Evolutionary Conditions for the Emergence of Robotic Theory of Mind with Multiple Goals

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***Abstract*— Theory of mind (ToM) has been recognized as one of important cognitive functions for human beings and allows us to understand/model other's mind from their facial expression, verbal conversations, and behaviors. It has been known that the functionality has been developed in the early stage of our life. Recently, there have been some works on developing automated algorithms for robotic theory of mind. Similar to human's ToM, the process collects information on other robots and infers the internal states of them using estimation-exploration algorithms (EEA). Although they're successful, they assume that the playground has only one simple target to pursue. In real-world settings, the environment has several targets giving confusion to observers. In this study, we attempt to test the robotic theory of mind in the existence of multiple goals. Experimental results show that there are some successful conditions to get the best theory of mind capability for robots with a noisy target. This study gives insight on the human's theory of mind robust to the existence of multiple goals.**

Keywords*— *Theory of Mind; Robots; Neural Network; Reverse Engineering; Goal Inference

I. Introduction

For human beings, it is one of essential virtues to communicate with each other. Given that we are intrinsically incomplete beings, thereby depending on other individuals at a lot of portion in our daily life, we need to understand the behavior and intention of others precisely. This ability, which refers to an ability to assume that others have similar mechanisms of mind and interpret their behaviors with those rules, is called 'theory of mind' (ToM) and has been intensively studied by researchers of various field [1][2][3][4].

With increasing interest for human studies related to ToM, it has been also important in the field of robotics, in that an ability to understand others' behavior is crucial for social interaction activities. Many of studies have tried to design a robot with functions of interaction and imitation. For example, researchers have shown that robot can read body movement, facial expression or gesture of human [5]. Also, it is known that robots can simulate human movement or emotional behaviors [6]. All of those investigations support that robots need human-like ToM to perform activities with social interactions.

While there have been a lot of studies that design a robot with imitating ability, it is still distant from what the animal is capable of. According to studies from cognitive psychology concerning human being and the animal, the underlying mechanism for ToM includes multistage processing, not just perceiving the movement [1][3][7]. At the beginning of the research of ToM, exact representation of the movement was underlined for action comprehension. The one of primary evidence for this hypothesis is the discovery of mirror neurons, which are the neurons fire both when the animal acts and when the animal observes the same action performed by another [8]. Although the function of mirror neurons is still a subject of speculation, many researchers in cognitive science and neuroscience believe that the capacity to imitate the observing behavior is key to understanding of that behavior, which emphasize the movement information for action comprehension.

Follow-up studies, however, demonstrated that we are experts at understanding the actions with change in environmental conditions or environmental constraints, which means that we don't rely on only movement information for action comprehension. For example, Fiorito *et al.* showed that an octopus can infer the color of the goal from watching the actor's behavior even when the location of the goal changed [9]. Also, it has been known that 6 month infants can encode the actions of other people focusing on the aspects of the actor's behavior that are relevant to his/her underlying intention [10]. Baron-Cohen suggested mind theory that also supports these results [1]. In this model, ToM mechanism has basic modules; Eye-direction detector (EDD) and Intentionality detector (ID). With the supposition the ID, this model assumes that cognitive aspect such as intention or goal is primarily processed for mind theory. In other words, all of these studies support that there exists stages that process information to infer the goal, belief, or intention for ToM.

Reverting to the robot studies, several studies have shown that robots can mimic the human's behavior or decode the intention of human or other robot. For example, Scassellati implemented the Baron-Cohen's ToM model for the humanoid robot, COG [4]. Breazeal *et al*. demonstrated that

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the animal-like robot can pass the false-belief test widely used to test ToM for young children [11]. Also, they tested simulation theory (agent tries to simulate other's behavior in his brain) with rat-like characters [12]. Kim *et al*. proposed to use the reverse engineering algorithm to reveal the internal model of other's self observing others behaviors [13][14].

In this paper, we adopt the theory of mind framework proposed by Kim *et al*. for simulated and real robots [13][14]. In the model, there are two robots named as "actor" and "observer," respectively. The actor uses a neural controller (implemented as an artificial neural network) to control his behavior from sensory information. The observer monitors the behaviors of the actor and tries to infer the internal model (neural network) of actor from the observation. The observer can use the inferred (estimated) other's self model to predict the future behavior of the actor. Instead of programming the other's internal model manually, this approach tries to learn other's self model interactively. Initially, the observer robot starts from a single actor's trajectory but it actively seduces the actor robot to show an additional trajectory which is the most useful for the learning. This process is based on the automated reverse engineering algorithm named as EEA (Estimation Exploration Algorithm) [15][16].

Although they have tried to demonstrate the possibility and usefulness of building and learning the ToM ability for the robots, they assumed that the robot has one clear goal without any distracting goals. From young children, humans start to grow his/her ToM ability and they show robust performance in the existence of uncertainty and multiple goals. In this work, we try to show the robot's ToM in the existence of multiple goals (one true goal and other distracting goals) (Figure 1).

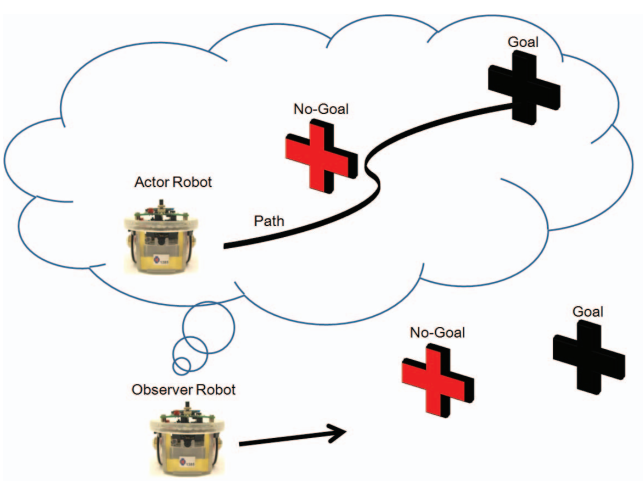

Figure 1. The observer tries to model the actor's internal model given the multiple goals (one true goal and other distracting goals). If the observer is successful to infer the actor's internal model to follow the goals, the robot can predict the actor's behavior.

In the existence of multiple goals, the robot should learn correct models that follow the "true" goal and predict actor's behavior when the position of the goals is different. In this study, we tested a number of conditions where the actual and distracting goals are placed in different positions. Human is very robust to infer the other's mind although the environment contains some distracting objects. In our experiments, we assume that there are two goals (one "true" goal and another "distracting" goal) and two robots (actor and observer). The actor robot was trained to follow the actual goal in the existence of multiple goals. The observer tries to reveal the internal minds (neural network) of actor using the reverse engineering algorithm. The purpose of the experiments is to see the difference of ToM ability of the robots in different settings of them. In the experiment, the positions of the two goals are changed to know the effect of the location of "true" and "distracting" goals.

Using the robotic theory of mind framework, we can conduct psychological experiments similar to human tests by changing experimental conditions. It can be compared to the results from human tests and sometimes, allows new experiments infeasible for humans. In the contexts of robot research, the implementation of theory of mind is important to make social robots. In this study, we attempt to go further to test the performance of the robot's theory of mind in the existence of multiple goals with different positions and distances. It is able to give important evidence to implement robust robotic theory of mind.

II. RELATED WORKS

A. ToM for Robots

Robots have been one of the important platforms to test theories on human behaviors, psychology and cognition [18]. For example, virtual agent, characters, simulated robots and real robots have been adopted for the interdisciplinary research. D. Floreano *et al*. investigated the emergence of communications using physics-based robot simulators [19] and H. Lipson *et al*. also used real robots and the physics-based robot simulator based on Open Dynamics Engine to show the robot's self modeling [16].

There have been several interesting works on the use of Theory of Mind for virtual agents, virtual character, simulated robots and real robots. Usually, there are more than two robots and their roles are one of "Actor" or "Observer." In the scenario, the observer robots infer the internal model (states) of the actor robot from the observation of the actor's behaviors. It is assumed that the internal model of the Observer is hidden to the Actor. As a result, the estimated internal model can be used to predict the behaviors of the actor. In past research, the actor's self models have been intentionally simple, typically allowing only a few discrete states.

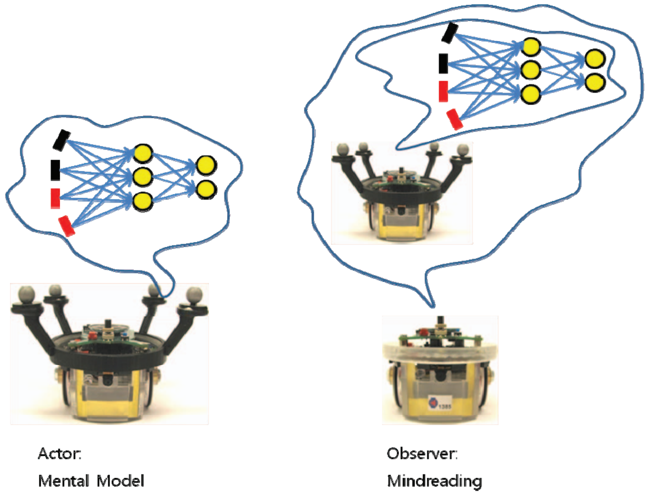

Figure 2. Neural-based theory of mind approach

B. Neural-based Theory of Mind

In this work, we followed the robotic theory of mind approach with neural networks [13][14][17]. There are lots of different definition of self and other's self representations ranging from symbolic states to complex neural models. For example, Lipson et al. [16] have used the morphological structure of robot as a self model. In that case, a robot has no vision to understand itself and attempt to construct the models of his body through iterative estimation-exploration steps. Kim et al. used a simple feed-forward network to represent other's self [13][14]. Although the (internal) neural network has only seventeen parameters, it is challenging to reconstruct other's self from the observation of behaviors. Figure 2 shows the concept of the robotic theory of mind.

In the previous works, Kim *et al*. demonstrate the possibility of the robotic theory of mind with physics-based robot simulators (PhyX) [13]. The simulation can be accelerated using specialized hardware embedded in graphic cards. In the simulation, they investigate the framework and the accuracy of the theory of mind predictions. Because the purpose of there is to test the feasibility of their approach, there is no extensive test for several issues of the theory of mind. Based on the successful results from the physics-based simulations, they apply the same framework to E-Puck robots with two wheels. Motion tracking devices are used to track the movement of the robot. Then, thousands of simulations are used to infer the internal models of the real robot. They also demonstrate the possibility of the framework with real E-Puck robot for the simple theory of mind [14].

III. Theory of Mind with Multiple Goals

In our scenario, there are two robots (Actor and Observer). Each robot is assumed to be controlled by a feed-forward neural network trained using evolutionary algorithm. Because they don't have direct access to the information on the other's controller, it is only possible to infer the model indirectly from the observation of the behaviors. In sum, the "Observer" robot monitors the behavior of the "Actor" and tries to infer the neural network (other's self). After the theory of mind process, if the model is found successfully, the "Observer" can predict the future behavior of the "Actor."

Unlike other works on the imitation of actor's behavior, the purpose of the theory of mind is to estimate the internal models of "Actor". From our experience, it is not possible to reconstruct the exact original neural network from the indirect inference but the theory of mind can provide alternatives to the original models. This is similar to the humans ToM and it is true that other's self models in our brain is not always the same to the one in their brains.

To reduce the complexity of the problem, we assume that two robots share the topology of the neural architecture. In other words, the actor and observer shares the same neural network topology but they have different connection weights to react to environments. Instead of "programming" the behaviors of the controller manually, the neural network was evolved from trial and errors in the environment. The environment has two light sources (each represent goals of the robot) illuminating different types of light. The "Actor" has special sensors dedicated to each light source.

A. The Evolution of "Actor" Neural Controller

We performed our experiments using simple wheeled robots (Figure 3) simulated with the PhysX engine (physics-based simulator). Each robot has four sensors and three wheels and detects light levels around the robot and uses them to control wheel velocities. The front wheel controls the direction of the robot and the remaining two wheels in the rear are for speed. An innate neural network processes the sensor inputs and generates outputs (wheel speed and/or steering angle). It has 23 connection weights including bias.

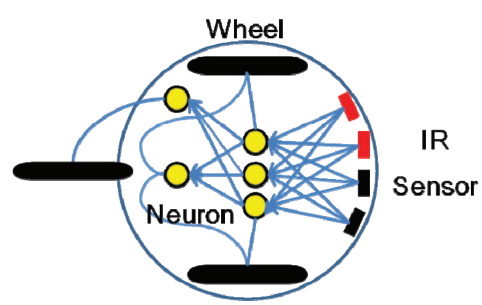

Figure 3. A virtual robot and the neural controller

The first robot (the *Actor*) learns to move towards light source (the Goal) by evolving an "innate" NN. However, there are also inputs from another light source (the No Goal). The robot has two light sensors for the Goal light source and additional two for the No Goal light source. The sensors are placed in the front side of the robot (left and right side of upper hemisphere). In animal society, the first light source (the Goal) can be regarded as a food source and the second is toxic food similar to the edible one. The robot tries to learn the behavior which follows the Goal light source while avoiding the dangerous place.

Inspired from natural evolution, this work adopts the artificial evolution to train the behavior of the "Actor." [20][21]. In this work, self-adaptive evolutionary strategy is used to evolve the weights of the neural network. This special ES (Evolutionary Strategy) has been successfully used in engineering applications (for example, analog circuit design and car racing controller optimization) [22][23].

B. Theory of Mind by "Observer"

In this stage, the "Observer" attempts to reveal the internal model (represented as a neural network) using the observation (trajectories of the "Actor"). The trajectories of the "Actor" are very important source of information to infer the internal model. If possible, it is desirable to collect as many as possible trajectories from the "Actor" to infer the model accurately. Unfortunately, the manipulation of the "Actor" by the "Observer" is not an easy problem and usually should be minimized. Human is also very sensitive to the explicit or implicit request (query) to mine his/her mind.

In this work, we adopted the Estimation Exploration Algorithm (EEA) to infer the Actor's neural network from the trajectories. In estimation stage, the algorithm uses an optimization algorithm to find a set of possible estimations on the "hidden" target system (in this paper, the neural network). Initially, the estimation starts from the minimal information (in this paper, a single trajectory starting from an arbitrary place). It is also important to get multiple estimations instead of a single solution. In Exploration stage, the purpose of this stage is to determine the best desirable sampling point (in this paper, the trajectory) to improve the estimation. The "Observer" seduces the "Actor" to the best sampling place to get a new trajectory. In the next iteration, the "Observer" uses the old and new trajectories together for the estimation stage. The cycle of "Estimation" and "Exploration" repeats until the maximum number of iteration is reached.

In this work, the self-adaptive evolutionary algorithm was used for the optimization in the estimation stage. The number of solutions from the estimation was set as five. To get the multiple solutions, the evolutionary algorithms ran five times with a different random seed. The best estimation for each run was chosen. The fitness function of the evolution was the similarity between the trajectories by the "candidate" NN and the real observation. Euclidean distance is straightforward but often leads to premature convergence. Instead, we use derivatives of the trajectories to measure similarity, where, Δx and Δy at each step are compared. To calculate the delta values, the robot with a candidate neural network is re-positioned to the original trajectory's (x_t, y_t) for every step. Figure 4 shows the details of the distance measuring.

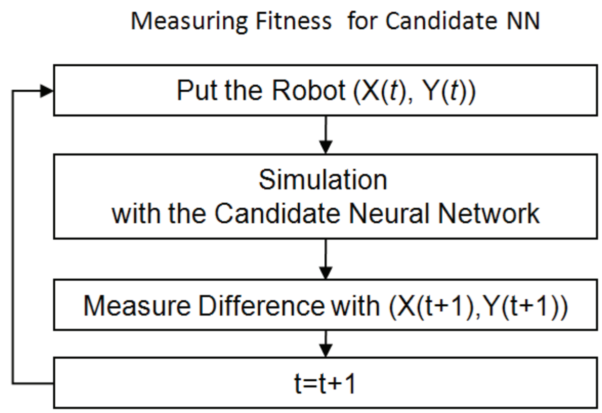

Figure 4. Distance measuring between two trajectories from the original and a candidate neural network (The (X(*t*), Y(*t*) means the position of the "Actor" robot at time step *t*).

For each cycle, the algorithm returns five estimated NNs and they are used to determine the next sampling point (active data sampling). The idea behind the choice is to see the disagreement of the predictions by the multiple hypotheses. If there are 100 starting points for the "Actor" and the problem is to select one of them to accelerate the learning. For each possible starting point, the "Observer" uses the five estimated NNs to predict the trajectory starting from the point. It results in five trajectories for each starting point. For each starting point, it is possible to calculate the disagreement of the five predictions on the "Actor" trajectory. Among the all possible starting point, it is the most desirable sampling point where the disagreement is maximized.

- Step 1) Initial Manipulation: Get an initial trajectory of the "Actor" in the default condition (in this work, the center of the environment).
- Step 2) Estimation Stage: Run the observer learning (evolutionary strategy) N times with different random seeds. It results in N candidate NN's.
- Step 3) Exploration Stage: For all possible conditions (in this work, the starting points of the "Actor"), get predictions of the N candidate NN's and calculate the disagreement of them.
- Step 4) Manipulation: Attract the Actor to show a trajectory in the condition with the maximum disagreement.
- Step 5) Add the new trajectory to the "Observer" repository and initialize the population of the estimation stage using the best NNs. Go to Step 2)

C. Theory of Mind with Multiple Goals

The goal of this study is to investigate the relationship between the performance of the theory of mind and the configuration of multiple goals (light sources). In the "Actor" learning stage, the Actor robot is evolved in the environment with two light sources. It is assumed that each light source emits different types of light and the Actor robot is able to detect each of them. For example, one of the lights is used as a food source and another is a toxic food. From the evolution, the Actor is trained to follow the Goal light source while avoiding the dangerous light.

Table 1 summarizes the placement of the goal and distraction to get sense of the effect to the theory of mind ability. The goal is placed in the center of the environment and the distraction is in the relatively far place (Exp I-1). The opposite of the case is also tested (Exp I-2). In the last setting, the goal and distractions are positioned relatively far place although they're not the same position (Exp I-3). In this setting, the distraction is out-of-line between the robot and the goal and it is expected that the theory of mind would be improved.

Table 1. The placement of the goal and distraction (in this work, T=20)

Experimental Settings		Positions	
		Goal	Distraction
Experiments	Condition 1	$(\frac{T}{2}, \frac{T}{2})$	(T, T)
	Condition 2	(T, T)	$(\frac{T}{2}, \frac{T}{2})$
	Condition 3	(T, T)	$(\frac{T}{2}, T)$

To estimate the observer's theory of mind performance, two kinds of error rates are calculated. For all possible starting positions, Euclidean distance is used to measure dissimilarity between the Observer's predictions using the estimated NN and the actual path of the Actor. The sum of the errors is used as the first performance measure (Error I). On the other hands, the second approach uses the distance between the final position of the predictions and the goal (Error II). If the trajectories of the prediction and the actual path are similar, the Error I might be low. Because Error II measures the distance between the goal and the final position in the prediction, it ignores the similarity between the two trajectories. It only measures the robot is successfully pointing the final target. Figure 5 summarizes the concepts of the error measurement.

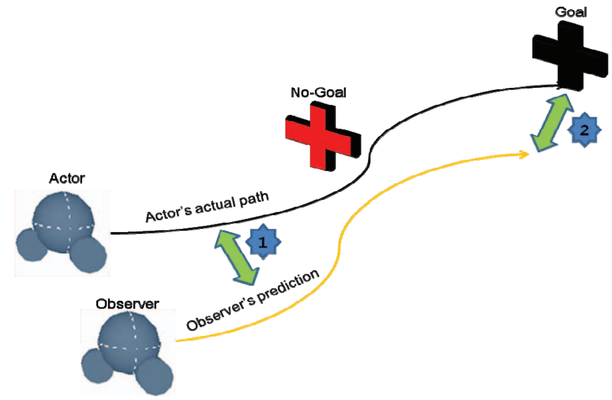

Figure 5. The error calculation between the prediction and the actual path (Error I and II).

IV. Experimental Results

Table 2 summarizes the parameters of the experiments. In the Actor learning, the maximum generation is a relatively small value. Because the purpose of the Actor learning is not to find the optimal neural controller, it is not necessary large number. However, the maximum generation for the Observer learning is 30,000. The purpose of the Observer learning is to maximize the similarity of the behaviors between the trajectories of estimated controller and Actor. Figure 6 shows the trajectories of the Actor.

Table 2. Summary of the parameters

	Parameters	Value
Actor Learning	Population Size	20
	Maximum Generation	50
	MAX_STEP	3000
Observer Learning	Population Size	20
	Maximum Generation	30000
	MAX_STEP	2000

* The simulation engine calculates the next position of the robot for each step ($\Delta t = 1/60$).

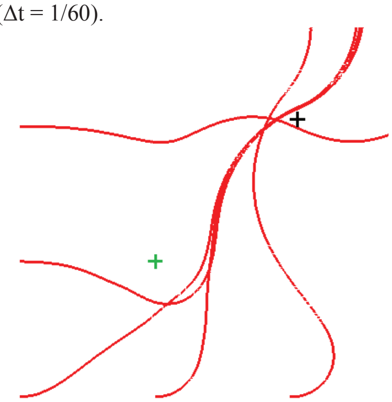

Figure 6. The trajectories of the "Actor" (The cross in the center is the "distraction")

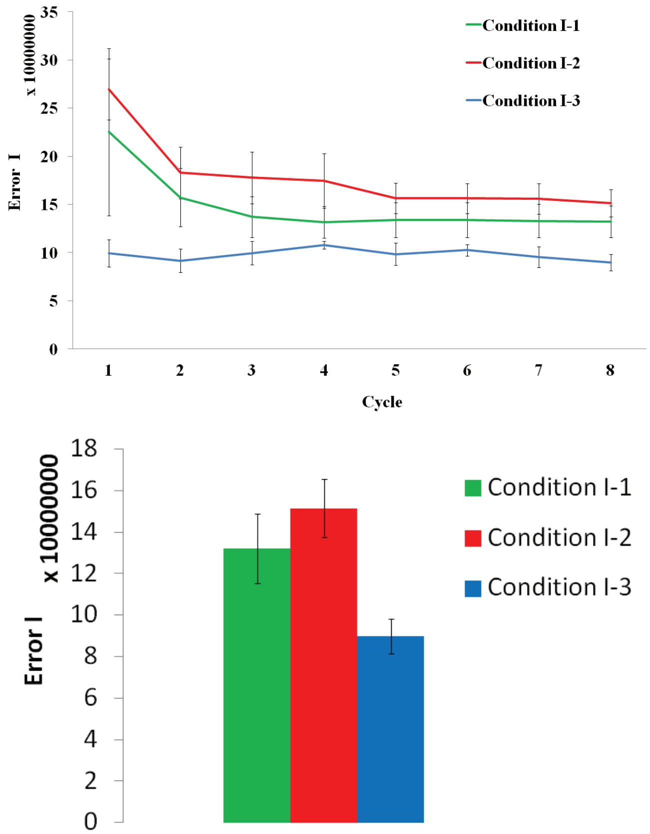

Figure 7. The change of the errors and the final error (at cycle 8) (Error I)

Figure 7 shows the change of the errors in the Observer learning. Because the learning is iterative, it continuously adds a new trajectory from the Actor and refines the estimated model. The Error I (Similarity of the trajectories) and Error II (Distance to the goal) show similar patterns. The experimental conditions change the position of the goal and distractions to see the effect of them. If the distraction is in the center of the environment (there is high chance that the robot will be close to the distraction), there is high Error I and Error II at the first cycle (Condition I-1, and I-2). However, they can decrease the errors continuously over the cycles. It means that the theory of mind is working for the two conditions. In the last condition (Condition I-3), it shows that the Observer gets the low errors at the first cycle and it converges in the next cycles. Because the distraction is not in the center of the environment, the effect is minimized and the Observer is able to do the theory of mind rapidly. It shows that the position of the distraction is important to determine the speed of the theory of mind. These results are related to human or animal studies that show the distraction vitiates the performance of visual search because it deprives the performer's attention [24].

One-way ANOVA is used to evaluate the observer's ToM performance among conditions and the final Error I and Error II are selected for statistical analysis (Figure 8). There were significant differences for Error I (F=0.27, p<0.05). As a result of schèffe post verification, Error I of Condition I-3 is significantly lower than one of Condition I-2 ($p < 0.05$). For Error II, there is no significant difference among conditions (F=2.212, p=.165). Figure 9 shows the trajectories of the Actor and the Observer's estimated NNs.

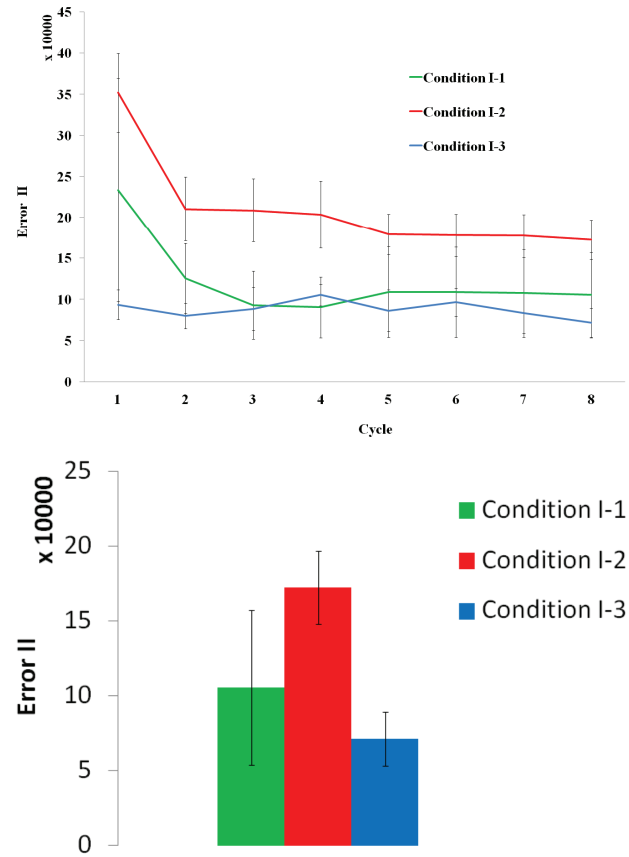

Figure 8. The change of the errors and the final error (at cycle 8) (Error II)

V. CONCLUSIONS AND FUTURE WORKS

In the present study, we examine whether the robot (the Observer) can infer and detect the goal of the other robot (the Actor) when the configuration is changed at the observation. The locations of the goal and distraction are purposely reconfigured for the Observer in order to provide new environmental conditions concerning the goal. Our finding suggests that the observer robot can find the goal even when the location of the goal has changed since its observation. It could find the goal with the trajectories of Actor evolved in different environment.

In sum, our study shows that the robots, like humans, can infer other's goal when environmental conditions about the goal and the distraction have changed. According to the [24], the ability to interpret the environmental condition is critical for action comprehension, and we human beings automatically consider these factors while watching others' behaviors, not just mentally simulating the same movement. Our results support that the robot can achieve the complicate version of "theory of mind." Because the change of object location occasionally happens in our real life, our results can primarily contribute to design a robot with social interaction ability with human or other robots.

This study shows that the robotic theory of mind platform can be used to investigate the interesting issues in several disciplines. For example, the visibility of the observation can be studied for robust theory of mind. For humans, theory of mind is still working although some information is not visible. It is possible to test several conditions that affect the theory of mind with the existence of information missing or broken.

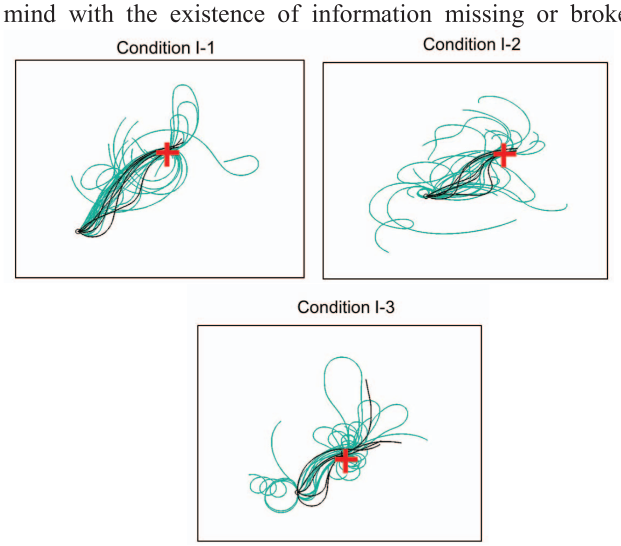

Figure 9. The Observer's best estimations (green lines) and the Actor's paths (black lines). A circle is the starting points and the red sign is a goal they should arrive.

ACKNOWLEDGEMENTS

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