

Adaptive Leader-Follower Role Switching Based on Rhythm Stability: Toward Modeling of Dynamic Infant-Caregiver Interaction

Ryo Iwaki
Graduate school of Engineering
Osaka university
Osaka, Japan
Email:
ryo.iwaki@ams.eng.osaka-u.ac.jp

Hideyuki Takahashi
Graduate school of Engineering
Osaka university
Osaka, Japan
Email:
hideyuki@ams.eng.osaka-u.ac.jp

Minoru Asada
Graduate school of Engineering
Osaka university
Osaka, Japan
Email:
asada@ams.eng.osaka-u.ac.jp

I. INTRODUCTION

Infants often synchronize rhythm pattern of their body movement with their caregivers. Developmental scientists assume that infant-caregiver body synchrony is a fundamental factor for maturing their close relationship and it facilitates social development of infants [1–2]. When multiple individuals are in synchrony, they tend to mimic each other’s behavior [3]. One agent generates own behaviors on the basis of self-initiated rhythms as a “leader”, and the other agent mimics (follows) the leader’s rhythm, as a “follower”. The relationship between two agents can be described by the four types of leader-follower combination as following: {agent A, agent B} = state 1{leader, follower}; state 2{follower, follower}; state 3{leader, leader}; state 4{follower, follower}[4]. We consider that synchrony is formed between two agents in the states where they take different roles (state 1 and 2). For example, in an orchestra, a skillful conductor leads the other members as a leader and each member follows the conductor as a follower.

An agent often switches his/her role through interactions, thus synchronization among multiple agents cannot be achieved easily. In particular, it is still unclear how the infant-caregiver synchrony can still stably form even when the infant’s motor ability and cognition change throughout their development process. The leader-follower role pattern sharing between multiple agents must be illustrated as a dynamical system, as opposed to a static system, because if a caregiver always controls his/her leader-follower role actively (active control) in a static system, it requires a high cognitive load from the caregiver. Ito & Tani [5] showed that during a human-robot interaction in which they are imitating each other’s movement, their movement patterns tend to be entrained into “stable” rhythm patterns. Ikegami & Iizuka [6] showed that spontaneous turn taking behaviors of two agents can emerge in a dynamical system.

We hypothesize that (1) the dynamics of rhythms in infant-caregiver interaction can be described as a kind of dynamical system, and (2) asymmetric motor capacities between infant and caregiver automatically lead them to synchrony without active control. To verify this hypothesis, we conducted a simulation study in which we utilized Recurrent Neural Network with Parametric Bias (RNNPB) [7].

II. OVERVIEW OF OUR PROPOSED MODEL

We used RNNPB to perform our simulation. RNNPB is a recurrent neural network model with parametric bias nodes in the input layer and can learn multiple sequential signal patterns by binding each pattern to an inherent PB vector. This network model is effective both for generation and recognition of learned temporal patterns. When a PB vector corresponding to a learned pattern is input to RNNPB, the network generates a

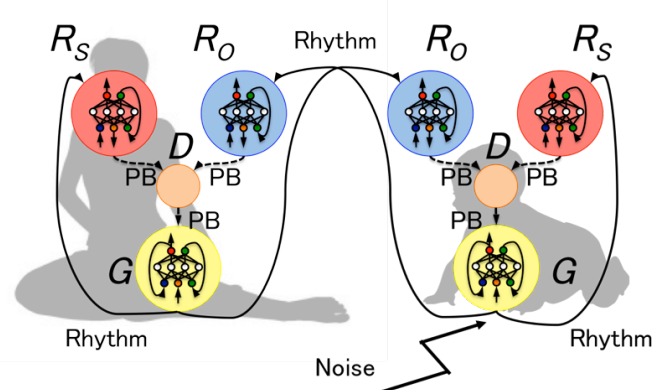


Fig. 1. Our proposed model: Each agent has inherent RNNPB in module G , R_S , and R_O . Module G generates signal flow, module R_S and R_O estimate both PB vectors of self and the other generated, respectively, and module D chooses PB vector of stable rhythm.

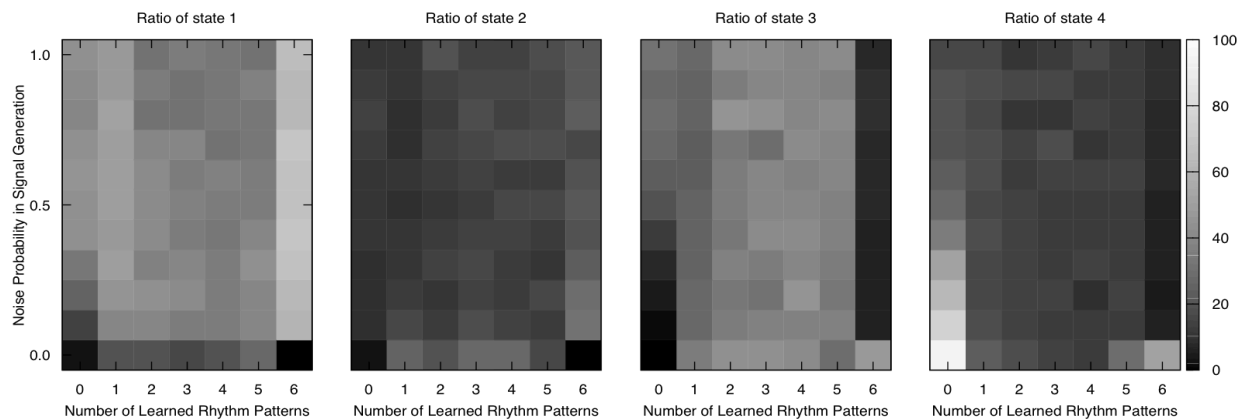


Fig. 2. Mean transition ratios of 4 states in terms of the immature agent's parameter sets. State 1 : Mature agent is a leader and immature agent is a follower. State 2 : Immature agent is a follower and immature agent is a leader. State 3 : Both agents are leaders. State 4 : Both agents are followers

signal sequence of the pattern (generation); RNNPB can also estimate a PB vector as a learned pattern index from a given signal flow (recognition). There are two agents in our simulation and each of agents was consist of four modules; G, Rs, Ro, and D (Fig. 1). The module G, Rs, and Ro has an inherent RNNPB with common parameters in each agent. An agent sequentially generated signal flow (binary information) as a rhythm pattern via its inherent RNNPB network in discrete time steps in module G. Further an agent sequentially estimated the PB vectors of both self and the other generated signal flows via its inherent RNNPB in module Rs and Ro, respectively. The agent monitored the stabilities of both agents' rhythm patterns by comparing the variances of the two PB vectors in module D. The signal flow of the agent was generated on the basis of a PB vector with lower variance in module G. We defined the agent as a "leader" when the PB vector of the self-generated rhythm was chosen and as a "follower" when the PB vector of the other agent was chosen in the module D.

In the simulation, the motor capacities of the two agents were not symmetric. Specifically, the two agents are defined as a "mature agent" and an "immature agent". The inherent RNNPB of the mature agent learned 6 kinds of rhythm patterns and no noise was added to the signal flow it generated. In contrast, the number of rhythm patterns the immature agent learned was in the range 0 to 6 and the generated signal was replaced by a random signal as noise with a constant probability (from 0 to 1 in increments of 0.1). Hence, the motor-immaturity of the agent was defined by a set of two parameters, "number of learned rhythm patterns" and "noise probability in signal generation". If the number of learned rhythm patterns is 6 and noise in signal generation is 0, the immature agent has the same parameter set as the mature agent.

We comprehensively calculated the mean transition ratios of 4 states in every parameter set of the immature agent (Fig. 2). In figure 2, if a pixel color is white, the transition ratio to the state is 100 % in the parameter set. In contrast, if a pixel color is black, the transition to the state never occurred. Our results indicated that two parameters dynamically influence role switching and synchrony formation between two agents.

III. DISCUSSION

Our results showed that the asymmetric motor capacities of the two agents affect role switching, and also indicate that the asymmetric motor capacities induce the rhythm pattern synchrony without active control. The asymmetric motor abilities of mature and immature agents may roughly approximate infant-caregiver interaction and our simulation has revealed one aspect of the complex dynamics comprising this interaction. However, this approximation is too simple to explain actual infant-caregiver interaction. The major limitation of our model is that it does not consider the motivation of the agents. In the future, we would like to add the agents' motivations to our model in order to develop a more realistic dynamics model of infant-caregiver synchrony.

REFERENCES

- [1] Reyna, B.A., Pickler, R.H., Mother-infant synchrony, *J Obstet Gynecol Neonatal Nurs*, 38(4), pp. 470-477, 2009.
- [2] Cohn, J.E., Tronick, E.Z., Mother-infant face-to-face interaction: Influence is bidirectional and unrelated to periodic cycles in either partner's behavior, *Developmental Psychology*, 24(3), pp. 386-392, 1988.
- [3] Lafrance, M., Postural mirroring and intergroup relations. *Personality and Social Psychology Bulletin*, 11(2), 207-217, 1985.
- [4] Boker, S. M., & Rotondo, J. L., Symmetry Building and Symmetry Breaking in Synchronized Movement, 2001.
- [5] Ito, M., Tani, J., On-line imitative interaction with a humanoid robot using a dynamic neural network model of a mirror system., *Adaptive Behavior*, Vol.12, No.2, pp.93-115, 2004.
- [6] Ikegami, T., & Iizuka, H., Joint attention and dynamics repertoire in coupled dynamical recognizers. *In the aish 03: the second international symposium on imitation in animals and artifacts*, pp. 125-130, 2003.
- [7] Tani, J., Ito, M., Sugita, Y., Self-organization of distributedly represented multiple behavior schemata in a mirror system: reviews of robot experiments using RNNPB, *Neural Networks*, 17(8), pp. 1273-1289, 2004.