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Interacting with NeuroCognitive Robots: A Dynamical Systems View

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Abstract

In this paper, we will explore possibilities of dynamic interactions between human and neuro-cognitive robots especially focusing on the psychological problems of joint attentions and turn-taking. Firstly, we will show that movement patterns of a joystick-type haptic device which are driven by a simple attractor-based memory dynamics of recurrent neural network (RNN) can introduce novel interactive experiences to human subjects based on their force and proprioceptional sensations. Secondly, we will show experiments of joint attention game between human and a humanoid robot based on imitation learning. In the experiments, an extended scheme of RNNs is utilized for constructing a mirror system by which recognition of other's movements and generation of owns can be naturally synchronized in the real-time imitation. These experiments suggest that spontaneous shifts in joint attentions as well as turn taking have resulted from so-called the open-dynamic structures where stable and unstable manifold coexist in the coupling between the robots and human cognitive processes.

1 Introduction

In entertainment robotics, achieving natural interactions between robots and their users is one of the most essential issues to be solved. Human communications involve dynamic processes such as joint attention and turn taking with others. Joint attention is to share behaviors, events, interests and contexts in the world among agents from time to time. It requires mutual awareness of companion's attentions. On the other hand, turn taking is to switch the initiatives in interactions among agents spontaneously. Turn taking is considered to be prerequisite for joint attention.

Recent research on robotics have implemented a model of joint visual attention [3] between robots and humans [9, 12]. In such models, the robot guess the human's attentional target by detecting their gazing and pointing, and also pays attention to it. And then joint attention can be archived by the recognition of the robot's attention by human. However, in human communications, it seems that there are more complex situations of joint attention that can never be achieved by simply using such static and explicit cues [8]. For example, to share topics in streams of dialogues or to share a dancing pattern from one to another between couples. It seems that the targets of such joint attention are determined in the flow of ongoing interactions in contextual ways where embodiments in terms of movements and haptics play an important role. We speculate that such context dependent communicative interactions could emerge in terms of a class of dynamical structures appeared in the mutual adaptation processes between robots and humans.

In order to explore such communicative interactions based on embodied dynamical systems approach, we have conducted some experimental studies using neuro-cognitive robotics platforms. Our first experiment presented in this paper is about force-based interactions with human and a joystick device which is implemented with a simple recurrent neural network (RNN) model for its adaptive processes. Even with this simple setting, a class of complex dynamic interactions appear where human users can experience novel phenomena especially in their haptic sensation.

In the second study [6], we conduct experiments of the so-called the joint attention game with a humanoid robot in which dynamical mechanism of mutual imitative interactions were explored by implementing an extended model of RNNs, recurrent neural network with parametric biases (RNNPB) [17, 18, 19, 15]. The imitation in our robot platform is not yet goal-oriented ones as have been discussed by [20]. Also the correspondence problems [4] between the perceptual space for others and motor space of own in learning are simplified. However, it has been observed that quite diverse and complex mutual adaptive processes could emerge by utilizing the distributed representation characteristics of the RNNPB for embedding multiple behavior schema.

It is highly speculated that these two experiments would account for crucial mechanisms on embodied communicative interactions of rather unconsciousness levels. The paper will discuss our hypothesis that the open dynamic structure [16] appeared in the coupling between the robots and human could account for the underlying mechanisms for spontaneous switching of joint attention as well as turn-taking.

2 Haptic interaction with "adaptive" joystick

In this section, a minimal form of an adaptive interactive system is introduced. For the purpose of realizing direct physical interactions with the machine, a force-feedback joystick is employed as an interface since it is considered that force is one of the most direct and the least articulated human sensory modalities. The force-feedback joystick is bi-directionally connected to an artificial neural network which is simulated in a real-time computer. When a subject manipulates the joystick with certain movement patterns repeatedly, the neural network learns to predict how the movement trajectory proceeds in future steps in an on-line manner. Upon this on-line learning, the neural net drives the joystick toward the direction of the prediction. If the prediction agrees with the movement patterns by the subject, the subject would feel that the joystick moves smoothly with less efforts in his or her hand. Otherwise, the subject would experience a resistant force against his or her will from the joystick. Our preliminary experiments explore what sorts of interactions can emerge between human subjects and this on-line adaptive haptic device. The next subsection describe the technical details of this system as well as the employed neural network model.

2.1 RNN and joystick device

Figure 1 illustrates how the force-feedback joystick is connected to a neural net model simulated in a computer. Upon the manipulation of the joystick, the current encoder positions of the driving motors of the joystick (x_t, y_t) is sent to the so-called recurrent neural net (RNN). The RNN is well known for its learning capability of temporal structures from example sequences utilizing its context feed-back loops[7]. The RNN, receiving (x_t, y_t) in the input layer, outputs its prediction at next time step as (x_{t+1}, y_{t+1}). This prediction outputs are sent back to the motors as the target position signals and the motor force are generated according to the position error between the target and the current ones. The actual motor positions are determined by the sum of the motor and the subject's forces. The subject feels the stronger force from the joystick when the RNN prediction error become larger. On the other hand, the subject feels easy to manipulate it as the error becomes smaller. The error detected between the predicted positions and their outcomes are used for on-line training of the RNN. The synaptic weights of the RNN is modified by means of the back-propagation through time algorithm [13] in an on-line manner.

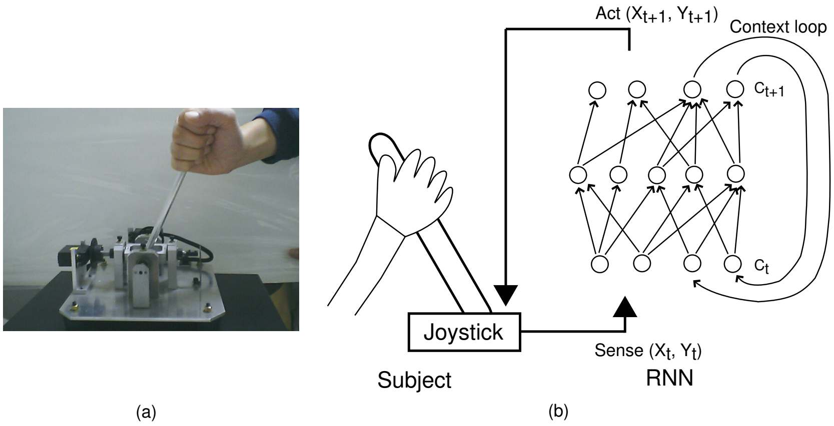

Figure 1: A force-feedback joystick (a) which is bi-directionally connected to a recurrent neural net (b).

2.2 Interaction experiments

In the first step of the experiment, the basic performance of the system was examined. We asked a subject to draw a circle with holding the joystick with about 2 seconds periodicity. It was found that the joystick starts to move autonomously along trajectories of this circle after the subject introduces this pattern for several periods. Then, the subject introduce a different pattern, such as a figure of eight to the joystick. During the introduction of this new pattern, the subject senses a strong anti-force from the joystick in the beginning. Then later after several periods, he senses less amount of anti-force and the joystick started to move autonomously with drawing the figure of eight. It could be interpreted that the subject senses through his haptics, a sort of resistance force of the machine to preserve its own memory self-organized in the RNN.

Nextly, we examined how the subjects interact with the adaptive joystick in rather more free setting. We repeated the following experiment session for several subjects. Before starting each session, we asked each subject to play with the joystick for a few minutes so that he or she could be accustomed to the system's behaviors. Then, in the experiment session, the subject was told to manipulate the joystick freely with closing his eyes. This eye closure procedure makes the subject to concentrate on his haptic sensation. The experiment was continued for three minutes while we recorded the RNN dynamics and the motor driving force. One of a typical session with a subject is introduced here.

We plotted the so-called bifurcation diagram of the RNN dynamics in the upper part of Figure 2 which illustrates how the neural dynamical structure modulates during the session.

The bifurcation diagram was obtained by observing the RNN context units activities at a certain Poincare section [23] at each time step. The lower part of Figure 2 shows the associated time-development of the absolute values of the motor forces. It is observed that there exist two distinct phases, the stable and the fluctuated phases, in the bifurcation diagram. It is also observed that the absolute value of the force decreases in the stable phases and it increases in the fluctuated ones. We further plotted the phase diagram of the RNN dynamics at typical time-windows in Figure 3. Figure 3 (a) (b) and (c) show the phase diagrams at time-windows during the stable phases and Figure 3 (d) and (e) do for those of the fluctuated phases. From the examination of the Lyapunov exponent for those dynamics, it was shown that the dynamics sampled in (a) (b) and (c) correspond to attractor of limit cycling and those in (d) and (e) do for strange attractor of chaos.

Although it is quite difficult to examine exactly what the subject felt at each moment, the oral report of the subject indicated that there are at the least two different phases, namely the automatic unconscious

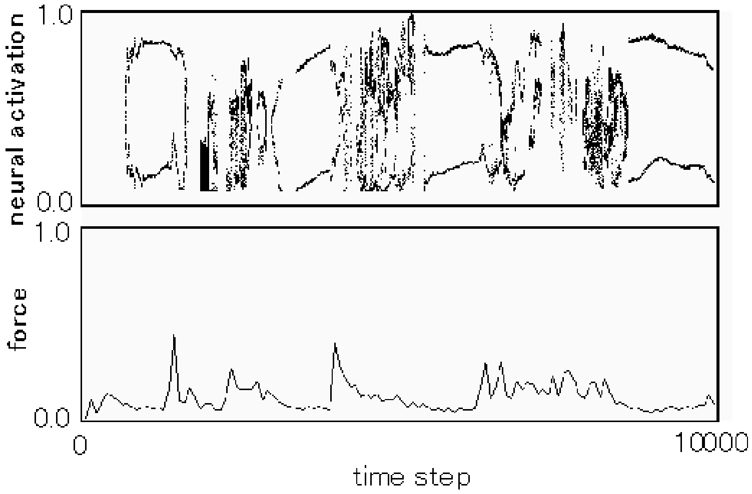

Figure 2: The bifurcation diagram of the RNN activities in the upper part and the motor force during the session.

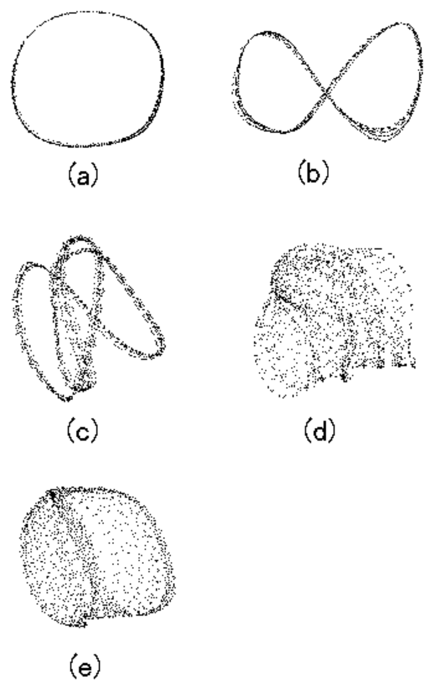

Figure 3: The RNN attractor appeared in typical time-windows in the session.

Figure 4: A user is interacting with the Sony humanoid robot QRIO SDR-4XII.

phase and the conflicting conscious phase. The former corresponds to the stable and coherent phases where the prediction of the RNN agrees well with the actual movement of the subject. The subject frequently reported that as if he or she floated smoothly in river flow passively in this phase. On the other hand, in the incoherent phase, the conflicting force initiated by means of the RNN prediction error make the subjects "conscious" about gaps appeared between the machines and themselves. It can be interpreted that joint attention is achieved for a movement pattern between the machine and the subjects in the coherent phase. However such joint attention can take place only momentary, as the current joint attention is likely to be shifted to another movement pattern intermittently by going through the incoherent phase. However, it is fair to say that the current analysis is only at the preliminary stage. Especially, the methodologies to examine the phenomenology of the subjects should be developed further.

3 Humanoid robot experiments

In the previous experiment on the haptic interactions, it was rather difficult to preserve multiple movement patterns simultaneously in the dynamic memory of the RNN. In the course of on-line learning, a learned movement pattern is destroyed later by learning another pattern. In our second experiment, the RNNPB which is an extended model of RNN is introduced for the purpose of preserving multiple movement patterns in the robot memory. The game of joint attention in this new experiment is that human subjects attempt to explore possible movement patterns memorized by the robot by attempting various interactions to the robot. If the subject happen to demonstrate one of the memorized pattern to the robot, the robot can synchronize to it by retrieving the corresponding memory.

The experiments were conducted by using the Sony humanoid robot QRIO SDR-4XII (see Figure 4). The movements of the subjects are restricted to their both arms movements in the current setting. As the subjects hold two differently colored balls in their both hands, the robot can recognize their hands positions by using the color information. The perceived hand positions of the subjects are utilized as the main sensory inputs for the robot. The robot is trained to imitate the hand movement patterns of the subjects by utilizing 8-DOF motor joints in its two arms by means of direct teaching. The robot learns to predict both of the subjects hand movements and its own corresponding arm movements for multiple movement patterns through the off-line supervised training of the RNNPB. After the learning is completed, the game of the imitative interaction is conducted in the interaction phase.

The next subsection will describe the RNNPB [17, 18] implementation regarding to the task. More details should be referred to [6].

3.1 RNNPB modeling

RNNPB is a version of the Jordan-type RNN [**?**] where the PB units allocated in the input layer play the roles of mirror neurons since their values encode both of generating and recognizing the same movement patterns. In generating patterns, the PB values function as control parameters for modulating the forward dynamics of the RNN. On the other hand in recognizing patterns, the corresponding PB values for currently perceiving patterns can be dynamically obtained by using the inverse dynamics of the RNN. It is, however, important to note that these recognition and generation processes are conducted simultaneously in the interaction phase i.e.– the robot generates corresponding patterns while recognizing the user's movement patterns. These ideas are detailed in the following associated with descriptions of the learning scheme.

A set of movement patterns is learned, in terms of the forward dynamics of the RNNPB, by self-determining both the PB values, that are differently assigned for each movement pattern, and a synaptic weight matrix that is common for all patterns. The information flow of the RNNPB in the learning phase is shown in Figure 5(a).

In the imitation learning of the subject movement patterns, the robot is directly taught with the motor joint movement patterns as corresponding to the subject's hand positions movement patterns which are visually perceived. The learning of the RNNPB is conducted by off-line with using both target sequences of the robot joint angles m_t and the subject's hand positions s_t.

With given m_t and s_t in the input layer, the network predicts their values at the next time step in the output layer as $\hat{m_{t+1}}$ and $\hat{s_{t+1}}$. The outputs are compared with their target values m_{t+1} and s_{t+1} and the error generated is back-propagated [13] for the purpose of updating both the synaptic weights and PB values. Note that the determined synaptic weights are common to all learning patterns, but the PB values are differently determined for each pattern.

c_t represents the context units where the self-feedback loop is established from c_{t+1} in the output layer to c_t in the input layer. The context unit activations represent the internal state of the network.

In the interaction phase, the pre-learned network is utilized without updating the synaptic weights. While the forward dynamics of the RNNPB generates the prediction of the sensory-motor sequences, the PB values are inversely computed by utilizing the error information obtained between the sensory prediction and the outcome. See Figure 5(b) for the information flow of the network in the interaction phase. The visually perceived hand positions are fed into the RNNPB as the target sequences. The RNNPB, when receiving s_t, attempts to predict its next value $\hat{s_{t+1}}$ in the outputs. The generated prediction error from the target value s_{t+1} in the outputs is back-propagated to the PB units and the PB values are updated in the direction of minimizing the error. Note that although the PB plays the role of the inputs for the forward computation, its values are gradually modulated in order to adapt to the current target sequence patterns. If pre-learned hand movement patterns are perceived, the PB values tend to converge to the values that have been determined in the learning phase while minimizing the prediction error. It is guaranteed that by minimizing the prediction error to zero the forward dynamics does not modulate anymore since the PB values converge. Then, the network becomes able to generate the associated motor patterns $\hat{m_{t+1}}$ as previously learned. The robot movement patterns are generated based on the PB values while these values are adapted by perceiving the hand movement patterns. An interesting feature of this model is that generation and perception are performed simultaneously in one neural dynamic system.

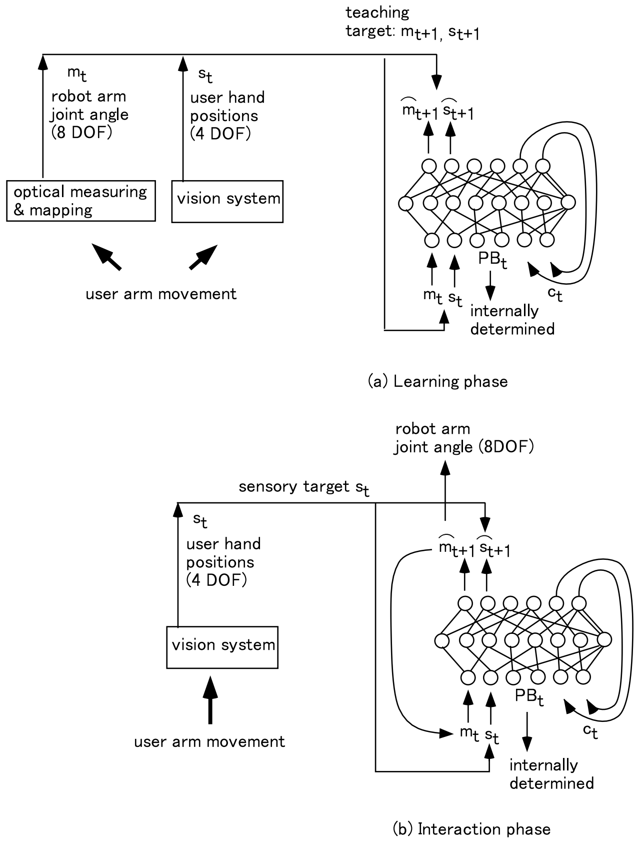

Figure 5: The system flow of RNNPB in learning phase (a) and interaction phase (b).

3.2 Imitation by synchronization

As the first step, we examined how the robot can imitatively regenerate one of learned movement patterns by synchronizing with the subject movement pattern. Firstly, the robot learns three movement patterns shown by user's hand movements in the learning phase. In the interaction phase, we tested how the robot can follow target patterns of the subject while the subject switches to demonstrate from one taught pattern to another.

The results of the experiment are plotted in Figure 6. It is observed that when the user hand movement pattern is switched from one of the learned patterns to another, the patterns in the sensory prediction and the motor outputs are also switched correspondingly by accompanying substantial shifts in the PB vector. Although the synchronization between the user hand movement pattern and the robot movement pattern is lost once during the transitions, the robot movement pattern is re-synchronized to the user hand movement pattern within several steps. The experiments also showed that once the patterns were synchronized they were preserved robustly against slight perturbations in the repetitions of the user's hand movements. Our further analysis concluded that the attractor dynamics system, with its bifurcation mechanism via the PB, makes the robot system manipulatable by the users as well as robust to possible perturbations.

3.3 Joint attention game

The previous experiments focused mainly on the adaptation in the robot side. We conducted another experiment which focus on bi-directional adaptation in mutual interaction between the robot and users. In this new experimental set-up, after the robot learns 4 movement patterns in the same way as described previously, subjects who are ignorant of what the robot learned are faced with the robot. The subjects are then asked to find as many movement patterns as possible for which they and the robot can synchronize together by going through exploratory interactions. Five subjects participated in the experiments. The settings of the network and the robot were exactly the same as those in the previous interaction experiments. Each subject was allowed to explore the interactions with the robot for one hour, including four 5 minute breaks.

Although most of the subjects could find all movement patterns by the end, the exploration processes were not trivial for the subjects. If the subjects merely attempted to follow the robot movement patterns, they could not converge in most situations since the PB values fluctuated when receiving unpredictable subject hand movement patterns as the inputs. If the subjects attempted to execute their desired movement patterns regardless of the robot movements, the robot could not follow them unless the movement patterns of the subjects corresponded with the ones learned by the robot.

One example of the interaction in imitation game is plotted in Figure 7. It is observed that joint attention to a certain movement pattern between the robot and the subject as synchronization is achieved after some exploratory phase. It is also observed that this joint attentional state is break down once but joint attention to another pattern is achieved again.

There are interesting points in this new experiment as compared to the previous one. First, the master-slave relation, which was fixed between the subjects and the robot in the previous experiments, is no longer fixed but is instead spontaneously switched between the two sides. (Recall that the subjects initiated new movement patterns while also switching among multiple learned patterns in the previous experiments.) When the subjects feel that the robot movement patterns become close to theirs, they just keep following the robot movement patterns passively in order to stabilize the patterns. However, when the subjects feel that they and the robot cannot match each other's movements, they often initiate new patterns, hoping that the robot will start to follow them and become synchronized. Second, there are autonomous shifts between the coherent phase and the incoherent phase after the subjects become familiar with the robot responses to some extent. When the subjects happen to find synchronized movement patterns, they tend

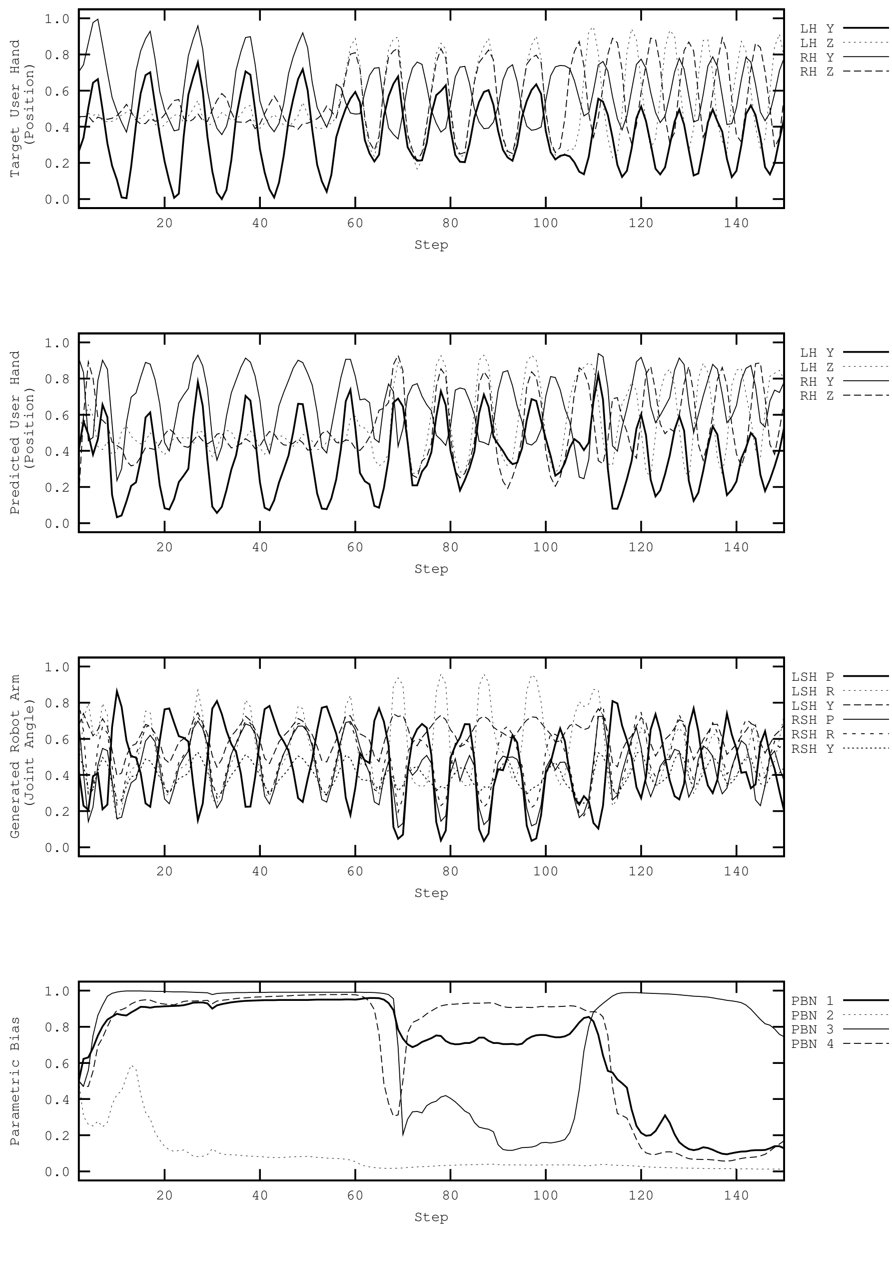

Figure 6: Switching of the robot movement pattern among three learned patterns as initiated by switching of user hand movement. User hand position and its prediction by the robot are shown in the first and the second row, respectively. The third and fourth rows show motor outputs and PB vectors, respectively.

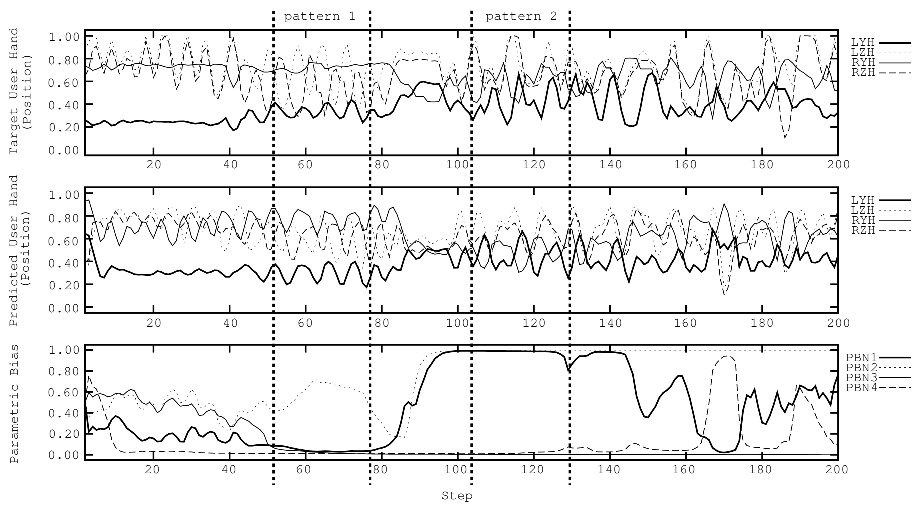

Figure 7: Joint attention as synchronization between the robot and the subject in imitation game. User hand position and its prediction by the robot are shown in the first and the second row, respectively. The third row shows PB vectors of the RNNPB.

to keep the achieved synchronization for a moment in order to memorize the patterns. However, this coherence can break down after a while through various uncertainties in the mutual interactions. Even small perturbations in the synchronization could confuse the subjects if they are not yet fully confident of the repertoire of the robot's movement patterns. Also, the subjects' explorations of new movement patterns makes it difficult for the robot to predict and follow their movements.

4 Discussion

The authors speculate that appropriate analysis of these observed phenomena might shed a ray of light on the mechanism of joint attention [2, 11] as well as turn taking behaviors [21]. In our experiments of the haptic interactions with the joystick device as well as the joint attention game with the humanoid, when movement patterns of the robot and human are synchronized, joint attention to the pattern is assumed to have been achieved . However, the current joint attention can break down and another joint attention (attending to another movement pattern) can emerge after a while. Although joint attention itself might be explained simply by synchronization [10, 1], a more interesting question is how a joint attention can break down and flip to another one spontaneously. This sort of spontaneity is also essential in turn taking behaviors. It was observed that the initiatives leading to synchronization switch spontaneously between the robot and the subjects. The essential question here is how the spontaneous shifts in turn taking behaviors can emerge.

Although extensive analysis of the observed data is required for further reasoning of the underlying mechanisms, the authors speculate that they might be closely related to the so-called open dynamic structure [16]. It was argued that the system state tends to flip between the coherent and the incoherent phases if stability, in terms of rational goal-directedness, and instability, caused by unpredictability of the open environment, coexist in cognitive systems. Tani [16] proposed one possible explanation of the spontaneous breakdown of self-consciousness through dynamic system characteristics. A more theoretical framework of this idea has been explained by the chaotic itinerary [22]. Furthermore, Ikegami and Iizuka [5] recently showed that spontaneous turn taking behaviors can emerge by evolving the coupled-dynamics for a simulated pair of agents. Their analysis indicated that both stable and unstable manifolds are generated in the evolved coupled dynamics. Our results could be explained in the similar way. In our experiments of mutual interactions, the stability originated from the synchronization mechanisms for shared memories of movement patterns between the robot and the subjects. The instability arose from the potential uncertainty in predicting each other's movements. It is likely that the coexistence of stable and unstable characteristics in the system dynamics might be the main cause for the spontaneous shifts. Recently, Sato [14] related this characteristics to the undecidability of the turing test in the theoretical analysis of imitation game, although further examination is required in this part of the analysis. Future collaborative research among developmental psychology, synthetic modeling studies, and theoretical non-linear dynamics studies would gain further understanding of the essential mechanisms in joint attention and turn taking behaviors.

In the joint attention game experiments, most of the subjects reported that they occasionally felt as if the robot had its own "will" because of the spontaneity in the generated interactions. It is speculated that the spontaneity originated from the total system dynamics including the users in the loop might play an important role in attracting people to play with entertainment robots.

5 Summary

Our human interaction experiments with adaptive neuro-cognitive robots have shown that diverse dynamic interactions can emerge in the form of either coherence or incoherence between the robot and the user. The robot can follow the learned user movement patterns synchronously by generating coherent dynamic states. It can be said that joint attention is accomplished for the current movement pattern shared in both the memories of the robot and the user. Our experiments of the mutual adaptation suggest that the essential mechanism for autonomous shifts in joint attention and turn taking behavior could be explained by the open dynamic structures in which stability, in terms of rational goal-directedness, and instability, caused by unpredictability of others coexist.

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