Learning of Joint Attention from Detecting Causality based on Transfer Entropy

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

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

I. Introduction

Joint attention, especially visual joint attention, is defined as looking at the same object at which someone else is looking. It is one of the most basic components of human communication because it appears to initiate communication with others. Joint attention has also been studied as a fundamental ability for human-robot communication [1]. A number of robotics researchers have pointed out that it may play an important role in enabling smooth communication between humans and robots [2], [3]. Synthetic studies have been also conducted to understand the underlying mechanisms of the development of joint attention [4], [5]. We can expect such studies to enable realizing adaptive robot to changes in an environment including humans as well as to help understanding of human development [6], [7].

Human infants seem to learn joint attention in uncertain situations in which their caregivers do not always attain joint attention with them. Previous synthetic studies have argued that causality between gazing behaviors of an infant and its caregiver can be utilized to learn joint attention in such uncertain situations [4], [5]. These studies assumed that a shift in the caregiver's gaze implies something salient in the direction of gaze, and such an object would also be salient to an infant robot.

This assumption implies underlying causality appearing as statistical bias in infants: they frequently find something salient by looking where a caregiver is looking. Previous studies [4], [5] have shown that a robot can acquire sensorimotor mapping to achieve joint attention by associating a pair of variables involved in such causal experiences, i.e., the action variable of shifting its gaze and the preceding perception variable of the direction of the caregiver's gaze. However, no work has, to our knowledge, presented a model to enable a robot to detect such causality. In other words, how a robot can select causal pairs of variables from possible candidates has not been addressed. Robots usually have many candidates of variables owing to their multiple perceptual modalities and many degrees of motor freedom. Moreover, it is unknown what kind of causality exists in the interaction since modeling human interaction itself is difficult. Building a robot that automatically selects pairs of perception and action variables that form a causal structure is therefore formidable.

An important first step in determining this is investigating how causality in interactions between a caregiver and a robot is quantified. *Transfer entropy* — an information theory measure that detects causality — appears to be promising in this regard. It shares some of the desired properties of mutual information but also takes into account the dynamics of information transport [8]. Transfer entropy has been shown to need fewer samples and cost in less calculation in detecting causality than other methods for detecting causality such as measures based on Granger causality [9]. 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, using transfer entropy [10]. However, they did not address the learning of new behavior based on the found causality. We studied how transfer entropy can be applied to detect causality in interactions with a caregiver and how to utilize it to learn new sensorimotor mapping, which appears to be a building block in basic social behavior, i.e., joint attention.

The rest of this paper is organized as follows. First, we explain the contingency learning reported by Nagai *et al.* [4] as a learning mechanism and the causality that a robot should find. Next, we introduce a computer-simulated setting involving face-to-face interaction to determine whether transfer entropy enables a robot to find the causality inherent in interactions with a caregiver. We discuss how to calculate transfer entropy and present experimental results. We show that the robot can acquire joint attention using the found causality. Finally, discussion on projected issues and concluding remarks are given.

II. Causality Detected in Joint Attention

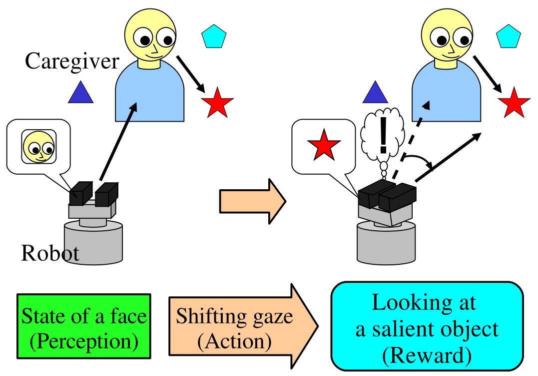

Fig. 1. Joint attention

Figure 1 shows joint attention behavior that a robot can acquire based on the learning mechanism proposed by Nagai *et al.* [4]. First, it observes the caregiver's face and then shifts its gaze to follow the caregiver's gaze. Instead of explicitly instructing the robot how to act, they showed 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 and sometimes failed to find the same object that the caregiver was looking at. In contingency learning, the robot evaluates only whether it successfully looked at the salient object in both occasionally succeeded and, unfortunately, failed attempts to look at the same object. When it looked at the salient object, its gaze shift and the preceding perception of the caregiver's face pattern (face orientation) were associated. The assumption that the caregiver looks at a salient object for the robot enabled it to acquire joint attention through contingency learning. This tendency derives causality form its own gaze shift: the robot observed something salient because its gaze frequently followed the direction of the caregiver's gaze. This causality appears as statistical bias based on frequent experiences of seeing something salient when looking in the direction of the caregiver's gaze. That is, by associating its gaze shift (an action variable) and the caregiver's face direction (a preceding perceptual variable), based on an internal reward for the consequences of its action, i.e., the robot observed an salient object, the robot can acquire a sensorimotor map for joint attention.

Nagai *et al.* showed that a robot can acquire joint attention by associating this causal pair of variables for internal reward even without explicit instructions. The designers, however, had to specify what kinds of variables should be associated to acquire it. We enhanced contingency learning [4] by investigating whether a robot could automatically find a causal pair of variables for an internal reward to be associated to acquire joint attention.

III. Environmental Setting

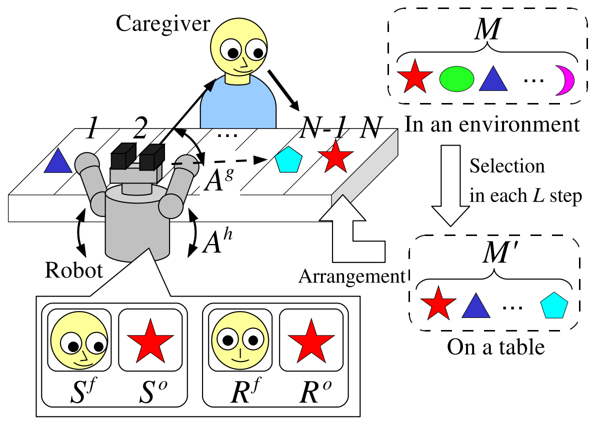

Fig. 2. Overview of caregiver-robot interaction

TABLE I
Types of variables in 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 gaze	$A^g = \{g_1, g_2, \cdots, g_N, g_c\}$
	moving hands	$A^h = \{h_1, h_2, \cdots, h_{N_h}\}$
reward	full face of caregiver	$R^f = \{0, 1\}$
	object	$R^o = \{0, 1\}$

To determine whether a robot can find a causal pair of variables for an internal reward with consequent experience in face-to-face interaction with a caregiver, we start with a rough model of the caregiver's gaze shift. We simulate almost the same interaction as in previous studies [4], [5]; but, for the robot, we add actions such as hand gestures and perceptual variables such as types of objects not related to joint attention. This experiment confirms whether the robot can eliminate unrelated variables from candidates for the elements of the sensorimotor map for joint attention.

A. Environment and interactions between caregiver and robot models

In an experimental computer simulation setting (Figure 2), the robot sits across from the caregiver at a fixed distance while objects are randomly placed on the table between them. Let N be the number of positions on the table, M' $(0 < M' < N)$ the number of salient objects placed on spots, and M the number of possible objects. M' objects are selected from M candidates every L steps and spots on which they are placed are determined randomly (only one object per spot). The robot gestures and shifts its gaze, and the caregiver only shifts her gaze.

The robot has three types of variables (Table I): perception, action, and reward. Perception variables mean the environmental and caregiver states observed by the robot. Action variables indicate robot actions. Reward variables denote whether the robot is satisfied with resulting experience based on pairs of actions and preceding perceptions. Note that reward variables represent only the robot's internal evaluation for external stimuli and are not used as a reinforcer to detect causality, unlike standard reinforcement learning.

The caregiver and robot take turns observing objects or the other side in each time step as below. First, the caregiver shifts gaze, then the robot observes the caregiver's face or a spot on the table as the current target, obtaining information about S^f, where the caregiver appears to be looking, or S^o, what objects are being observed. We assume that the robot prefers both the caregiver's full face and salient objects to the caregiver's profile because infants appear to prefer the full human face [11] and objects with complex textures or symmetrical patterns [12]. The robot has reward variables representing such preferences. In the observation timing, it also perceives reward variables of the caregiver's full face, R^f, and objects, R^o. After observation, the robot gestures (A^h), then shifts its gaze (A^g).

B. Robot model

Current perception variable states of the caregiver's gaze, S^f, and objects, S^o, are obtained when the robot observes a target. The direction of the caregiver's gaze in the t-th step is denoted by $s_t^f \in S^f = \{f_1, \cdots, f_N, f_r, f_\phi\}$, where $f_1, \cdots, f_N$ indicates at which spot the caregiver is looking, f_r means the caregiver is looking at the robot, and f_ϕ means the robot is not looking at the caregiver's face. The perception variable for objects in the t-th step indicating what it is looking at is denoted by $s_t^o \in S^o = \{o_1, o_2, \cdots, o_M, o_\phi\}$, of which $o_1, \cdots, o_M$ correspond to possible objects and o_ϕ indicates that it is looking at something else.

Current states of reward variables for the caregiver's full face, R^f, and for objects, R^o are obtained in observation timing. These variables in the t-th step are denoted by $r_t^f \in R^f = \{0, 1\}$ and $r_t^o \in R^o = \{0, 1\}$, where "1" means that the robot is looking at its preferred face or an object while "0" means "NOT."

After these observations, it shifts its gaze and gestures. The gaze shift in the t-th step is denoted by $a_t^g \in A^g = \{g_1, \cdots, g_N, g_c\}$, indicating the target to be gazed at, i.e., a certain location on the table ($g_1, \cdots, g_N$) or the caregiver's face (g_c). The gesture in the t-th step is denoted by $a_t^h \in A^h = \{h_1, \cdots, h_{N_h}\}$, indicating the type of movement, and N_h indicating the number of different hand gestures. The robot randomly selects one element in both A^g and A^h at each time step.

C. Caregiver model

A caregiver responds to an infant's behavior and induces the infant's response in interactions with the infant in addition to looking at a salient object as a basic and natural behavior. We modeled behavior so that the caregiver looks randomly at the robot or at one of the objects and shows responsive and inductive behaviors regarding robot behavior.

In the caregiver's gaze shift, three options exist for shifting the gaze when looking at the robot or at an object on the table (Figure 3): (1) following the robot's gaze — responding to joint attention (RJA) —; (2) shifting gaze to draw the robot's attention — initiating joint attention (IJA) —; and (3) randomly selecting a target to gaze at (neutral) excluding behavior identical to the RJA and IJA. Note that the caregiver invariably looks at the robot's face or at an object on the table.

In each time step, the caregiver first perceives a target and selects an option based on what is being looked at. If the robot's face is being looked at, the caregiver selects either RJA with probability p_{rja}^c or the neutral process with probability $1 - p_{rja}^c$. Otherwise, (looking at a object on the table, for example), the caregiver selects either IJA with probability p_{ija}^c or the neutral process with probability $1 - p_{ija}^c$. In RJA, the caregiver shifts her gaze to follow the direction of the robot's face. If the robot is not looking at an object, the caregiver selects an object at random and shifts her gaze to it (box, bottom left, Figure 3). In IJA, the caregiver shifts her gaze as if trying to lead the robot's gaze to the object that the caregiver is currently looking at, looking back at the robot and shifting her gaze to the target object in the next step again (box, bottom right, Figure 3).

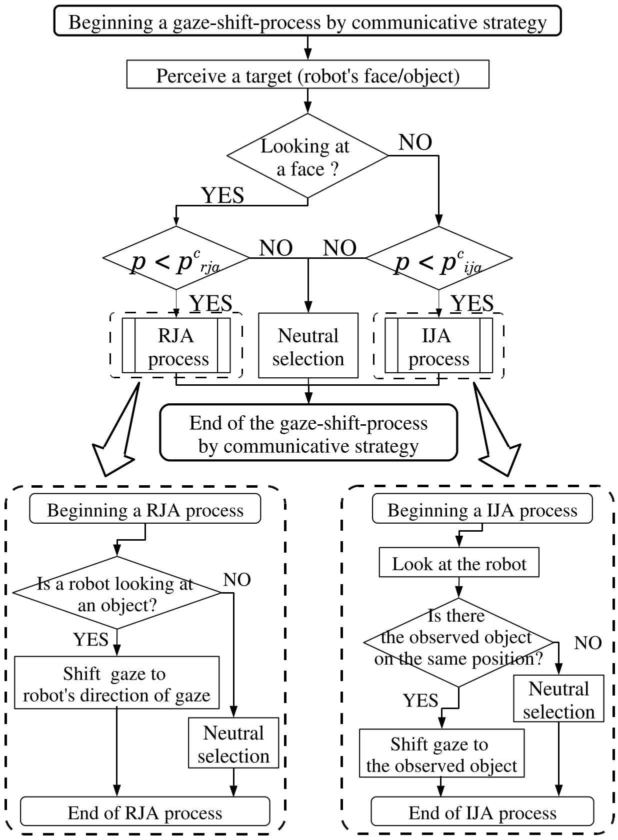

Fig. 3. Caregiver's gaze shift

IV. Transfer entropy

We use transfer entropy [8] to quantify causality between a perception and an action for a reward. Transfer entropy is an information measure that represents the flow of information between stochastic variables that cannot be extracted by other information criteria such as mutual information.

We assume that the current state of stochastic variable X is only influenced by the last state of X and the last one of another stochastic variable Y. Transfer entropy that indicates the influence of stochastic variable Y on stochastic variable X is calculated by

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

where x_t and y_t are observables of X and Y at time step t. This is equivalent to Kullback-Leibler entropy between $p(x_{t+1}|x_t)$ and $p(x_{t+1}|x_t, y_t)$.

We calculate transfer entropy $T_{A^m,S^l\to R^k}$ indicating the influence of a pair of perception variables S^l $(l = f, o)$ and actions A^m $(m = g, h)$ for a reward R^k $(k = f, o)$:

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

An observed consequence is often strongly included in causality inherent in specific actions. Here, shifting the gaze, for example, has a strong causal relationship with the reward for the caregiver's full face: the robot cannot look at the caregiver's face if it shifts its gaze to a spot on the table. In such cases, transfer entropy would not work in finding causal actions coordinated by any perception for reward because the causality between a reward and an action is too strong. We introduce transfer entropy T^C that focuses on the effect of combining perception and action variables for reward variable:

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

which indicates the combinatorial influence of perception variable S^l and action variable A^m for reward variable R^k. This appears equivalent to Kullback-Leibler entropy between $p(r^k_{t+1}|r^k_t, s^l_t, a^m_t)$ and $p(r^k_{t+1}|r^k_t, a^m_t)$.

V. Experiments

A. Experimental setup

We conducted a computer simulation to determine whether the robot could find the causal structure in face-to-face interactions using the proposed causality measure to acquire joint attention. Calculating transfer entropy requires determining joint probabilities and conditional probabilities for each combination. We estimated them using histograms of observable combinations of three variables: perception, action, and reward — the history of the robot's experience. To demonstrate the potential of the proposed measure, we iterated interaction steps and observed the transition of transfer entropy calculated from histograms.

In experiments, we set nine spots on the table ($N = 9$), ten objects in the environment ($M = 10$), and three objects on the table ($M' = 3$). Note that we set the number of possible objects $M = N + 1$ to nearly equal the number of elements between perception variables because the finer the resolution of a stochastic variable is, the larger the transfer entropy. For the same reason, the number of hand gestures $N_h = N + 1$. Other parameters $(L, p^c_{rja}, p^c_{ija}) = (10, 0.8, 0.2)$. Experiments lasted while absolute differences between transfer entropies of all combinations of variables between consecutive steps exceed constant value θ. Here, $\theta = 1.0 \times 10^{-7}$.

B. Transfer entropy in face-to-face interaction

As shown in previous studies [4], [5], the direction of the caregiver's gaze s_t^f leads to a predictable consequence of the robot's shifting its gaze a_t^g, that is, finding a salient object r_{t+1}^o. Conversely, the robot's hand gestures, a_t^h, are not causal because the caregiver does not respond to them and her gaze direction does not lead to any predictable consequence related to them. We expect the robot to find pair S^f and A^g for R^o matching the pair to which joint attention acquisition is attributed in previous study [4].

Figure 4 shows examples of time courses of T^Cs among perceptions, actions, and rewards in interactions. The vertical axis indicates the logarithmic value of T^C, and the horizontal axis indicates time steps. Since the estimated probability distribution was less accurate at the beginning of interactions, T^Cs seemed overestimated. After interactions are iterated, however, $T^C_{A^g,S^f\to R^o}$ (blue line in Figure 4) appeared larger than the others, i.e., the combination of the perception of the caregiver's gaze, the change in the robot's gaze, and the reward for salient objects was causal, indicating that the robot detected a causal combination of variables with transfer entropy, that was used to acquire joint attention in previous work [4].

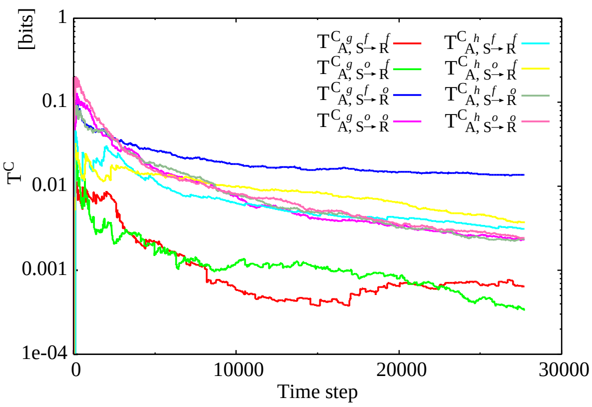

Fig. 4. Time courses of causal measure of combinations of variables in face-to-face interactions between caregiver and robot

To evaluate the robustness of transfer entropy measure for finding a causal combination of variables, we analyzed the influence of other parameters, such as M', p^c_{rja}, and p^c_{ija} on target transfer entropy ($T^C_{A^g,S^f\to R^o}$) and the difference between target transfer entropy and the highest transfer entropy among other combinations ($\max_{k,l,m} T^C_{A^m,S^l\to R^k}$). Note that this difference must be larger than zero for target combinations of variables to be causal. We call the difference ΔT^C_{diff}. We varied p^c_{rja}, p^c_{ija}, and M' at 0.25, 0.50, and 0.75 for p_{rja} and p_{ija}, and $M' = 1, 2, \cdots, 9$. For each parameter setting, we ran ten 30,000-step simulations and plotted the averages and standard deviations of ΔT^C_{diff} in the 30,000-th step for the number of objects in Figure 5. Note that ΔT^C_{diff}s for most parameter settings exceeded zero except in the case of $M' = 8, 9$, confirming that the target combination of variables was causal for all parameter settings except extreme cases in which almost all places are salient for the robot, although absolute differences appear to reflect the number of objects M'. Note also that p^c_{rja} and p^c_{ija} do not affect ΔT^C_{diff} from standard deviations in Figure 5.

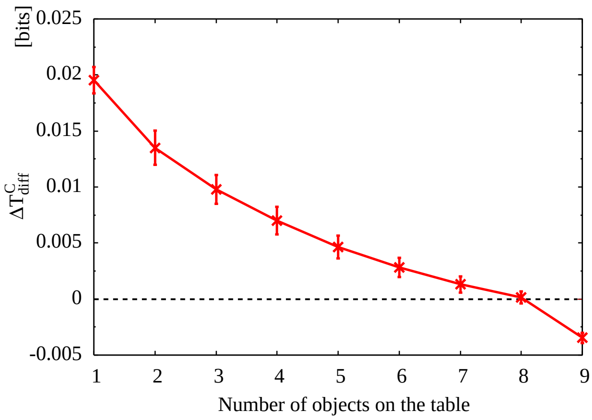

Fig. 5. Change of difference between $T^C_{A^g,S^f\to R^o}$ and largest T^C in other combinations in situations of different combinations of p^c_{ija}, p^c_{rja}, and M'

C. Influence of uncertain causality

In actual interaction between a caregiver and infant, the caregiver may look at an object not salient to the infant. Therefore, we examined to what extent the proposed mechanism depends on the assumption that a caregiver tends to look at something salient to the infant.

We changed the caregiver model to one that behaves as described in Section III-*C* with probability p^c_c and looks at the robot or an empty spot with probability $1 - p^c_c$. If we set p^c_c to a lower value, the caregiver looks less often at an object and more often at empty spots on the table and behaves completely randomly around $p^c_c = 0.5$. We compared the transfer entropies calculated in the 30,000-th step in interactions with different of p^c_c under the above setting.

Figure 6 shows the averages and standard deviations for ten simulations of ΔT^C_{diff}. Since the difference became positive and $T^C_{A^g,S^f\to R^o}$ had a higher value when p^c_c exceeded 0.6, the proposed mechanism appeared effective when the caregiver looked sometimes at objects salient to the robot. Note that the difference again became positive when $p^c_c < 0.2$, meaning that T^C detects opposite causality, i.e., if the robot follows the direction of the caregiver's gaze, it cannot look at any salient objects. The proposed mechanism detects causal combinations in face-to-face interaction regardless of whether structures are related to the acquisition of joint attention. The robot thus use the detected combination to acquire joint attention if the caregiver looks often at objects salient to the robot, i.e., $p^c_c > 0.6$.

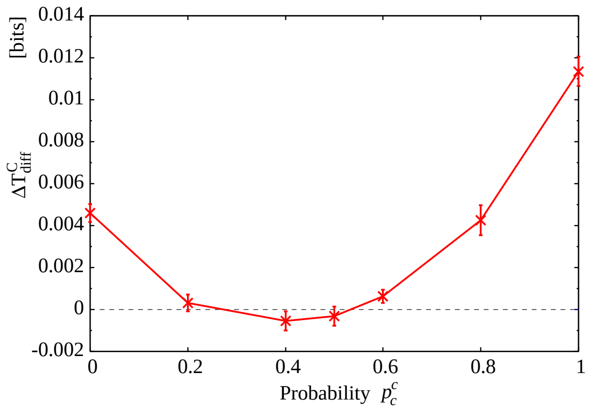

Fig. 6. Change in difference between $T^C_{A^g,S^f \rightarrow R^o}$ and highest T^C in other combinations based on probability p^c_c

D. Learning joint attention with detected causal variables

We studied whether a combination of variables with maximum T^C ($T^C_{A^g,S^f \rightarrow R^o}$) enables the robot to learn joint attention. Before having the robot do so, we confirmed that causality of found combinations showed the robot's experience from which it learned joint attention. Figure 7 shows histograms of experience in which the robot observed the caregiver's face and chose to shift its gaze to a spot before observing an object through interaction. Diagonal elements correspond to joint attention, and showed that the robot tended to successfully observe an object when it occasionally performed the same behavior as joint attention.

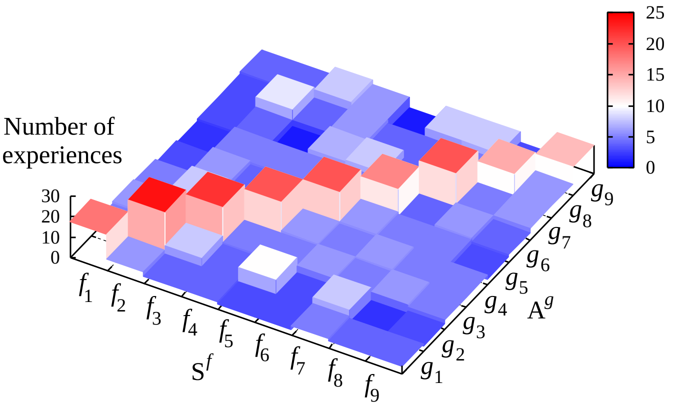

Fig. 7. Distribution of experiences to $R^o = 1$ in interactions between a caregiver and a robot. In this graph, pairs with the identical number of suffixes, e.g., (f_1, g_1), correspond to behavior of joint attention

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

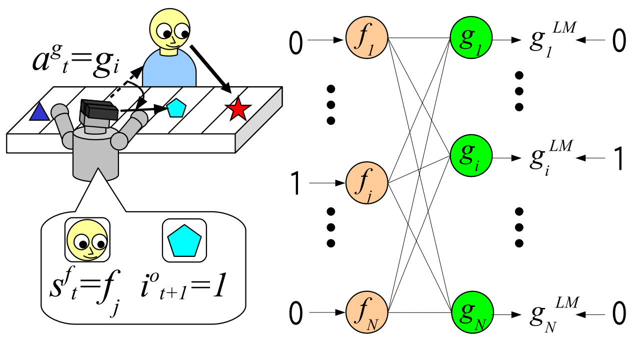

Fig. 8. Network to learn joint attention.

Perception and action variables included in the causal combination with the highest T^C were assigned to input and output layers of a two-layered perceptron (Figure 8). Since contingency learning was conducted by associating sensorimotor variables regardless of joint attention success, it is implemented using the current observable action variable A^g as the desired value of the output layer in backpropagation learning. The perceptron was trained with data obtained through 30,000 interactions in which actions of the caregiver and the robot were determined by models described in Section III. Perception (action) variables were encoded so that input (output) to only one node was "1" while others "0". Suppose that the robot finds something salient ($r^o_{t+1} = 1$) by shifting its gaze to the i-th spot on the table ($a^g_t = g_i$) after observing the caregiver's face, perceived as looking in the j-th direction, ($s^f_t = f_j$). The perceptron receives an input vector of which f_j is one while the others are zeros and receives a reference vector of which g_i is one while the others are zeros (Figure 8).

After ten trials, each consisting of 30,000 interactions, we examined the average success rate for joint attention, testing whether the perceptron output the action variable corresponding to the caregiver's gaze for each of N perceptual inputs. Success rate for each trial was calculated by the number of pairs of input and output achieving joint attention. Average success rate was 84%, confirming that causal variables selected by the proposed mechanism can be utilized to learn joint attention.

VI. DISCUSSION AND CONCLUSIONS

We did not focus on parameters L, N, M, and N_h in experiments because the behavior of L and N is easily predicted.

As either L or N increases, a robot needs more interactions to detect the target combination (A^g, S^f, R^o) because transfer entropies are overestimated due to the inaccuracy of the estimated probability distribution. We set M and N_h as $N+1$ to reduce differences between transfer entropies that attribute to different numbers of possible elements of variables. An infant, however, appears to have the different resolution of multimodal sensations and various kinds of actions because these components develop in parallel and at different time schedules. We should therefore utilize normalized transfer entropies in the number of elements to adequately estimate the causality of combinations that consist of different numbers of elements.

Experimental results showed that responsive and inductive behaviors of a caregiver influence the causality inherent in interactions between the caregiver and a robot only negligibly because the robot did not respond to the caregiver's actions. The caregiver's behavior helps the robot to detect the causal combination for joint attention if we design the appropriate robot responses to the caregiver's actions. We should also add other action modalities, such as pointing or vocalization to the caregiver. We plan to study what sort of causality is detected in interaction with such mutual responses.

Observations in developmental psychology imply that many causal structures are inherent in infant-caregiver interaction [12]. Infants start to become sensitive to social causality from about three months of age [13], and acquire related social skills [14], [15]. Such a causal structure is used to acquire joint attention [16]. Our mechanism appears plausible in that a robot acquires joint attention only by finding the causality of interactions with humans. We cannot yet, however, explain information processing in the human brain for detecting such causality. We plan to use mechanisms to detect such causality in the human brain to propose biologically plausible mechanisms.

Our mechanism can be applied to the acquisition of other social skills besides joint attention. As stated by Triesch *et al.* [5], the acquisition of point following, defined as looking at an object that someone else is pointing at, appears based on a causality similar to visual joint attention, the causality between the infant's gaze shift and the caregiver's hand use when looking at a salient object. Our mechanism may also enable social skills to be cumulatively acquired. If a robot acquires and use new behavior, this behavior changes the caregiver's behavior and modifies causality, leading the robot to acquire subsequent behavior. Through such acquisition, we expect the mechanism to help us understand what sorts of relationships should be found between the developmental processes of skills and how a caregiver should behave to help a robot acquire skills more easily.

We expect that skills acquired by a robot will be suitable to individual humans and tasks. Useful social skills are required by social robots to communicate smoothly with humans. Pre-programming such abilities is, however, difficult because the usefulness of social skills depends on whom the robots communicates with and what tasks they are involved in. As one key to avoid such difficulty, we focused on the fact that many social skills are causal in interactions with humans. We expect that our mechanism will help us realize social robots with social skills appropriate to humans and tasks.

We only evaluated the effectiveness of the proposed mechanism using computer simulations, so we must determine to what extent the proposed mechanism detects causality in real-world interaction. We may start by adding other action modalities expected to enrich human-robot interaction, inducing natural behavior of the caregiver in the robot. We must modify our mechanism so that it learns a sensorimotor map within a reasonable time because our mechanism needs too many interactions at least 10,000 steps to detect causality.

In conclusion, we have shown that transfer entropy is promising in detecting the causality inherent in face-to-face interaction. Transfer entropy helps a robot detect important variables constituting the causal structure inherent in interaction. We also have shown that appropriately chosen causal variables can be used in learning joint attention.

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