Reproducing Interaction Contingency Toward Open-ended Development of Social Actions: Case Study on Joint Attention

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***Abstract*—How can human infants gradually socialize through interaction with their caregivers? This paper presents a learning mechanism that incrementally acquires social actions by finding and reproducing the contingency in interaction with a caregiver. A contingency measure based on transfer entropy is used to select the appropriate pairs of variables to be associated to acquire social actions from the set of all possible pairs. Joint attention behavior is tested to examine the development of social actions caused by responding to changes in caregiver behavior due to reproducing the found contingency. The results of computer simulations of human-robot interaction indicate that a robot acquires a series of actions related to joint attention such as gaze following and alternation in an order that almost matches the infant development of joint attention found in developmental psychology. The difference in the order between them is discussed based on the analysis of robot behavior, and then future issues are given.**

***Index Terms*—joint attention, transfer entropy, contingency chain, sequential acquisition of social behavior**

I. Introduction

Human infants acquire a variety of social actions and gradually develop the ability to communicate with others. In particular, the ability to achieve joint visual attention is the basis for sharing attention with others since what one is looking at often indicates what one is interested in. Therefore, understanding how infants acquire actions related to joint attention such as gaze following, pointing, gaze alternation, and social referencing is a central topic in developmental psychology [1]. Infants incrementally acquire various kinds of actions related to joint attention; after learning gaze following, they begin to show gaze alternation, i.e., successive looking between a caregiver and an object, social referencing, and pointing [2]. However, it remains a mystery why most infants acquire several actions related to joint attention in such an order.

Recent imaging technology developments have been applied to investigate the early sensitivities for actions related to joint attention in infant brains [3], [4], [5]. Mundy *et al*. reported EEG data that show that the parietal and frontal areas are related to the development of responding to others' attentions and attracting them to an interesting object, respectively [4]. An ERP study by Striano *et al*. reported that enhanced negativity is observed in the middle frontal area of nine-month-old infants engaged in a joint attention interaction with a caregiver [5]. However, it remains difficult to investigate the links among these sensitivities and caregiver interactions through developmental courses due to the limitations of current imaging technology.

In robotics, joint attention studies have recently been receiving increased attention [6], not only from the viewpoint of building communicative robots [7] but also from synthetic approaches to modeling and understanding human developmental processes [8]. Previous synthetic studies addressed how infants acquire gaze following with/without external evaluation [9], [10], [11]. The latter utilized contingency among a preceding stimulus, one's own action, and its consequence. An infant can frequently find an object by looking where a caregiver is looking as long as the object at which the caregiver is looking is salient for the infant. Previous studies have shown that a robot can acquire gaze following by learning sensorimotor mapping from a human face pattern to its own motor command to gaze at an object due to the contingency [10], [11]. However, in these studies, the robot was given *a priori* knowledge about what kinds of sensory and motor variables should be associated. Communicative robots [12] usually have many candidates for sensory and motor variables to be associated to acquire such social actions because they are supposed to have multimodal sensorimotor experiences that reflect contingency in interaction with humans. This indicates that it is not trivial for a robot to select such a pair of sensory and motor variables by itself to model contingencies involved in interaction.

We focus on finding contingencies in pairs of sensory and motor variables as well as learning sensorimotor mapping to acquire behavior. Information theoretic measures to find causal relationships between sensory and motor data appear promising [13]. From this viewpoint, we previously showed that a measure of contingency is useful for robots when searching for an appropriate combination of variables that enables gaze following [14]. However, the robots lacked a learning mechanism for behavior acquisition.

Infants seem to easily find contingency in their environment and act to experience the found contingency [15]. It has also been reported that a few interactions with a contingently responsive robot lead infants to follow the gaze of the robot [16]. We call the activity to experience such found contingency "reproducing contingency" and hypothesize that it leads to further novel contingencies that emerge from interactions with a caregiver by introducing contingent responses

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from the caregiver to the robot. We expect that this loop of finding and reproducing contingencies enables open-ended development of social actions such as those related to joint attention. Therefore, we model the developmental process of joint attention by finding a contingency and its reproduction; the joint attention behavior acquired by a robot may change the caregiver's response and induce a novel contingency in the interaction to acquire another action related to joint attention.

This paper presents a learning mechanism based on the above hypothesis. A contingency measure based on transfer entropy is used to select appropriate pairs of variables to be associated to acquire social actions from possible pairs. A mechanism constructs a sensorimotor mapping to reproduce behavior based on the found contingency. In the iterative process, two new variables that express whether each sensorimotor mapping was used or is being used are added to find not only a single new contingency but also chains of contingencies that depend on other contingencies. Joint attention behavior is tested to examine the development of social actions caused by changes in the caregiver's behavior due to reproducing the found contingency. As a first step, we simplify caregiver-robot interaction by focusing on their gazes and gestural modalities and suppose a quantized sensorimotor space where sensory and motor variables have discrete values. The results of computer simulations of the interaction indicate that a robot acquires a series of actions related to joint attention such as gaze following and alternation in an order that almost matches the infant development of joint attention found in developmental psychology. The difference between them is discussed based on the analysis of robot behavior, and finally future issues are given.

II. Contingency inherent in interaction

The contingency infants find in interaction with caregivers depends on what capabilities they have and how they and their caregivers interact with each other. To clarify these elements involved in contingency, we first identify the phase of infant development to be simulated. The behavior of the infants and the contingency are then modeled using discrete stochastic processes. Finally, the expected changes of the contingency in the interaction are described.

A. Initial phase of joint attention development

Before infants begin to follow the gaze of another person around six months [17], their behavior changes drastically around five months. Five-month-old infants can control their heads [18] and begin to pay attention to their environments as well as their caregivers [19]. Their caregivers follow the attention of five-month-old infants or attract it to an object [19]. Since these are expected to help infants develop their joint attention capabilities, we simulated the developmental process for several months starting from a five-month-old infant.

Infants are already sensitive to contingency in their environment before five months [20], [15], [21], but their contingency detection ability is limited because they can only detect contingency for a few seconds [22]. Therefore, we assume that an infant model can only detect the contingency for a short time.

B. Interaction procedure

We assume a simplified face-to-face interaction between a caregiver and an infant (hereafter a robot), both of whom take turns observing their environments and the other agent at the t-th time step as follows:

1) Robot observes part of its environment including the caregiver and obtains sensory information $\boldsymbol{s}^t = (s_1^t, s_2^t, \cdots, s_{N^s}^t)^T$, where s_i^t is a value in S_i^t called a sensory variable ($i = 1, 2, \cdots, N^s$; N^s denotes the number of types of sensory data).
2) Robot takes plural actions $\boldsymbol{m}^t = (m_1^t, m_2^t, \cdots, m_{N^m}^t)^T$ in parallel, where m_j^t is a value in M_j^t called a motor variable ($j = 1, 2, \cdots, N^m$; N^m denotes the number of different kinds of actions).
3) Caregiver observes part of her environment including the robot and then acts.
4) Robot observes sensory information $\boldsymbol{r}^{t+1} = (r_1^{t+1}, r_2^{t+1}, \cdots, r_{N^r}^{t+1})^T$ after its last action $\boldsymbol{m}^t$, where r_k^{t+1} is a value in R_k^{t+1} called a resultant sensory variable ($k = 1, 2, \cdots, N^r$; N^r denotes the number of types of resultant sensory data).

We discriminate resultant sensory variables from sensory variables to distinguish between cause and effect, although they should represent the same information. We call a time sequence of variables a process, namely, sensory process $S_i = \{S_i^t\}$, motor process $M_j = \{M_j^t\}$, and resultant sensory process $R_k = \{R_k^{t+1}\}$. A triplet of processes (S_i, M_j, R_k) is called an *event*. Here, the contingency of event (S_i, M_j, R_k) is evaluated as the dependency of R_k on S_i and M_j. We call an event that involves strong dependency a *contingent event*. Some observations of human infants suggest that they change their behavior after finding contingency [15]. Therefore, we separate the robot task into two parts: finding a contingent event and acquiring a sensorimotor map with which it can obtain the contingent consequence.

C. Changes of contingency in social interaction

In caregiver-infant interaction, the social response of a caregiver (which is contingent) to infant behavior leads the infant to acquire a social action [23], [21], [15]. Some findings show that the caregiver gradually changes how she responds to infant behavior as her infant's communicative abilities emerge [24], [25]. This change may produce not only a single contingency but also a chain of contingencies that enable the infant to acquire social behavior that consists of a sequence of acquired actions.

Actually, several social actions consist of a sequence of contingent sub-actions. For example, social referencing might be performed by two social actions: following the other's gaze to find an object and then looking back at the other's face to determine why the other is looking at it.

Therefore, we assume that a robot can observe the use of an acquired action to promote finding the chain.

III. Proposed mechanism to successively develop social behavior

The mechanism shown in Fig. 1 consists of four modules: (1) a contingency detector, (2) contingency reproduction modules (CMs), (3) reactive behavior modules (RMs), and (4) a module selector. The number of RMs is constant, but at the beginning of learning there are no CMs because they are generated by the contingency detector once it finds a contingent event through interactions between the caregiver and robot.

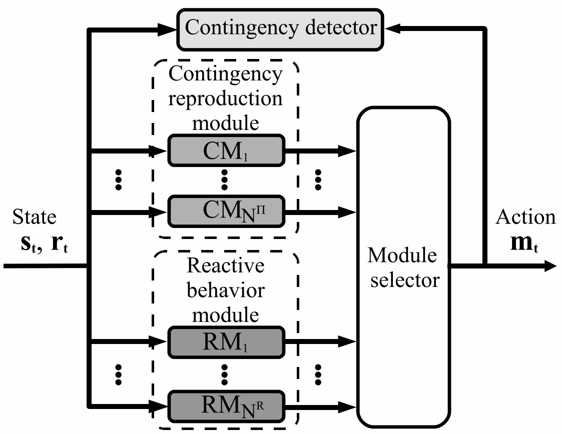


Fig. 1. Proposed mechanism to successively develop social actions

RMs and CMs output motor commands to be executed and reliability values for the current state. The reliability, which indicates the appropriateness of motor commands selected by each RM and CM, is calculated based on information theory. The module selector decides robot actions based on the reliabilities. The history of the current state and the selected motor command are stored with the resultant state in the contingency detector to find contingent events and to generate subsequent CMs based on them.

A. Contingency detector

A contingency detector has two roles: finding a contingent event and generating a new CM based on it. We proposed an information theoretic measure of contingency based on transfer entropy [26] to quantify the contingency of events experienced through interactions with a caregiver [14]. Transfer entropy is a kind of information measure that can quantify the dependency of one stochastic process on another process based on conditional transition probabilities [1] [26]. The contingency detector evaluates the contingency in interaction by calculating the measures for all events. This measure is slightly extended and applied to all events that are possible combinations of sensory, motor, and resultant sensory variables.

Let $X = \{X^{t+1}\}$ and $Y = \{Y^t\}$ be two discrete random processes that may be approximated by a stationary Markov process of order k and l. When X^t takes value x^t at time t, the evolution of process X is denoted by transition probability $p(x^{t+1}|\boldsymbol{x}^t(k))$, where $\boldsymbol{x}^t(k) = (x^t, \cdots, x^{t-k+1})$. Transfer entropy indicating the dependency of process X on process Y is given by:

$$T_{Y\to X} = \sum_{x^{t+1},\boldsymbol{x}^t(k),\boldsymbol{y}^t(l)} p(x^{t+1}, \boldsymbol{x}^t(k), \boldsymbol{y}^t(l)) \times \log \frac{p(x^{t+1}|\boldsymbol{x}^t(k), \boldsymbol{y}^t(l))}{p(x^{t+1}|\boldsymbol{x}^t(k))}. \qquad (1)$$

Here, we set $k = l = 1$ because of the limitation of causality detection mentioned in Section II-A.

To construct a sensorimotor map from sensory signals to motor commands that provide a robot with contingent consequences, the robot needs to evaluate the dependency of a resultant sensory process on the sensory and motor processes. Therefore, we introduce saliency of contingency (C-saliency) $C^j_{i,k}$, which is extended from the original transfer entropy as follows to quantify the joint effect of sensory process S_i and motor process M_i on the resultant sensory process R_k:

$$\begin{aligned} C^j_{i,k} &= T_{(S_i,M_j)\to R_k} - (T_{S_i\to R_k} + T_{M_j\to R_k}) \\ &= \sum_{s^t_i, r^t_k} p(r^t_k, s^t_i) \sum_{r^{t+1}_k, m^t_j} e(r^{t+1}_k, m^t_j | r^t_k, s^t_i), \end{aligned} \qquad (2)$$

where $e(r^{t+1}_k, m^t_j | r^t_k, s^t_i)$ is called an element of C-saliency under a pair of observed values (r^t_k, s^t_i) and is given by:

$$\begin{aligned} e(r^{t+1}_k, m^t_j | r^t_k, s^t_i) = \\ p(r^{t+1}_k, m^t_j | r^t_k, s^t_i) \log \frac{p(r^{t+1}_k | r^t_k, s^t_i, m^t_j)}{p(r^{t+1}_k | r^t_k, s^t_i)} \\ -p(r^{t+1}_k, m^t_j | r^t_k) \log \frac{p(r^{t+1}_k | r^t_k, m^t_j)}{p(r^{t+1}_k | r^t_k)}. \end{aligned} \qquad (3)$$

The element of C-saliency represents the strength of the dependency of the state transition from r^t_k to r^{t+1}_k on pair $(s^t_i, m^t_j,)$. The first term represents the difference between $p(r^{t+1}|r^t, s^t)$ and $p(r^{t+1}|r^t, s^t, m^t)$ and indicates how the transition from r^t to r^{t+1} depends not only on s^t but also on m^t. The second term represents the difference between $p(r^{t+1}|r^t)$ and $p(r^{t+1}|r^t, m^t)$ and indicates how the transition from r^t to r^{t+1} only depends on m^t. The second term is subtracted from the first to capture the combinatorial dependency of s^t and m^t on the transition from r^t to r^{t+1}. If they share strong dependency, the element of C-saliency increases.

Note that C-saliency becomes smaller when the state transition from r^t_k to r^{t+1}_k is not only independent of s^t_i and m^t_j but is also fully predicted by the sensorimotor map. Using the sensorimotor map reduces the uncertainty of a motor signal given a sensory signal. As a result, the difference between the denominator and the numerator in the first term of Eq. (3) becomes smaller. Therefore, C-saliency is used to find the salient contingency that a robot cannot reproduce by the acquired sensorimotor map before finding it.

After calculating C-saliencies for all events, the detector determines whether to generate a new CM for a contingent event. We regard an event with the highest C-saliency value as a contingent event because it is unclear how a high C-saliency generates a useful CM. A new CM is generated if its C-saliency retains the highest value during T^C time steps and the absolute difference of the values for the last consecutive time steps during this period is smaller than constant value

[1]This measure is equivalent to the conditional mutual information [27], [28] but unlike mutual information, it is designed to detect the dependency between two processes based on the idea of finite-order Markov processes.

θ. To avoid generating too many similar CMs, the contingency detector generates only one CM per contingent event. Hereafter, a CM that is constituted for event (S_i, M_j, R_k) is denoted as $\mathbf{\Pi}(R_k|S_i, M_j)$.

To find a chain of contingencies depending on a found contingency, a robot identifies whether it reproduced the found contingency as CM activities. When the contingency detector generates the i-th new CM, it begins to observe the CM activities, which we express as two different kinds of binary random processes, M^{Π_i} and S^{Π_i}, to investigate the simplest chain of contingencies related to the CM. $M^{\Pi_i,t}$ takes value "1" at time step t when an output from Π_i is selected as a current motor command by the module selector and "0" otherwise. $S^{\Pi_i,t}$ takes value "1" at time step t when an output from Π_i is selected as a last motor command and "0" otherwise. Therefore, if the number of generated CMs is N^{Π}, the contingency detector calculates C-saliencies $C^j_{i,k}$, where $S_i \in \{S_1, \cdots, S_{N^s}, S^{\Pi_1}_{N^s+1}, \cdots, S^{\Pi_{N^\Pi}}_{N^s+N^\Pi}\}$ and $M_j \in \{M_1, \cdots, M_{N^m}, M^{\Pi_1}_{N^m+1}, \cdots, M^{\Pi_{N^\Pi}}_{N^m+N^\Pi}\}$. We expect this extension to enable the contingency detector to find not only a contingency for one time step but also one for several steps related to the generated CM.

B. Contingency reproduction module

A CM $\mathbf{\Pi}(R_k|S_i, M_j)$ for contingent event (S_i, M_j, R_k) is composed of a sensorimotor map from S_i^t to M_j^t that reproduces a contingent change of R_k^t based on elements of C-saliency (see Eq. (3)). Given observed values of S_i^t and R_k^t, a value of M_j^t called a contingent motor command is selected to reproduce the contingent change represented in the CM. A contingent motor command is defined as the value of M_j^t whose C-saliency element is the highest among all possible C-saliency elements.

Therefore, contingent motor command m^* is given by:

$$(\hat{r}^*, m^*) = \arg\max_{\hat{r}'_k, m'_j} e(\hat{r}'_k, m'_j|r_k, s_i), \tag{4}$$

where r_k and s_i are the current observations and $\hat{r}^*$ is the expected resultant sensory information that predicts the change by the contingent motor command. Hereafter, we call a pair of $\hat{r}^*$ and m^* a contingent estimation.

CM also calculates the reliability of the contingent estimation for the current observation that is used by a module selector, as described in Section III-D. We denote such a reliability of the contingent estimation of the l-th CM as $Z_l(\hat{r}^*, m^*|r_k, s_i)$. It is designed based on the z-score of the C-saliency elements so that the module selector uses a contingent estimation whose C-saliency element is not only high compared with any other pairs in the event but also more salient than other possible pairs under the current observation [2].

After they are calculated, the sensorimotor map and the reliabilities in a CM are not updated, but the C-saliency for the event used to generate the CM continues to be calculated.

C. Reactive behavior module

An RM outputs a motor command to perform a simple action such as shifting gaze based on a fixed policy given by the designer. RMs play more important roles in the early stage of development since the robot behavior is only determined by them before acquiring any CMs. To separate as much as possible the proposed mechanism's contribution from that of super-tuned RMs for the development, we adopted the two simplest RMs in the experiment: one is for gaze behavior by which the target position of looking at is randomly selected and the other is for hand gestures by which the hand's target posture is randomly selected. We might be also able to use more biased selection because infants have innate preferences for such things as human faces [29] or objects with complex textures [30].

Fixed constant α is used for the reliabilities of the RMs. A constant α influences the probability of selecting outputs from the CMs as actual motor commands. A higher value of this parameter prevents the module selector from selecting outputs from CMs. As a result, a robot spends too much time before finding the contingency related to an acquired CM or even sometimes fails. In the experiment, we set α to almost half of the reliabilities of the contingent estimations; that is, $\alpha = 1.0$.

D. Module selector

Given the reliabilities of all CMs and RMs, a module selector decides which of these outputs should be selected as the robot's motor command. In the current implementation, we assume that the robot can simultaneously select multiple motor commands if they belong to different categories. For example, it can simultaneously perform both gaze and hand movements.

For each motor command category, the module selector chooses one of the outputs of all RMs and CMs belonging to the same category by softmax selection based on the reliabilities. Note that to avoid deadlocks in specific states, the RMs and CMs reliabilities are discounted by an exponential factor of periods when the state transition of the sensory and resultant sensory variables involved in the modules do not change.

E. Sequential acquisition of behavior based on reproducing the acquired behavior

The proposed mechanism is expected to continue to acquire different sensorimotor mappings as follows. At the beginning of learning, the module selector selects the outputs of RMs (at

[2]In the current implementation, $Z_l(\hat{r}^*, m^*|r_k, s_i)$ was calculated by

$$Z_l(\hat{r}^*, m^*|r_k, s_i) = \frac{e_l(\hat{r}^*, m^*|r_k, s_i) - \mu_l^{r_k,s_i}}{\sigma_l^{r_k,s_i}}, \tag{5}$$

where $\mu_l^{r_k,s_i}$ and $\sigma_l^{r_k,s_i}$ denote the average and standard deviation of all C-saliency elements under values (r_k, s_i). Eq. (5) is applied for the reliability of the contingent estimation that meets the following requirements:

$$e(\hat{r}^*, m^*|r_k, s_i) - \{\max_{\hat{r}''_k, m''_j} e(\hat{r}''_k, m''_j|r_k, s_i)\} > Z_\theta \tag{6}$$

$$(\hat{r}''_k \neq \hat{r}^* \cap m''_j \neq m^*)$$

$$e(\hat{r}^*, m^*|r_k, s_i) > 0.2\{\max_{\substack{\hat{r}'_k, m'_j,\\ r'_k, s'_i}} e(\hat{r}'_k, m'_j|r'_k, s'_i)\}. \tag{7}$$

$Z_l(\hat{r}^*, m^*|r_k, s_i) = 0$ if the contingent estimation does not satisfy them.

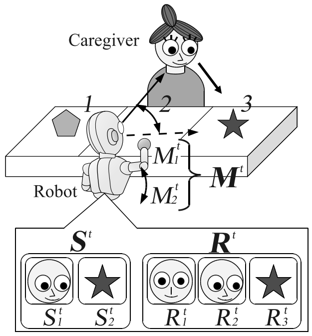


Fig. 2. Experimental setting for acquisition of actions related to joint attention

TABLE I

INITIAL VARIABLES IN ROBOT

Type	Name	Symbol	Variables
$\boldsymbol{S}^t$	caregiver's face	C	$S_1^t = \{f_1, f_2, f_3, f_r, f_\phi\}$
	object	O	$S_2^t = \{o, o_\phi\}$
$\boldsymbol{M}^t$	gaze shift	G	$M_1^t = \{g_1, g_2, g_3, g_c\}$
	hand gesture	H	$M_2^t = \{h_1, h_2, h_3, h_4\}$
$\boldsymbol{R}^t$	frontal face of caregiver	F	$R_1^t = \{0, 1\}$
	profile of caregiver	P	$R_2^t = \{0, 1\}$
	object	O	$R_3^t = \{0, 1\}$

random selection) as motor commands since there are no CMs. As interaction between caregiver and robot is iterated, the contingency detector generates a new CM with a sensorimotor map to reproduce the found contingency. Once a CM has started to be used, the robot's behavior might affect the dynamics of its environment; for example, its caregiver might regard it as more communicative and change her response to it. Such a change causes the invention of subsequent CMs, which hopefully create further inventions in a catenative way.

Whenever a new CM is generated, the contingency detector starts to observe whether the new CM was used and is going to be used, respectively. It also starts to evaluate new events including these activities of the CM expressed as new sensory process S^{Π} and motor process M^{Π}. Such events may be selected as the next contingent event if the found contingency leads to novel contingency. Therefore, the robot is expected to find a chain of contingent events.

IV. COMPUTER SIMULATION OF BEHAVIORAL DEVELOPMENT RELATED TO JOINT ATTENTION

The proposed model's performance was tested in computer simulations of a robot and a caregiver model, both of which manipulated a sensorimotor space in face-to-face situations where they used gazes and hand movements.

A. Experimental setting

1) Environment and infant model: Figure 2 shows an overview of the setting in the computer simulation. The robot sits across from the caregiver at a fixed distance. There are three spots on a table, and two objects are randomly placed every ten time steps (no more than one object at one spot). Here, the objects are not identified for simulation simplicity since the differences between them do not affect the robot and caregiver behavior.

The initial set of variables is listed in Table I [3]. The sensory variable for the caregiver's face is denoted by S_1^t, which takes a state at which the robot is looking at her frontal face (f_r), or her face looking at spot i on the table, f_i ($i = 1, 2, 3$), or does not look at the caregiver (f_ϕ). The sensory variable for an object is denoted by S_2^t, which takes a state at which the robot is looking at an object (o) or at something else (o_ϕ). The robot cannot simultaneously look at both the caregiver's face and spots on the table. For example, when it is looking at the caregiver's frontal face, $(s_1^t, s_2^t) = (f_r, o_\phi)$.

We select resultant sensory variables $\boldsymbol{R}^t = \{R_1^t, R_2^t, R_3^t\}$ that reflect the infant's innate preferences. Human infants appear to like both the caregiver's face [29] and salient objects [30]. In particular, they prefer frontal faces to profiles [29]. Thus, we prepared three types of variables: caregiver's frontal face R_1^t, caregiver's profile R_2^t, and object R_3^t. These binary variables indicate whether the robot is looking at its preferred face or an object ("1") or neither ("0"). Since the robot can look at either the caregiver's face or spots on the table, only one or none of the components of $\boldsymbol{R}^t$ can be "1" at the same time.

The robot can simultaneously shift its gaze and gestures. Its gaze shift is denoted by M_1^t, which indicates the target of its gaze, i.e., a particular location on table g_i ($i = 1, 2, 3$) or the caregiver's face (g_c). The gesture is denoted by M_2^t, which takes one of four different hand gestures: hitting the table with its right hand, its left one, both of its hands, or not hitting it.

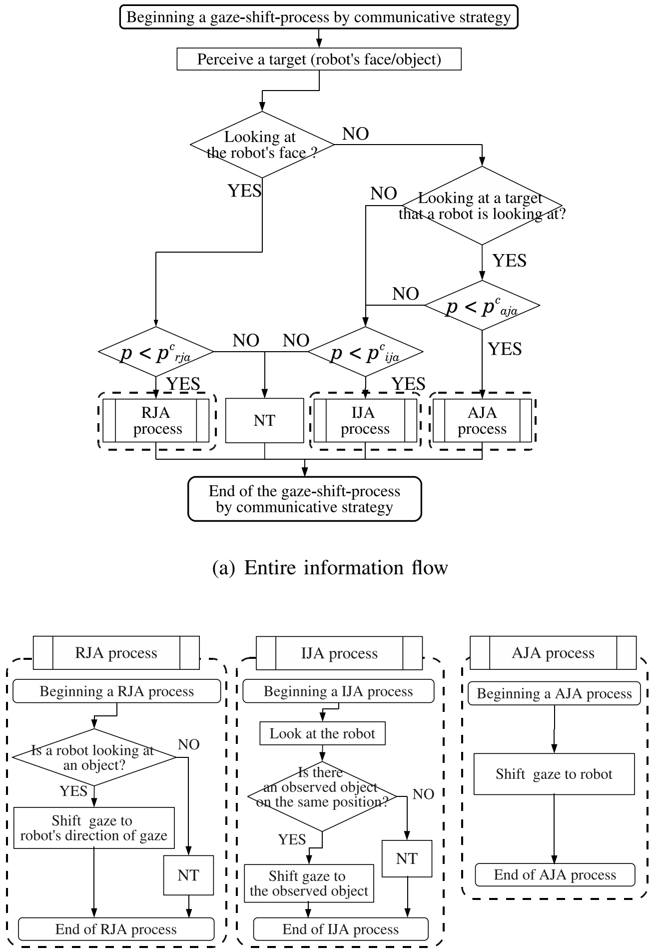
The robot first uses two RMs to determine gaze movements and hand gestures by randomly selecting a member of M_1^t and M_2^t. After CMs are found, the motor commands for these actions are determined by the module selector that integrates the outputs of these RMs and the generated CMs. The parameters in the proposed mechanism are set as $(T^C, \theta, Z_\theta, \alpha) = (30, 5.0 \times 10^{-5}, 0.5, 1.0)$. The joint and conditional probabilities in Eq. (3) were calculated based on the histograms of the values of events.

2) Behavior rules for caregivers: The caregiver strategies are designed to resemble actual caregiver behavior because, to the best of our knowledge, there are no quantitative investigations on how a caregiver's gaze-shift behavior is affected by the development of her infant [4]

The caregiver only shifts her gaze at each time step while the robot moves its hands and shifts its gaze. The caregiver, who always looks at either the robot's face or an object on the table, has four optional strategies to shift her gaze (see Fig. 3(a)): 1) following the robot's gaze, in other words,

[3] Instead of allowing the complicated diversities of the results by assigning all sensory variables both for $\boldsymbol{S}^t$ and $\boldsymbol{R}^t$, we selected different sets of variables for each $\boldsymbol{S}^t$ and $\boldsymbol{R}^t$. Note that such a reduced problem still involves finding appropriate variables as causes and results as well as that we can observe a similar tendency in the order of the acquired modules as those obtained in the current reduced setting.

[4] There is a theoretical study on the influence of caregiver behavior on the learning process in a simple reinforcement learning model of gaze following [31].



(a) Entire information flow

(b) Details of each process

Fig. 3. Flow chart of caregiver's gaze shift

responding to joint attention process (RJA); 2) shifting her gaze to draw the robot's attention, in other words, initiating joint attention process (IJA); 3) looking at the robot after achieving joint attention to acknowledge joint attention, in other words, acknowledging joint attention process (AJA); and 4) randomly looking at a target selected (NT). After one of these strategies is selected, a target is chosen based on the strategy. Note that in the NT strategy, targets that could be selected in other strategies are excluded from the candidates. For example, the caregiver is controlled so that she does not follow the robot's gaze in the NT strategy. The robot, who does not know which strategy the caregiver is engaged in, just acts based on outputs from RMs or from CMs at each time step regardless of the caregiver's current strategy. Therefore, the caregiver does not necessarily succeed in attracting the robot's attention when she selects the IJA process.

At each time step, the caregiver selects one of the strategies depending on what she is looking at. She usually selects NT. The other strategies, RJA, IJA, or AJA, can be selected in the following cases (Fig. 3(a)): if the caregiver is looking at the robot's face, she selects either RJA with probability p^c_{rja} or NT with probability $1 - p^c_{rja}$. Otherwise, (looking at an object on the table), the caregiver selects either IJA with probability p^c_{ija} or NT with probability $1 - p^c_{ija}$, except when the caregiver and the robot are looking at the same object. In such cases, the caregiver selects either AJA with probability p^c_{aja}, IJA with probability $p^c_{ija}(1 - p^c_{aja})$, or NT with probability $(1 - p^c_{ija})(1 - p^c_{aja})$.

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 (left in Fig. 3(b)). In IJA, the caregiver shifts her gaze from an object to the robot and then shifts her gaze to the object at the next time step again (center in Fig. 3(b)). In AJA, the caregiver shifts her gaze to the robot's face as if to confirm that joint attention was achieved with the robot (right in Fig. 3(b)).

B. Sequential acquisition of joint attention behavior

We ran 100,000 time step simulations ten times where $(p^c_{rja}, p^c_{ija}, p^c_{aja}) = (0.5, 0.5, 1.0)$. At the beginning of learning, robot motion was controlled by RMs, but it sometimes accidentally achieved gaze following or gaze alternation. It gradually, however, acquired CMs related to joint attention through interaction with the caregiver. The average number of CMs found by the contingency detector was 4.1. In all the simulations, a particular set of CMs was generated in the following fixed order: $\mathbf{\Pi}(R_3|S_1, M_1)$, $\mathbf{\Pi}(R_1|S_3^{\Pi_1}, M_1)$, and $\mathbf{\Pi}(R_2|S_3^{\Pi_1}, M_1)$. Hereafter, we express these CMs using the symbols in Table I to avoid confusion:

$$\mathbf{\Pi}(R_3|S_1, M_1) = \mathbf{\Pi}(O|C, G) \quad (8)$$

$$\mathbf{\Pi}(R_1|S_3^{\Pi_1}, M_1) = \mathbf{\Pi}(F|{}^s\Pi(O|C, G), G) \quad (9)$$

$$\mathbf{\Pi}(R_2|S_3^{\Pi_1}, M_1) = \mathbf{\Pi}(P|{}^s\Pi(O|C, G), G), \quad (10)$$

where ${}^s\Pi(O|C, G)$ indicates a symbol expressing whether the robot used the last output of $\mathbf{\Pi}(O|C, G)$.

These CMs were often generated earlier than other CMs for different events. Table II shows examples of the found contingent estimations (i.e., outputs) for specific inputs in these CMs with their reliabilities. Each of these CMs allowed the robot to achieve social behavior: following the caregiver's gaze ($\mathbf{\Pi}(O|C, G)$, hereafter the *following-gaze* module), shifting its gaze to the caregiver after using the output of the *following-gaze* module ($\mathbf{\Pi}(F|{}^s\Pi(O|C, G), G)$, hereafter the *returning (following-gaze)* module), and shifting its gaze to the caregiver regardless whether the robot used outputs of the *following-gaze* module at last time step ($\mathbf{\Pi}(P|{}^s\Pi(O|C, G), G)$, hereafter the *returning (no-condition)* module).

Fig. 4 shows examples of the time courses of C-saliencies for several events whose C-saliency was the highest or the second highest during at least one time step in the simulation. The vertical axis indicates the logarithmic value of the C-saliencies. We also show the timing of generating new CMs as arrows at the top of the graph. Since at the beginning of the simulation the statistics are based on few samples, C-saliencies tended to be overestimated. After sufficient interaction data were collected, $C^1_{1,3}$ became the highest among all C-saliencies (red curve in Fig. 4). As a result, a new CM ($\mathbf{\Pi}(R_3|S_1, M_1)$) corresponding to the *following-gaze* module

TABLE II
SENSORIMOTOR MAP AND RELIABILITIES IN TYPICALLY GENERATED CMS

Type of CM	name	input (r^t, s^t)	output $(\hat{r}, m^t)$	reliability
$\mathbf{\Pi}(O\|C,G)$	*following-gaze*	$(0, f_1)$	$(1, g_1)$	1.86
		$(0, f_2)$	$(1, g_2)$	1.81
		$(0, f_3)$	$(1.g_3)$	1.79
$\mathbf{\Pi}(F\|^s\mathbf{\Pi}(O\|C,G),G)$	*returning (following-gaze)*	$(0, 1)$	$(1, g_c)$	1.73
$\mathbf{\Pi}(P\|^s\mathbf{\Pi}(O\|C,G),G)$	*returning (no-condition)*	$(0, 1)$	$(0, g_c)$	1.73
		$(0, 0)$	$(1, g_c)$	1.82

was generated at the 4504th time step, and $S_3^{\Pi_1}$ and $M_3^{\Pi_1}$ were added as sensory and motor processes, respectively.

The robot then began to follow the caregiver's gaze using output from the *following-gaze* module when it looked at the caregiver who was looking at an object. This increase of gaze following increased the opportunities for the caregiver to look at the robot in responses to the achievement of joint attention. By iterating the interaction, $C_{1,3}^1$ gradually decreased because using particular output based on the acquired sensorimotor map reduces the difference between $p(r_3^{t+1}|r_3^t, s_1^t, m_1^t)$ and $p(r_3^{t+1}|r_3^t, s_1^t)$ (the first term of Eq. (3)). This decrease made $C_{3,1}^1$ the next highest value. The found contingency implied that the robot observed the caregiver's frontal face when it looked at the caregiver after using output from *following-gaze*. Based on the contingency, the next CM ($\mathbf{\Pi}(R_1|S_3^{\Pi_1}, M_1)$) corresponding to the *returning (following-gaze)* module was generated at the 37838th time step. This enabled the robot to direct its gaze to the caregiver after following the caregiver's gaze.

Using output from the *returning (following-gaze)* changed the contingency in the interaction again and promoted not only a decrease of $C_{3,1}^1$ but also an increase of $C_{3,2}^1$ (blue curve in Fig. 4). This caused the generation of the third CM ($\mathbf{\Pi}(R_2|S_3^{\Pi_1}, M_1)$) corresponding to the *returning (no-condition)* module at the 43078th time step. This enabled the robot to shift its gaze to the caregiver without depending on the *gaze-following* output. As a result, the robot alternately shifted its gaze between the caregiver and an object: it acquired gaze alternation. The robot acquired not only gaze following but also gaze alternation through the repetition of finding and reproducing a chain of contingencies in an interaction that changed using output from existing CMs.

C. Influence of caregiver behavior

In natural interaction between caregiver and infant, the caregiver might behave in different ways from those simulated in the previous section. We examined to what extent the sequence of acquired actions depends on caregiver behavior.

In the simulations, probabilities p_{rja}^c, p_{ija}^c, and p_{aja}^c that the caregiver selects RJA, IJA, and AJA processes, respectively, were set to 0.0, 0.5, or 1.0. If we set $p_{aja}^c = 1.0$, the robot is expected to look at the caregiver's frontal face when it shifts its gaze to her after gaze following for the caregiver, but not if

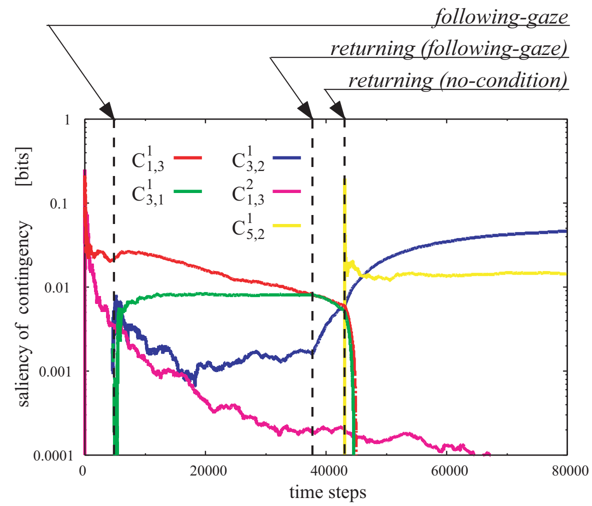


Fig. 4. Time courses of saliency of contingency of events in simulation face-to-face interactions between caregiver and robot

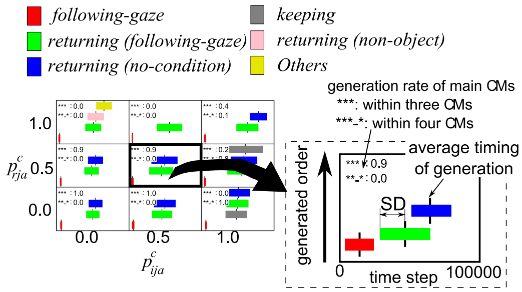
$p_{aja}^c = 0.0$. For each parameter setting, we ran a 100,000-step simulation ten times.

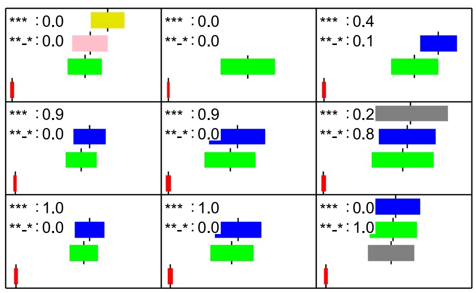
Each block in Fig. 5 shows the average timing when new CMs were generated. Note that in this analysis, we only picked CMs that were generated in more than five simulations under each parameter set. The horizontal axis in a block indicates the time steps. The median in the colored rectangles denotes the average, and its width represents the standard deviation. A colored rectangle for a CM is stacked based on the average timing. To investigate whether the *following-gaze*, *returning (following-gaze)*, and *returning (no-condition)* modules are generated in the same order shown in the previous section, we showed the rate at which they were generated in the order until the third or fourth CM was generated at the top left/right corner of each block in Fig. 5.

Following-gaze was generated first under most of the parameter sets at almost the same time step regardless of the value of p_{aja}^c. A main difference between the values of p_{aja}^c was the types of CMs generated after *following-gaze*. For $p_{aja}^c = 1.0$, the robot acquired *returning (following-gaze)* and *returning (no-condition)* in the same order shown in the previous section under most of the parameter sets. However the robot could not acquire *returning (no-condition)* if p_{rja}^c was high and p_{ija}^c was low (Fig. 5 (a)). Instead, $\mathbf{\Pi}(P|O,G)$ was generated after *returning (following-gaze)*, which enabled its gaze to be shifted to the caregiver despite achieving looking at an object. As a result, the robot acquired gaze alternation.

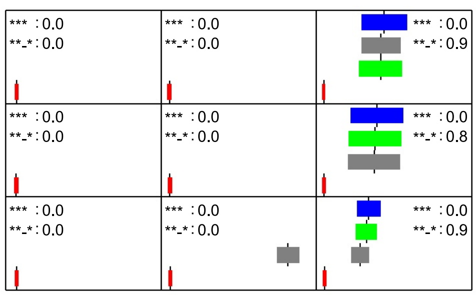
The robot could acquire *returning (following-gaze)* and *returning (no-condition)* when p_{ija}^c was high for $p_{aja}^c = 0.5$ because the IJA process sometimes makes the caregiver perform the same behavior as one performed under the AJA process; the caregiver can look at the robot not under the AJA process but the IJA one after achieving joint attention with the robot. Therefore, the robot could find the contingency to acquire those two modules even when p_{aja}^c is low. The robot did not acquire those modules as p_{ija}^c gets lower.

For $p_{aja}^c = 0.0$, the other CMs were generated after

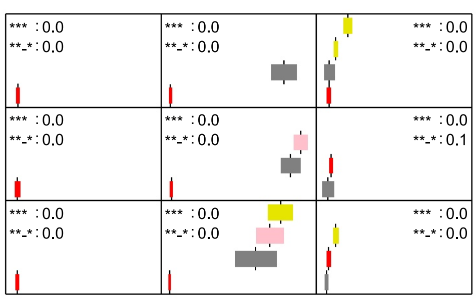




(a) case of $p^c_{aja} = 1.0$.



(b) case of $p^c_{aja} = 0.5$.



(c) case of $p^c_{aja} = 0.0$.

Fig. 5. Timing of CM generation under different parameter sets $(p^c_{rja}, p^c_{ija}, p^c_{aja})$ in face-to-face interactions between caregiver and robot

following-gaze was generated under some parameter sets (Fig. 5 (c)). $\mathbf{\Pi}(P|O,G)$, found in the case of high p^c_{ija}, seems to be another version of shifting the gaze to the caregiver by *returning (following-gaze)*, which enabled the robot to shift its gaze to the caregiver when it was looking at a spot on the table or the caregiver's frontal face. We call $\mathbf{\Pi}(P|O,G)$ the *returning (non-object)* module. $\mathbf{\Pi}(P|C,G)$, which was called *keeping* and generated before the *returning (non-object)* module, constituted a sensorimotor map with which the robot kept looking at the caregiver after it established eye contact. These CMs had contingent connections with *following-gaze*, but not with each other because using the output from the *keeping* module did not positively influence the generation of the *returning (non-object)*, such as promoting an increase of $C^1_{2,2}$, although using output from the *returning(following-gaze)* module promoted the increase of $C^1_{3,2}$ *returning (no-condition)* for $p^c_{aja} = 1.0$, as shown in the previous section.

These results indicate that a caregiver should often shift her gaze to a robot after achieving joint attention with it to acquire gaze alternation. We also confirmed that a high value of p^c_{aja} promotes the generation of *returning (following-gaze)* and *returning (no-condition)* in the experiments for different parameter settings of p^c_{aja}.

V. Discussion

A. Correspondence to developmental psychology

1) Developmental process of joint attention: Previous studies in developmental psychology have suggested that a human infant begins to follow the gaze of a caregiver and then acquires gaze shifting to her [2]. However, in previous synthetic studies regarding gaze following acquisition, gaze alternation was pre-programmed [10] or acquired before gaze following [11]. In the experiment, the robot acquired gaze following ability and alternation in an order that resembles infant development. The iteration of finding and reproducing the contingency inherent in the interaction with a caregiver might provide the order of infant development.

However, our simple model cannot explain about mastery of each behavior. For example, infants begin to follow the gaze of the others in their field of view and then acquire gaze following to targets outside their visual field. Some synthetic studies have addressed this development process [10], [32]. We will extend our model to address this issue as future work.

2) Behavioral analysis: We examined what kinds of behavioral changes of the robot occurred through simulated development with CM generations. Fig. 6 shows the transitions of the frequency of typical infant actions in an example of simulated development where $(p^c_{rja}, p^c_{ija}, p^c_{aja}) = (0.5, 0.5, 1.0)$. Here, we focus on three types of actions: gaze follow, gaze keep, and gaze return. Gaze follow and keep indicate the behavior of following the caregiver's gaze and continuing to look at her, respectively, while gaze return indicates looking back at the caregiver. We calculated the moving average of the occurrence rate of these behaviors among the last 1,000 time steps.

Interestingly, generating CMs of *following-gaze* and *returning (following-gaze)* promoted little change in the robot's behavior (P2 and P3 in Fig. 6), while generating the *returning (no-condition)* drastically changed the robot's behavior (P4 in Fig. 6). Generating the CM of the *returning (no-condition)* promotes the behavior of gaze follow (red curve in P4 in Fig. 6) as well as gaze keep and return (blue and green curves in P4 in Fig. 6) because performing gaze follow and keep with these CMs required the robot to have already looked at the caregiver, which could be promoted after the CM of the *returning (no-condition)* had begun to be used.

This transition might explain a conflict in the previous studies of observing infant development. While six-month-old

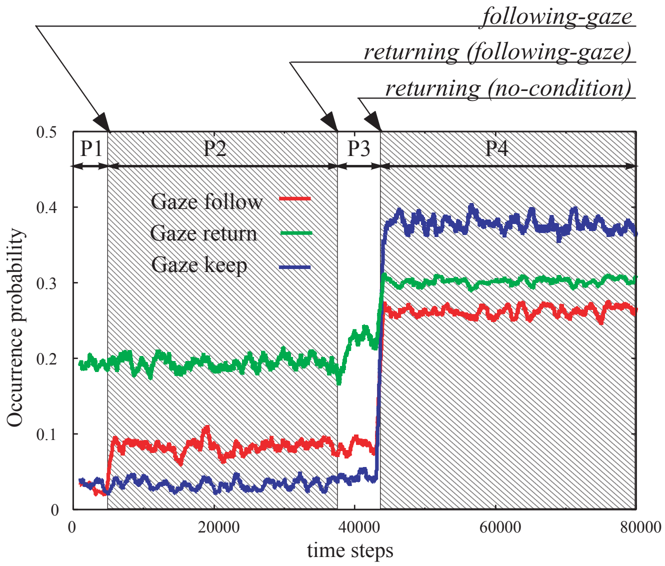


Fig. 6. Change of robot's behavior in face-to-face interactions with caregiver.

infants can successfully follow the gaze of their caregivers after establishing eye contact [17], [33], [34], they have difficulty returning their gaze to their caregivers after looking at an object. This indicates that they cannot fully exploit their gaze following ability in interaction with caregivers. At 12 months, they frequently coordinate their attention between caregivers and an object in daily interaction [35]. Interestingly, infants begin to follow the gaze of others more accurately around almost the same time [17].

The simulation reproduced such a delay of looking back at the caregiver and showed that looking back at the caregiver promotes following the caregiver's gaze. This suggests that the delay in the development of gaze following can be explained by the delay in the development of another skill: looking back at the caregiver, instead of the delay of gaze following skill itself.

B. *Contingency as intrinsic motivation*

Some researchers in developmental psychology have suggested that the preference for social contingency leads human infants to learn social skills [21], [15]. Such activity motivated by internal satisfaction is called intrinsic motivation in psychology [36].

Intrinsic motivation has recently been gaining increased attention in developmental robotics since it might enable a robot to develop in an open-ended manner [37]. Oudeyer *et al.* showed that the maximization of learning progress, i.e., a decrease of prediction errors, enables a real 4-leg robot to incrementally acquire more complex behavior [38]. Mugan and Kuipers proposed a learning mechanism to find sets of contingencies between a robot's body and an object and to acquire single behavior such as hitting an object by reproducing the found contingencies [39]. Its basic strategy for open-ended development seems to shared with ours, that is finding and reproducing contingency. A stronger point of both of these mechanisms is the treatment of continuous time data. However, they lack the mechanism to add variables representing the use of acquired skills, which seems to be necessary to find skills for some types of social interaction depending on history of own and other's actions. For example gaze alternation requires to perform gaze following in advance and is successfully acquired by the proposed method.

C. *Future implementation*

We evaluated the effectiveness of the proposed mechanism using computer simulations because acquiring actions is too time-consuming. As a next step, we must examine to what extent the proposed mechanism can reproduce the development of joint attention in real-world interactions. Here, we mention some issues to be addressed to apply the mechanism to a real robot.

1) Adaptive partitioning: In the experiment, we assumed that the variables were partitioned in advance and fixed from the beginning. However, it is not trivial for the designers to effectively partition them to communicate with a social partner. If there are more spots on the table, such rough partitions as S_1^t and M_1^t in the current simulation would not be effective to predict where the caregiver is looking. Moreover, partitioning helps contingency detection for high-dimensional continuous sensory data. Although the proposed method can find contingency in such data, it is required to reduce the dimensionality of the sensory and motor data with maintaining its informational content due to high computational cost. To solve these problems, we extended the proposed method by applying a clustering technique to contrast the contingency [40].

2) Temporal contingency detection: We assumed that both the robot and the caregiver take turns at fixed time steps since we focused on detecting which pair of sensory signal and motor command leads to contingent consequence, namely, sensorimotor contingency detection. However, this assumption is not feasible in a real world because we cannot exactly specify the fixed time steps. The robot has to detect when a contingent stimulus is observed since the robot's last action, namely, temporal contingency detection. Movellan proposed an infomax controller to detect temporal contingency in vocal interaction [41]. However, the robot was given sensorimotor space to detect temporal contingency. The contingency detector in our mechanism should be extended to detect temporal contingencies in interaction with a human caregiver as future work.

3) Contingencies originated from other modalities: In the simulation, the contingency structures inherent in interaction between caregiver and robot were limited since we assumed simple interaction by mainly focusing on mutual gaze shifting. An infant and a caregiver, however, build a variety of contingency structures by observing multimodal information and performing multimodal actions. A number of contingencies seem to help the development of joint attention [42], [43], [44]. Therefore, we plan to study what sort of contingency structure can promote the development of joint attention by extending the current simulation settings to involve such multimodal sensorimotor experiences.

4) Scheduling of caregiver's behavior: The robot was able to experience changes in interaction with the caregiver; once it had begun to follow the caregiver's gaze, the caregiver had more chances to select an AJA strategy. As a result, it could find the behavior of shifting its gaze to the caregiver after achieving gaze following. In the experiment, however, such changes in caregiver responses were very limited since the caregiver's strategies were fixed. In more natural interaction between caregiver and infant, the caregiver shows a variety of changes in her responses to the infant as it grows up [25]. Analyzing the responses of human caregivers to a real robot will help us design more plausible caregiver models. Modifying the caregiver model more faithfully remains a future issue for understanding the effect of longitudinal changes in mother-infant interaction on the development of specific social skills.

VI. Conclusion

We proposed a mechanism to enable a robot to developmentally acquire social actions based on finding and reproducing contingency inherent in face-to-face interaction by a measure proposed in a previous work [14]. We reproduced behavioral aspects in the infant development of social skills such as their order, that is, first gaze following and then gaze alternation, and the delay of the occurrences of the behavior of gaze following after acquiring gaze alternation. We will investigate the development of other actions related to joint attention by modeling more realistic interaction between robots and caregivers in the future.

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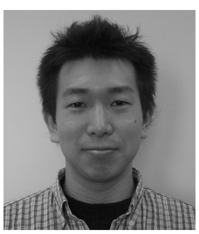

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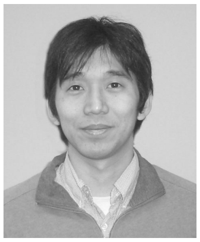

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