., objects near other individuals, the state of an object), to predict others' next action primitives and their goals, to generate a motivation signal (i.e., PE), and to generate behavior that minimizes the PE, respectively. The four modules share and use the knowledge of the system's past experiences, which are represented by a statistical action tree. Details about the modules and tree are explained in the following subsections.

A. Statistical action tree

In order to memorize the system's past experience, we created a statistical action tree based on a model developed by Doya et al. [22]. The statistical action tree is made of nodes $\mathbf{S}$ that represent all of the previously observed actions. These nodes can be of two types: the action nodes $\mathbf{A}$ represent action primitives, and the condition nodes $\mathbf{C}$ represent the context of the action primitives. The nodes are Boolean variables and can take a value of 1 (active) or 0 (inactive).

$$\mathbf{S} = \{\mathbf{A} \cup \mathbf{C}\}, \tag{1}$$

$$\mathbf{A} = \{A_1, A_2, ..., A_i\} \text{ and } \mathbf{C} = \{C_1, C_2, ..., C_j\}. \tag{2}$$

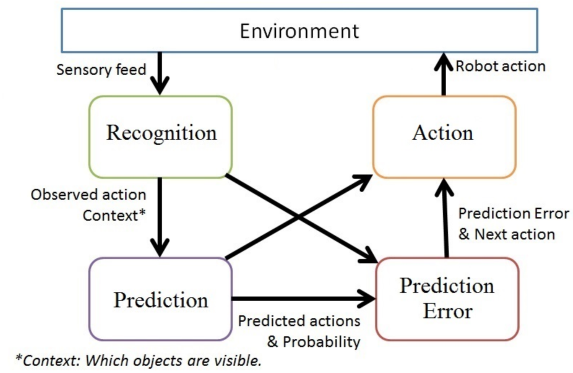

Figure 1. Model for emergence of altruistic behavior. The four modules share and use the knowledge of the system's past experiences through a tree structure built from the observation of others' actions.

Fig. 2 shows an example action tree for two observed actions: "*Reach* for the *Ball* and *Take* it, and then *Throw* the *Ball*" and "*Reach* for the *Ball* and *Take* it, and then *Open* the *Box* and *Put* the *Ball* inside the *Box*." In this example, $\mathbf{A} = \{A_1, A_2, A_3, A_4, A_5\}$ and $\mathbf{C} = \{C_1, C_2\}$. A_2 is the child node of A_1, while A_1 is the parent node of A_2.

The action node corresponding to the observed action primitive is denoted as $A_{i(n)} \in \mathbf{A}$, and the condition nodes representing its context are contained in the subset $\mathbf{C}_{Ai(n)} \subset \mathbf{C}$. n represents the current discrete time step of the system. In Fig. 2, for instance, the action primitive "*Put* the *Ball* inside the *Box*" is described by the action node "*Put*" ($A_{5(n)}$) and the condition nodes "*Ball*" and "*Box*," which are contained in $\mathbf{C}_{A5(n)} = \{C_1, C_2\}$.

The statistical action tree is built and updated when the system observes actions[1] performed by others. The action tree construction is ruled by different mechanisms. When a new action primitive is observed, the action node $A_{i(n)}$ is added to the action tree and is connected to the corresponding condition nodes $\mathbf{C}_{Ai(n)}$. If some of the condition nodes are not included in the action tree, they are added. The average duration of the action primitives $T_{Ai(n)}$ is measured, and the number of occurrences is initialized $O_{Ai(n)} = 1$. If the observed action primitive is already contained in the tree, $T_{Ai(n)}$ is updated, and $O_{Ai(n)}$ is incremented. When an action primitive is observed after another and if the duration of the first action primitive $T_{Ai(n)}$ is lower than the value T_{max}, a new observed action node $A_{i(n)}$ is connected with the previously observed action primitive $A_{h(n-1)}$ by the directed arrow $N_{h,i} = \{A_{h(n-1)}, A_{i(n)}\}$. However, if $T_{Ai(n)} > T_{max}$, the system assumes that it has observed a new action and thus

[1]Hereafter, the term "action" refers to a sequence of action primitives.

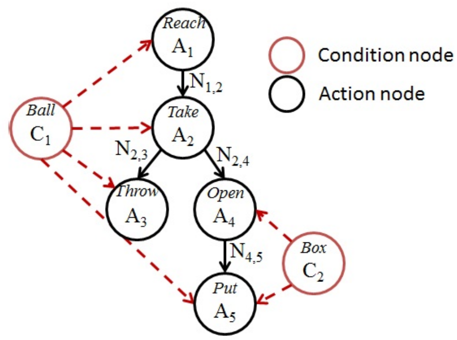

Figure 2. Example of statistical action tree created after observation of the sequence of action primitives: "Reach for the ball and take it, then throw the ball" and "Reach for the ball and take it, then open the box and put the ball inside the box."

applies the same mechanism as if the new action primitive was independently observed.

B. Recognition module

This module recognizes the action primitives and the contextual information from a currently observed action. These two kinds of information are sent to the statistical action tree (see Section II-A) and are compared with the action nodes $A_{i(n)}$ and context nodes $C_{Ai(n)}$. When a certain action primitive and context are recognized, $A_{i(n)} = 1$ and $C_j = 1; \forall C_j \in \mathbf{C}_{Ai(n)}$. In the current experiment, we used symbolic representations of actions and contexts; thus, the system did not need to extract these kinds of information from the image.

C. Prediction module

The prediction module tries to predict the next action primitive to be executed by others based on the last observed action primitive and the knowledge contained in the statistical action tree. This module calculates the probability of a child action node $A_{l(n+1)}$ to be activated knowing the observed action $A_{i(n)}$ and conditions for the next action $\mathbf{C}_{Al(n+1)}$:

$$P(A_{l(n+1)} = 1 | A_{i(n)}, \mathbf{C}_{Al(n+1)}). \tag{3}$$

In the system, $P(A_{l(n+1)} = 1 | A_{i(n)}, \mathbf{C}_{Al(n+1)}) = 0$ if the value of at least one of its conditions $C_j \in \mathbf{C}_{Al(n+1)}$ is 0. If $C_j = 1; \forall C_j \in \mathbf{C}_{Al(n+1)}$, then the probability of the child action node $A_{l(n+1)}$ depends only on the observed action primitive $A_{i(n)}$, as described in the following equation:

$$\begin{aligned} P(A_{l(n+1)} = 1 | A_{i(n)}, \mathbf{C}_{Al(n+1)}) &= \\ \min(\mathbf{C}_{Al(n+1)}) \cdot P(A_{l(n+1)} &= 1 | A_{i(n)}). \end{aligned} \tag{4}$$

Finally, this module predicts the future action node $A_{predict}$ with the highest probability to be activated, and its probability is denoted as $P(A_{Max(n+1)})$:

$$P(A_{Max(n+1)}) = \max(P(A_{l(n+1)} = 1 | A_{i(n)}, \mathbf{C}_{Al(n+1)})). \tag{5}$$

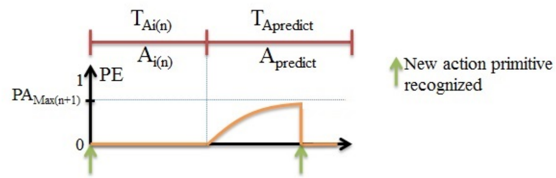

Figure 3. Example of PE generation.

D. Prediction error module

The PE module measures the PE for the most probable future action primitive $A_{predict}$ to occur. The PE depends on three main components:

1) The probability of $A_{predict}$ to be activated: $P(A_{Max(n+1)})$.
2) The number of occurrences $O_{A_{predict}}$ of $A_{predict}$.
3) The difference between the average duration $T_{Ai(n)}$ of the observed action $A_{i(n)}$ and the elapsed time (defined as t_e) since the action node $A_{i(n)}$ has been recognized.

The choice of the PE is reasoned by the fact that, if the prediction of an action primitive is not certain or if an action has only been observed a few times in the past, the PE value should not be high. In addition, the prediction should be higher if the elapsed time t_e is higher than the average duration $T_{Ai(n)}$ of the observed action $A_{i(n)}$.

Thus, the value of PE for $A_{predict}$ is given by

$$\begin{aligned} PE = \beta \cdot P(A_{Max(n+1)})(1 - e^{-O_{A_{predict}}}) \cdot \\ \cdot (1 - e^{(T_{Ai(n)} - t)}), \end{aligned} \tag{6}$$

where $\beta = 0$ when $T_{Ai(n)} \geq t$, else $\beta = 1$. β sets $PE = 0$ when the elapsed time is shorter than the average duration $T_{Ai(n)}$ of the observed action $A_{i(n)}$. The PE then increases as t becomes greater than $T_{Ai(n)}$.

Fig. 3 depicts an example of PE generation.

E. Action module

The action module generates actions to minimize PE. Based on the mirror neuron system [20], we hypothesized that observing others' failure to execute their actions activates infants' self-action as a response. Thus, if $PE > \Theta$, where Θ is a threshold empirically fixed at 0.6, the action module executes the predicted action primitive $A_{predict}$ as an output of the system.

III. Experiments

We designed experiments to examine what cognitive abilities are required by the system to estimate a high PE signal and whether a system based on PE minimization can generate altruistic behavior without any external rewards.

A. Method

The experimental method was inspired by the procedures developed by Tomassello and Warneken [6], [7], who conducted developmental studies on infants' altruistic behavior.

The system was first trained with different series of fully accomplished actions. During this training phase, the system created a statistical tree, as presented in Section II-A. Then, during the testing phase, series of non-accomplished actions were presented to the system while the PE was measured. In order to study the effects of the system's cognitive abilities (i.e., recognition and prediction) on the calculation of the PE, the amount of experience given to the system during the training was varied. The actions used for our experiments and the method to build the statistical tree are described below.

1) Actions: For our experiments, we defined fourteen actions that are combinations of eight different condition nodes (ball, book, mug, table, opened closet, closed closet, opened box, closed box) and six different action primitives (reach for, grasp, open, close, put, carry). Table I gives example actions.

	Actions
action 1	Take the ball from the table and carry it to the closed box
action 2	Take the ball from the table and carry it to the opened box
action 3	Take the ball from the table and put it in the closed closet
...	...
action 12	Take the book to the table
action 13	Take the book from the closed closet to the table
action 14	Take the book from the opened closet to the table

Table I
EXAMPLE ACTIONS

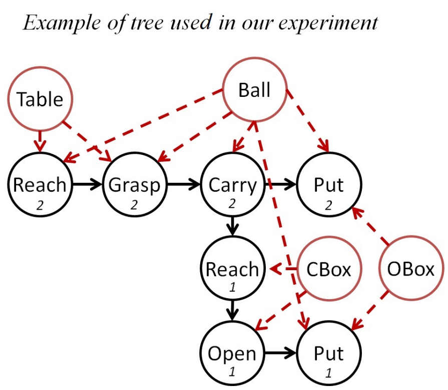

Figure 4. Example tree for action "Take the ball from the table and carry it to the closed box" executed once and action "Take the ball from the table and carry it to the opened box" executed twice. The red nodes are conditions, and the black nodes are actions. The numbers inside the action nodes are the number of times these action primitives were observed.

These actions were designed to have different difficulties of prediction. For some actions, the goals (i.e., next action primitives) were easily predicted because only one possible future node exists. For others, prediction was more difficult because there were several possible future nodes. Actions could also fail for some reasons. For example, "out-of-reach" caused a failure to reach for an object, and "physical obstacle" caused a failure to use or interact with an object because of a physical constraint (e.g., failure to open a door because of the large size of the object being carried). We expected that these failures would trigger an increase in the PE.

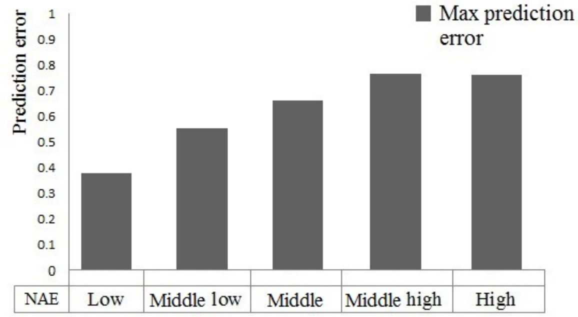

Figure 5. Average maximum value of PE after time $t = t_{MAX}$ as function of number of actions experienced (N_ae). Five levels of N_ae were used : small, small-medium, medium, large-medium, and large.

2) Action tree: As noted in Section II-A, the action tree was built by observing a sequence of actions, as presented in Table I. During the training phase, all actions were correctly performed, and each action primitive was followed by a pause of 1–2 s. The context of the actions (e.g., objects, states of objects) was also known for the action tree during the training phase. Fig. 4 shows an example action tree created by presenting action 1 once and action 2 twice (see Table I for the definitions of actions 1 and 2). The number of activations of each action primitive, which is indicated by the number in each node, was used to estimate the transition probabilities between the nodes.

B. Experiment 1: prediction error generation

1) Experiment setting: This experiment was aimed at measuring the influence of the recognition and the prediction module's efficiency on the generation of a PE. To study the efficiency of these modules, we gradually increased the number of actions used to train the system and the number of times each action was used. The number of actions used during the training and how many times each action was used are denoted as the number of actions experienced (or N_ae). The experiment was conducted several times for five different levels of N_ae, which are defined below:

Small: four observed actions once;
Small-medium: six observed actions twice;
Medium: eight observed actions twice;
Large-medium: twelve observed actions three times;
Large: fourteen observed actions four times.

2) Results: Fig. 5 depicts the maximum PE in terms of N_ae when $e^{(t_{Ai(n)}-t)} = 1$ (see Eq. 6), which is arranged from small to large. The results showed that the maximum PE was low when N_ae was small and that it increased when N_ae became larger. These results are summarized in Table II and show that the system needed to receive sufficient experience to estimate a large enough PE superior to the minimization threshold $\Theta = 0.6$.

C. Experiment 2: prediction error minimization

As we demonstrated that a PE could be generated when N_ae was large enough, the second experiment was intended to

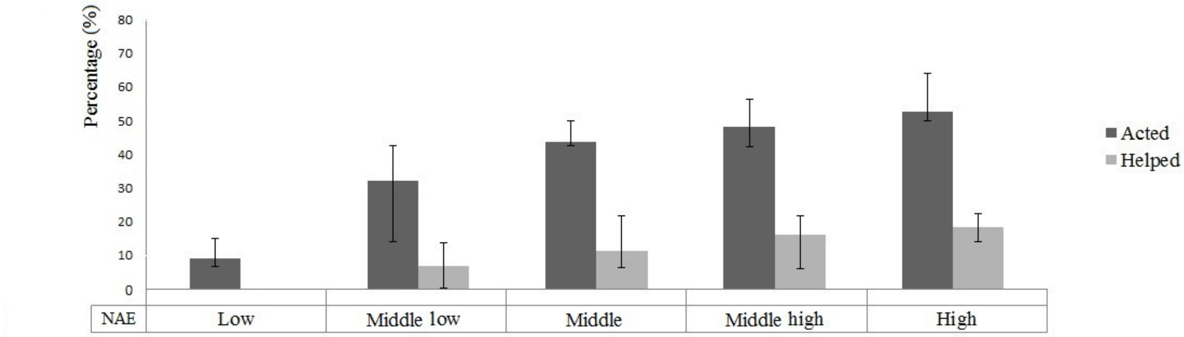

Figure 6. Percentage of times system acted and helped while observing others' unsuccessful actions as function of number of actions experienced (N_ae). The acted value means "how many times (in percentage) the system performed an action for the failed observed actions." The helped value means "the number of times (in percentage) the system succeeded at minimizing the PE for the failed observed actions." Five levels of N_ae were used: small, small-medium, medium, medium-large, and large.

N_ae	Average maximum PE	Acted	Average action delay	Helped	Wrong action	Wrong prediction
Small	0.377	9.52%	10.4s	0%	100%	0%
Small-medium	0.555	33.33%	9.7s	7.14%	60%	40%
Medium	0.6619	45.24%	6.8s	11.90%	71.43%	28.57%
Large-medium	0.7653	49.99%	4.3s	16.66%	78.58%	21.42%
High	0.7625	54.76%	3.6s	19.04%	80%	20%

Table II

RESULTS SUMMARY: MEAN VALUES OF ALL RESULTS FROM EXPERIMENTS 1 AND 2. THE DIFFERENT LEVELS FOR THE NUMBER OF ACTIONS EXPERIENCED (N_AE) ARE AS FOLLOWS. SMALL: FOUR OBSERVED ACTIONS ONE TIME, SMALL-MEDIUM: SIX OBSERVED ACTIONS TWO TIMES, MEDIUM: EIGHT OBSERVED ACTIONS TWO TIMES, LARGE-MEDIUM: 12 OBSERVED ACTIONS THREE TIMES, HIGH: 14 OBSERVED ACTIONS FOUR TIMES. THE COLUMNS FOR WRONG ACTION AND WRONG PREDICTION REPRESENT WHEN THE SYSTEM COULD NOT HELP WHEN IT ACTED.

show that PE minimization could allow the system to generate action primitives to help others.

1) Experiment setting: The setting was similar to that of experiment 1, and the tests were performed with the five same levels of N_ae in order to examine how N_ae affects the emergence of helping behavior. In this experiment, however, when PE was larger than the fixed threshold ($PE > \Theta$), the system generated the predicted action primitive. For instance, if the system predicted the next action primitive to be "open the door" and $PE > 0.6$, the system would generate the action primitive "open the door."

2) Results: Fig. 6 shows the percentage of action executions (acted) and successful help (helped) in terms of the different N_ae. The acted values are the percentage of times the system executed an action to try to minimize PE when a failed action was observed. The helped values are the percentage of times the system successfully helped and thus minimized PE when it acted. The results presented in Table II are explained below.

Small: the system rarely generated any actions (9.52%) because the PE almost never reached the threshold.

Small-medium: the system generated few actions (33.33%) and rarely succeeded at helping others (7.14%) because most of the predicted actions required helping for "out-of-reach."

Medium: the system generated actions for 45.24% of the observed actions but minimized PE for only 11.90% of the trials for similar reasons as "small-medium."

Large-medium: the system acted for 49.99% of the observed actions and efficiently helped others and minimized PE for 16.66% of the trials.

Large: the system acted for 54.76% of the observed actions and efficiently helped others and minimized PE for 19.04% of the trials.

The "acted" performance of the system was satisfactory, which means that the system could predict the future action primitive with enough certainty to reach $PE > \Theta$. However, the "helped" performance remained relatively low. Two reasons why the system failed to help may be because the best action primitive to help others was sometime different from the predicted one (76.7% of the cases) and because the prediction was incorrect and thus the executed action primitive to minimize the PE was inadequate (23.3% of the cases). With our current model, the system did not know how to efficiently help in these cases.

This experiment also showed that the system's performances improved along with N_ae. Furthermore, the actions used during the training phase and the testing phase were different, which means that the system was able to generalize its knowledge for relatively novel situations.

IV. DISCUSSION

In this study, we attempted to explain the emergence of altruistic behavior in young infants by proposing PE minimization as sufficient behavioral motivation. We conducted two experiments to verify that action recognition and prediction ability are required by young infants to estimate PE and that PE minimization is a possible motivation to account for helping behavior.

The results of the first experiment showed that being able to recognize others' actions and to predict others' goals were required to estimate a large PE. These finding were consistent with those of other developmental scientists, as presented in the introduction [6]–[8].

The results of the second experiment confirmed that PE minimization is a possible source of motivation for altruistic behavior. Indeed, the system was able to generate actions in order to minimize PE for various types of actions. However, the system was sometimes unable to efficiently help others because the best action primitive to help others was different from the predicted one or because the prediction was incorrect. In fact, the differences in perspective between the system and others may have prevented our model from executing efficient actions.

To further support our main hypothesis, the next step will be to highlight what gives infants the ability to understand which actions would help others in a given context when they cannot achieve their goals by themselves. One solution is that infants can change their visual perspective while observing others performing actions. This cognitive ability is noted by Tomassello et al. [9] as a socio-cognitive need for infants' altruistic behavior. Instead of understanding "what should I do to perform this action," infants must find "what is the best way to help others accomplish their action." Moll et al. [21] showed that 24-month-old infants required the perspective-taking ability in order to help others achieve unsuccessful goal-directed actions. Another possible solution is to measure the PE in terms of the state and not in terms of the action as we did here. Finally, the fact that action recognition and prediction may not be sufficient for the emergence of altruistic behavior suggests that infants from 14 months of age might also become able to predict the best way to help others.

V. Conclusion and Future Work

We showed that the ability to recognize and predict others' actions is required to estimate the PE and that minimizing the PE may indeed motivate altruistic behavior without any given or expected rewards.

Our experiments confirmed the hypothesis that minimizing the PE can motivate the emergence of altruistic behavior to a certain extent. However, the results also showed that the actions performed by the system to attempt to minimize the PE were not able to efficiently help others accomplish their actions when the best way to help them could not be directly predicted. Future research will be aimed at improving the system performance by integrating infants' ability to perform perspective taking while observing others executing actions and showing that this ability is required for the emergence of infants' altruistic behavior.

Acknowledgment

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References

[1] Stevens, Jeffrey R., and Marc D. Hauser. "Why be nice? Psychological constraints on the evolution of cooperation." Trends in Cognitive Sciences 8.2 (2004): 60-65.

[2] Brown, Jerram L. "Cooperation: a biologist's dilemma." Advances in the Study of Behavior 13 (1983): 1-37.

[3] Darwin, C. (1871). The Descent of Man. D. Appleton and Company.

[4] Axelrod, Robert, and William D. Hamilton. "The evolution of cooperation." Science 211.4489 (1981): 1390-1396.

[5] Trivers, R. L. (1971). The evolution of reciprocal altruism. Quarterly Review of Biology, 35-57.

[6] Warneken, Felix, and Michael Tomasello. "Helping and cooperation at 14 months of age." Infancy 11.3 (2007): 271-294.

[7] Warneken, Felix, Frances Chen, and Michael Tomasello. "Cooperative activities in young children and chimpanzees." Child Development 77.3 (2006): 640-663.

[8] Warneken, Felix, and Michael Tomasello. "Altruistic helping in human infants and young chimpanzees." Science 311.5765 (2006): 1301-1303.

[9] M. Tomasello, M. Carpenter, J. Call, T. Behne, and H. Moll, "Understanding and sharing intentions: The origins of cultural cognition," Behavioral and Brain Sciences, vol. 28, pp. 675691, 2005.

[10] Provasi, Jolle, Corine D. Dubon, and Henriette Bloch. "Do 9-and 12-month-olds learn means-ends relation by observing?." Infant Behavior and Development 24.2 (2001): 195-213.

[11] Kanakogi, Yasuhiro, and Shoji Itakura. "Developmental correspondence between action prediction and motor ability in early infancy." Nature Communications 2 (2011): 341.

[12] Baldwin, Dare A., et al. "Infants parse dynamic action." Child Development 72.3 (2001): 708-717.

[13] Liebal, Kristin, et al. "Helping and cooperation in children with autism." Journal of Autism and Developmental Disorders 38.2 (2008): 224-238.

[14] Kenward, Ben, and Gustaf Gredebck. "Infants Help a Non-Human Agent." PloS One 8.9 (2013): e75130.

[15] Schultz, Wolfram, and Anthony Dickinson. "Neuronal coding of prediction errors." Annual Review of Neuroscience 23, no. 1 (2000): 473-500.

[16] Berridge, Kent C. "From prediction error to incentive salience: mesolimbic computation of reward motivation." European Journal of Neuroscience 35, no. 7 (2012): 1124-1143.

[17] Yamashita, Yuichi, and Jun Tani. "Spontaneous prediction error generation in schizophrenia." PloS One 7.5 (2012).

[18] Haruno, Masahiko, Daniel M. Wolpert, and Mitsuo Kawato. "Mosaic model for sensorimotor learning and control." Neural Computation 13, no. 10 (2001): 2201-2220.

[19] Lalle, Stephane, et al. "Towards a platform-independent cooperative human robot interaction system: Iii an architecture for learning and executing actions and shared plans." IEEE Transactions on Autonomous Mental Development 4.3 (2012): 239-253.

[20] Rizzolatti, Giacomo, and Laila Craighero. "The mirror-neuron system." Annual Review of Neuroscience 27 (2004): 169-192.

[21] Moll, H., and Tomasello, M. (2006). Level 1 perspectivetaking at 24 months of age. British Journal of Developmental Psychology, 24(3), 603-613.

[22] Doya, Kenji, ed. Bayesian Brain: Probabilistic Approaches to Neural Coding. MIT Press, 2007.