Causality Detected by Transfer Entropy Leads Acquisition of Joint Attention

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Abstract— **Joint attention, i.e., the behavior of looking at the same object another person is looking at, plays an important role in both human communication and human-robot communication. Previous synthetic studies have focused on modeling the developmental process of joint attention and have proposed learning methods without any explicit instructions for joint attention. The causal structure between a perception variable (the caregiver's face directions or individual objects) and an action variable (gaze shift to the caregiver's face or object locations) is given in advance to learn joint attention. However, such a structure is expected to be found by the robot through the interaction experiences. This paper investigates how the transfer entropy, that is an information theoretic measure, can be used to quantify the causality inherent in the face-to-face interaction. In the computer simulation of human-robot interaction, we examined which pair of perceptions and actions are selected as the causal pair and showed that the selected pairs can be used to learn a sensorimotor map for achieving joint attention.**

Index Terms— **joint attention, transfer entropy, contingency learning**

I. Introduction

Joint attention, especially visual joint attention, is defined as looking at an object that someone else is looking at. It can be seen as one of the basic components in human communication since it appears to initiate communication with other people. Joint attention has also been studied as a fundamental ability for human-robot communication [1]. Some robotics researchers have pointed out that joint attention may play an important role in enabling smooth communication with humans [2], [3]. Synthetic studies are also being conducted to promote understanding of the underlying mechanisms of the development of joint attention [4], [5].

Human infants seem to learn joint attention in ambiguous situations where their caregivers do not always intend to attain joint attention behavior with them. Previous synthetic studies have proposed that the causality between gazing behaviors of an infant and its caregiver is utilized to learn joint attention in such ambiguous situations [4], [5]. These studies assumed that a shift in the caregiver's gaze implies that there is something salient in the direction of her gaze, and the salient object would be salient and hopefully preferred by an infant robot, too.

This assumption implies an underlying causality, which appears as the statistical bias in the infant: it frequently finds something salient if it looks where its caregiver is looking. Previous studies [4], [5] have shown that a robot can acquire a sensorimotor mapping to achieve joint attention merely by associating a pair of variables concerning such causal experiences, namely the action variables to shift its gaze and the preceding perception variables of the direction of caregiver's gaze. However, no previous work presented a model for detection of such a causality by a robot. In other words, how a robot can select out the causal pairs of variables from possible candidates has not been addressed. Robots usually have many candidates of variables due to their multiple perceptional modalities and many degrees of motor freedom. Moreover, it is unknown what kind of causality would exist in the interaction due to the difficulty in modeling human interaction. Development of a socially developmental robot, building a robot that automatically selects out pairs of perception and action variables that form a causal structure is, therefore, a formidable challenge.

An important first step is to investigate how the causality in the interactions with a caregiver can be quantified. *Transfer entropy* is an information theoretic measure to detect causality that shares some of the desired properties of mutual information but also takes account of the dynamics of information transport [6]. This seems a promising measure since it has been shown to need smaller samples and less computational cost involved in detecting causality [7]. Sporns *et al.* showed that a robot with eyes can detect the causal structure inherent in a given sensorimotor coordination (i.e., visual tracking behavior) by using the transfer entropy [8]. However, they did not address the issue of learning new behavior based on the found causality. In this study, therefore, we investigated to apply the transfer entropy to detection of causality in interactions with a caregiver, and then to utilize it to learn new sensorimotor mapping, which appears to be a building block for a basic social behavior, i.e., joint attention.

The rest of this paper is organized as follows. First, we explain the contingency learning mechanism reported by Nagai *et al.* [4] as one of the previous learning mechanisms and the causality that a robot should find. Next, we introduce a computer-simulated setting of the face-to-face interaction to examine whether transfer entropy enables a robot to find the causality in the interaction with a caregiver. We describe how we calculate the transfer entropy, and then present our experimental results with it. Finally, discussion on a future issues and concluding remarks are given.

II. Causality to be detected in joint attention

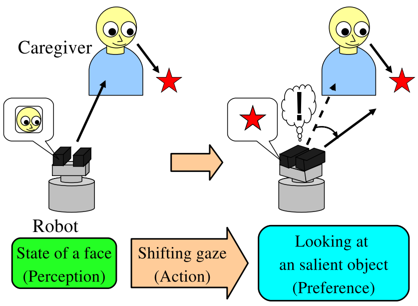

Fig. 1. Behavior of joint attention

Figure 1 illustrates the behavior of joint attention that a robot can acquire based on the learning mechanism proposed in previous work [4]: it first observes the caregiver's face and then shifts its gaze to follow her gaze. Instead of explicitly instructing how to perform such a behavior, Nagai *et al.* [4] proposed that a robot could acquire a sensorimotor map for joint attention by what they called *contingency learning*.

Since the robot had no experience with joint attention, it sometimes succeeded but sometimes failed in finding the same object that the caregiver was looking at. In the contingency learning, its gaze shift and preceding perception of the caregiver's face direction were associated in both occasionally succeeded and unfortunately failed attempts. The assumption on the robot's part of an implicit tendency on the part of the caregiver to look at objects that are salient to a robot enabled it to acquire joint attention through contingency learning. This tendency derives a causality on its own gaze shift: when the robot has observed something salient, it is frequently because its gaze followed the direction of the caregiver's gaze. This causality appears as the statistical bias based on frequent experiences of seeing something salient when looking in the direction of the caregiver's gaze. That is, by associating the pairs of variables, its gaze shift as an action variable and the caregiver's face direction as a preceding perceptual variable, the robot is able to acquire the sensorimotor map for joint attention.

Nagai *et al.* demonstrated that a robot could acquire joint attention by associating this causal pair of variables even with no explicit instructions on how to perform joint attention. However, the designer had to specify what kinds of variables should be associated to acquire joint attention. We extended the method of contingency learning proposed by Nagai *et al.* [4] to investigate whether a robot could automatically find a causal pair of variables to be associated to acquire joint attention.

III. Environmental setting

To examine whether a robot can find the causal pair of variables in face-to-face interaction between a robot and a caregiver, we start from a rough model of the caregiver's gaze shift. We simulate almost the same interaction as in the previous studies [4], [5], but we add more actions such as hand motion and more perceptual variables such as types of an object that are not related to joint attention. The purpose of this experiment is to confirm whether the robot can eliminate such unrelated variables from candidates of elements of sensorimotor map for joint attention.

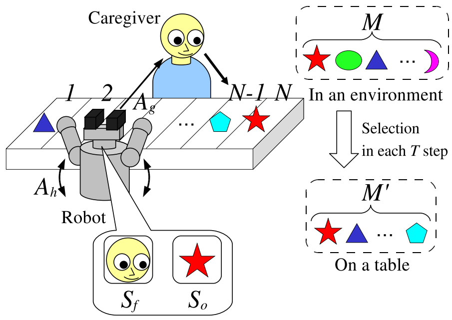

Fig. 2. Overview of caregiver-robot interaction.

TABLE I

Types of variables in the robot.

type	name	elements
perception	caregiver's face	$S^f = \{f_1, f_2, \cdots, f_N, f_r, f_\phi\}$
	type of object	$S^o = \{o_1, o_2, \cdots, o_M, o_\phi\}$
action	shifting the gaze	$A^g = \{g_1, g_2, \cdots, g_N, g_c\}$
	moving the hands	$A^h = \{h_1, h_2, \cdots, h_{N_h}\}$
preference	frontal face of caregiver	$I^f = \{0, 1\}$
	object	$I^o = \{0, 1\}$

A. An environment and interactions between the caregiver and robot models

Figure 2 shows the experimental setting of the computer simulation. The robot sits across from the caregiver at a fixed distance. Some objects are randomly placed on the table located between the robot and the caregiver. Let N be the number of spots of the positions on the table, M' ($M' < N$) be the number of the objects placed on it, and M be the number of possible objects. In such an environment, the robot moves its hands and shifts its gaze, while the caregiver only shifts her gaze.

In this simulation, the robot has three types of variables as shown in Table I: the perception, action, and preference variables. The perception variables mean the environmental and the caregiver's states observed by the robot. The action and the preference ones indicate the robot's actions and the preferences for the consequent experiences of the actions, respectively. The details of these variables are described later.

The caregiver and the robot take turns observing objects or the other side in each time step as below. First, the caregiver shifts her gaze. Then, the robot observes the caregiver's face or a spot on the table as a current target, that is, obtains the information where the caregiver appears to looks at, S^f, or what kinds of objects are observed, S^o. We assume that the robot prefers both a frontal view of the face of the caregiver and any objects to a profile view of her face. In the timing of the observation, it also updates the preference variables of a frontal face of the caregiver, I^f, and objects, I^o. After the observation, the robot moves its hand, A^h, and shifts its gaze once, A^g.

The objects selected from M candidates and where they are placed are changed every T steps. Note that placement is re-arranged such that the observation of the caregiver and the robot do not change: if the caregiver or the robot gazes at a spot where there is no object, no object will be placed on the spot; if the caregiver or the robot gazes at an object on a certain spot, the object is not moved to another spot.

B. A robot model

The perception variables of the caregiver's gaze, S^f, and objects, S^o are updated when the robot observes a target. The direction of the caregiver's gaze in the t-th step is denoted by $s_t^f = \{f_1, \cdots, f_N, f_r, f_\phi\}$, which indicates what spot she is looking at ($f_1, \cdots, f_N$), whether she is looking at the robot (f_r), or whether it is not looking at her face (f_ϕ). The perception variable about objects in the t-th step indicates what it is looking at and is denoted by $s_t^o = \{o_1, o_2, \cdots, o_M, o_\phi\}$, which corresponds to possible objects ($o_1, \cdots, o_M$) or indicates that it is looking at the caregiver or at a spot with no object on it (o_ϕ).

The preference variables on a frontal view of the face of the caregiver, I^f, and on objects, I^o are updated in the timing of the observation. These variables in the t-th step are denoted by $i_t^f = \{0, 1\}$ and $i_t^o = \{0, 1\}$, respectively, where "0" means that the robot does not look at its preferred face or object while "1" means the opposite.

After determining these variables, it shifts its gaze and moves its hand. The gaze shift in the t-th step is denoted by $a_t^g = \{g_1, \cdots, g_N, g_c\}$, which indicates the target to be gazed at, namely a certain position on the table ($g_1, \cdots, g_N$) or the face of the caregiver (g_c). The hand motion in the t-th step is denoted by $a_t^h = \{h_1, \cdots, h_{N_h}\}$, which indicates the type of the motion ($h_1, \cdots, h_{N_h}$), where N_h indicates the number of hand motions and is set as $N_h = N + 1$ to make up the number of elements between the action variables. The robot select one of elements in the A^g and A^h randomly at each time step.

C. A caregiver model

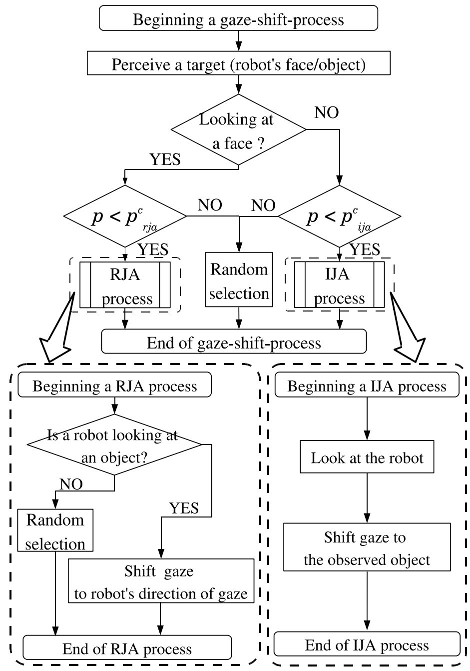

Fig. 3. Caregiver's change in gaze based on communicative strategy.

Generally, a caregiver should be able to choose one from communicative and non-communicative behaviors. Communicative behaviors on the caregiver's part would be responding to the infant's behaviors and trying to draw the attention of the infant. Non-communicative behaviors would appear to be random motions. Therefore, we modeled the caregiver's behavior such that it combined responsive, inductive, and random behaviors with regard to the robot.

In each step, the caregiver first selects a behavior strategy: she shifts her gaze based on a communicative strategy with probability p_c^c or by a completely random strategy. When using the communicative strategy, she looks at the robot or at an object on the table. We suppose that a caregiver tends to shift her gaze using a communicative strategy, which enables the robot to detect causality. Using the communicative strategy, the caregiver has three options in shifting her gaze: following the robot's gaze (RJA process), shifting her gaze as if trying to lead the robot's gaze (IJA process), and randomly selecting a target (random process). On the contrary, she always randomly selects a target to gaze at using the completely random strategy. Note that she may look at the spots without any objects when using this strategy.

Figure 3 represents the process flow of the caregiver change in gaze in the communicative strategy. The caregiver first perceives a target and then selects an option based on what she is looking at. If she is looking at the robot's face, she selects either the RJA process with probability p^c_{rja} or the random process. Otherwise, she selects either the IJA process with probability p^c_{ija} or the random process. In the RJA process, she shifts her gaze to follow the direction of the robot's face. If the robot is not looking at an object, she selects an object at random and shifts her gaze to it (see the box on the bottom left in Figure 3). In the IJA process, she shifts her gaze as if trying to lead the robot's gaze to an object that she is currently looking at. She first looks back to the robot and then shifts her gaze to the target object in the next step again (see the box on the bottom right in Figure 3). Note that she randomly changes target objects only when the placement of the target object is changed during the IJA process.

D. Causality in the current setting

As shown in the previous studies [4], [5], the caregiver's direction of gaze s^f_t leads to the predictable consequence of the robot shifting its gaze a^g_t, that is, in response to detection of a salient object, i^o_{t+1}. Conversely, the robot's hand motions, namely a^h_t, is not causal because the caregiver does not respond to those motions and her gaze does not lead to any predictable consequence of those motions. Therefore, we can expect that the robot to find the pair S^f, and A^g on I^o, that matches the one to which the acquisition of joint attention is attributed in the previous work [4] if it can quantify the causal relation of a combination of a perception, an action, and own preference.

IV. Transfer entropy

We adopt the transfer entropy [6] to quantify the causality between a perception and an action on preference. Transfer entropy is a kind of information measure that represents the flow of information between stochastic variables, which cannot be extracted by other information criteria such as mutual information.

The transfer entropy that indicates the influence of a stochastic variable Y on a stochastic variable X is calculated by

$$T_{Y\to X} = \sum_{x_{t+1},x_t\in X}\sum_{y_t\in Y} p(x_{t+1},x_t,y_t)\log\frac{p(x_{t+1}|x_t,y_t)}{p(x_{t+1}|x_t)}, \quad (1)$$

where x_t and y_t are elements of X and Y at the time step t, respectively. This measure equates with the Kullback-Leibler entropy between $p(x_{t+1}|x_t)$ and $p(x_{t+1}|x_t, y_t)$.

Here, we calculate transfer entropy $T_{A^m,S^l\to I^k}$ which indicates the influence of a pair of a perception variable S^l ($l = f, o$) and an action A^m ($m = g, h$) on a preference I^k ($k = f, o$):

$$T_{A^m,S^l\to I^k} = \sum_{I^k,S^l,A^m} p(i^k_{t+1}, i^k_t, s^l_t, a^m_t)\log\frac{p(i^k_{t+1}|i^k_t, s^l_t, a^m_t)}{p(i^k_{t+1}|i^k_t)}, \quad (2)$$

However, if an action and a preference have a strong causal relationship, transfer entropy would not work for finding the causal actions coordinated by any perception for the preference. Therefore, we introduce transfer entropy, which focuses on the effect of the combination of a perception variable and an action variable (TC). TC is defined as

$$\begin{aligned} TC_{A^m,S^l\to I^k} &= T_{A^m,S^l\to I^k} - T_{A^m\to I^k} \\ &= \sum_{I^k,S^l,A^m} p(i^k_{t+1}, i^k_t, s^l_t, a^m_t)\log\frac{p(i^k_{t+1}|i^k_t, s^l_t, a^m_t)}{p(i^k_{t+1}|i^k_t, a^m_t)}, \end{aligned} \quad (3)$$

which indicates the combinatorial influence of a perception variable S^l and an action A^m on a preference I^k. This appears to equate with the Kullback-Leibler entropy between $p(i^k_{t+1}|i^k_t, s^l_t, a^m_t)$ and $p(i^k_{t+1}|i^k_t, a^m_t)$.

V. Experiment

A. Experimental setting

We conducted a computer simulation to examine whether the robot could find the causal structure in face-to-face interactions using the proposed measure of the causality and thereby acquire joint attention. To calculate transfer entropy, it is necessary to estimate probability distributions of each combination. To demonstrate the potential of the proposed measure, we iterated the steps of the interaction and observed the transition of the transfer entropy calculated from the history of the robot's experiences.

In experiments, we set the spots on the table at $N = 9$, the number of objects in the environment at $M = 10$, and the number of objects on the table at $M' = 3$. The other parameters were set at $(T, p^c_{rja}, p^c_{ija}) = (4, 0.8, 0.27)$. The experiments lasted until the absolute difference between the transfer entropies of all combinations of variables between steps became less than the constant value θ. Here, we set it as $\theta = 1.0 \times 10^{-8}$.

B. Transfer entropy in face-to-face interactions

Figure 4 shows the time courses of TCs among perceptions, actions, and preferences in the interactions. The vertical axis indicates the value of TC shown in the logarithmic scale and the horizontal one indicates time steps. Note that the probability of selecting the communicative strategy p_c^c was set at 1.0 in this simulation. Since the estimated probability distribution was less accurate at the beginning of interactions, the TCs seemed over-estimated. After the iteration of the interactions, however, $TC_{A^g, S^f \rightarrow I^o}$ (the blue line in Figure 4) appeared to be larger than the others. In other words, the combination of perception of the caregiver's gaze, the change in gaze of the robot, and the preference for salient objects was found to be causal. This result shows that the robot was able to detect a causal combination of variables by using transfer entropy and utilize the found combination to learn joint attention. Note that we also analyzed the robustness of the result in terms of the differences in the parameters, p_{rja}^c and p_{ija}^c, of the caregiver's model. Excepting in an extreme case that the caregiver always selected the IJA process ($p_{ija}^c = 1$), we confirmed that the same combination of variables was successfully found as causal combination.

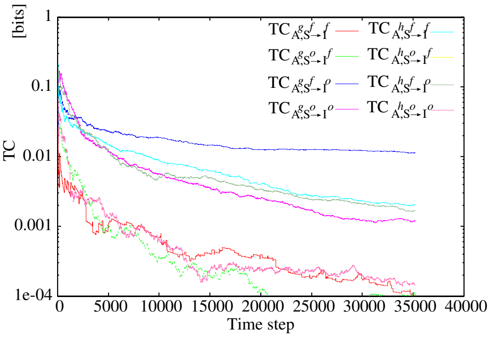

Fig. 4. Time courses of causal measure of combinations of variables in face-to-face interactions between a caregiver and a robot.

We also examined to what extent the proposed method depends on the assumption that the caregiver tends to look at something. We compared the transfer entropies calculated in the 40,000-th steps in the interactions with different probabilities of the communicative strategy. If we set p_c^c as a lower value, the caregiver became less communicative, in other words, she came to look more frequently at empty spots on the table. Figure 5 shows the averages and standard deviations for ten trials of the difference between $TC_{A^g, S^f \rightarrow I^o}$ and the highest TC among other combinations. Since the difference became positive and $TC_{A^g, S^f \rightarrow I^o}$ had a higher value when p_c^c was larger than 0.4, the proposed mechanism seemed to work if the caregiver was somewhat communicative.

C. Learning joint attention with the detected causal variables

We also examined whether the combination of variables with the maximum TC enables the robot to learn joint attention. Figure 6 shows the histograms of experiences where it had observed the caregiver's face and chose to

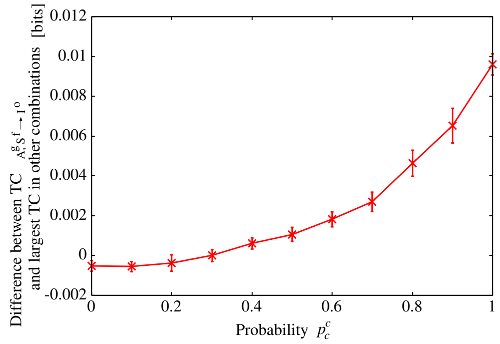

Fig. 5. Change in difference between $TC_{A^g, S^f \rightarrow I^o}$ and largest TC in other combinations based on probability p_c^c.

shift its gaze before observing an object. Note that the value of each quantum $\bar{H}(f, g)$ in the histograms indicates the difference between the number of occurrences of quantum $H(f, g)$ and the average number of occurrences among the quanta concerning the same perception:

$$\bar{H}(f, g) = H(f, g) - \frac{1}{N} \sum_{g} H(f, g). \tag{4}$$

The diagonal elements in Figure 6 correspond to the behavior of joint attention. Therefore, Figure 6 shows that the robot tended to succeed in observing an object when it occasionally performed the same behavior as joint attention.

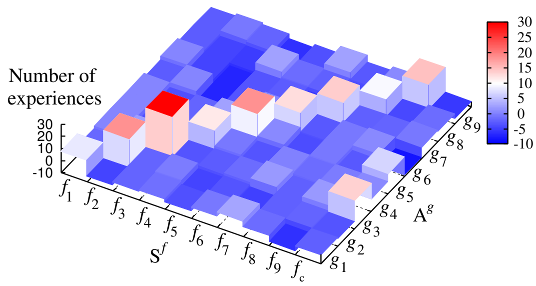

Fig. 6. Distribution of experiences to $I^o = 1$ in interactions between a caregiver and a robot. In this graph, the pairs with the same number of suffix, e.g., (f_1, g_1), corresponds to the behavior of joint attention.

As shown by Nagai *et al.*, a robot can learn joint attention using contingency learning [4] in situations where the experience of the robot is biased to occasionally succeed in achieving joint attention. In the subsequent computer simulation, we examined whether it could learn a sensorimotor map for joint attention by contingency learning based on the detected pair of perception and action variables.

The perception variable and the action variable included in the causal combination with the highest TC were assigned to the input and the output layer of a two-layered perceptron, respectively (see Figure 7). Contingency learning is performed by associating the sensorimotor variables despite success in joint attention. Therefore, it can be implemented by using the current action variables of gaze shifting as the desired value of the output layer in backpropagation learning of the perceptron. The perceptron was trained with data obtained through 40,000 interactions in which the actions of the robot and the caregiver were determined by the robot model and the caregiver model described in section III, respectively. Perception and action variables were encoded in an exclusive way. For example, suppose that the robot finds something salient by shifting its gaze to the i-th spot on the table after observing the caregiver's face, which is perceived as looking in the j-th direction. In this case, the perceptron receives an input vector of which the j-th element is one while the others are zeros and receives a reference vector of which the i-th element is one while the others are zeros.

After running ten learning trials each of which was constituted by 40,000 interactions, we examined the average success rate for joint attention. We tested whether the perceptron could output the corresponding action variable to the caregiver's gaze direction for each N kinds of perceptional input. The result shows that the success rate was 87%. Therefore, it was confirmed that the causal variables selected by the proposed method could be utilized to learn joint attention.

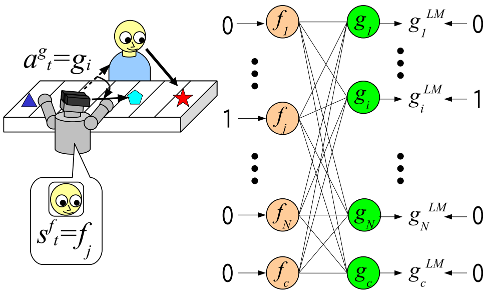

Fig. 7. Network to learn joint attention.

VI. Discussion and Conclusion

We used transfer entropy as a measure to detect the causality between perception and action variables in human-robot interaction. We focused on face-to-face interaction and showed that transfer entropy helped a robot to detect important variables that constitute a causal structure inherent in the interaction.

We also showed that causal variables selected by the proposed method could be utilized in learning joint attention. Since we evaluated the effectiveness of the proposed method using the computer simulations only, we should examine to what extent the proposed method can detect causality in real-world interactions. We may start by adding other action modalities such as pointing or vocalization, which are expected to make human-robot interaction richer, thereby to induce the robot in the natural behaviors of the human caregiver.

The resolution of the random variables may influence the estimation of transfer entropy concerning the variables. An infant seems to be faced with situations in which the resolutions of multimodal sensation or various kinds of action are not even because these components develop in parallel and according to a different time schedule. The resolutions of random variables would improve incrementally along with the infant's development. Therefore, we should address the issue of how a robot can improve such resolutions and maintain the development of social skill based on the detection of the causalities.

Observations in developmental psychology imply that many causalities are inherent in infant-caregiver interaction [9] and that infants seem to acquire various social skills based on these causalities. Our simulation can be regarded as demonstrating a possible mechanism that leads the robot to realize such an inherent causality in the interaction and constitutes its behavior based on the causality. The acquired behaviors would modify the causality and thereby lead the robot to acquire the next behavior. In the future, therefore, we should simulate how a robot can develop its social skills based on the experienced causalities that were modified by the ongoing process of acquiring new social skills. This would be extended to the issue of parallel learning of social skills. Furthermore, analyzing the elements found in higher social skills might give us hints to model how others can be understood by a bottom up way.

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