The Role of Imitation in Generating a Shared Communication System

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Abstract

What types of learning or reasoning are involved in forming a new communication system? To answer this question, this paper presents a computational model for forming a new communication system. The model was developed with ACT-R (Adaptive Control of Thought-Rational). In the model, two agents autonomously assign their roles to themselves. Agents also posses general learning mechanisms implemented in ACT-R. By incorporating imitative learning into these general learning mechanisms, this paper studies the role of imitation in the process of forming a new communication system. Finally, we compared the proposed model against a human experiment. The results of the simulation indicate that through imitation, after a short period of interaction, an isomorphic system is created. The result of the simulation also suggests the existence of imitation in the process of forming a human communication system.

Keywords: Communication; Imitation; ACT-R

Introduction

People try to communicate with others even when they do not have a common language. They also understand intentions of others through repeated interactions. Apparently, humans have the ability to develop a new communication system where only a few common ground rules are shared in advance. How can a new communication system be developed? What types of learning or reasoning are involved in this process? Addressing these questions will contribute not only to understand the origins of our communication but also to predict changes in our communication in this era of globalization.

Some researchers have examined these questions by designing communication environments in the laboratory (for a review Scott-Phillips & Kirby, 2010). For example, Galantucci (2005) conducted an experiment to observe the formation of communication systems in which a pair of participants communicated through a medium that restricted the use of standard communication means such as utterances and letters. He observed the process of forming a new communication system, and discussed that implicit information was conveyed through routine behavior, and reported that a temporal order of messages was built into communication systems. However, this study cannot answer the questions above because he did not identify the cognitive mechanism involved in this process.

The present study focuses on imitation as the type of reasoning in forming a new communication system. Imitation has been investigated in various fields of cognitive science (Barnes & Thagard, 1997; Gergely, Bekkering, & Király, 2002; Tomasello, 1999; Thagard, 2001). For example, Tomasello (1999) described the role of imitation in language acquisition by the infant/child. He especially argued that a type of imitation called "role-reversal", in which the child aligns herself with the adult speaker, is essential for producing a communicative symbols.

However, there is an important difference between language acquisition and forming a new communication system. In language acquisition, there is a clear distinction between a learner and an instructor (or a demonstrator). On the other hand, a new communication system usually emerges from a situation where no predefined roles exist. Although several studies concerning imitation exist, only few studies have dealt with this situation.

We argue that the model-based approach is the best method to explore the role of imitation in an interactive situation. From this perspective, we present a computational model, in which two agents autonomously assign roles to themselves. Agents also posses general learning mechanisms such as reinforcement learning and instance-based learning to form a new communication system. By incorporating imitative learning into these general learning mechanisms, we investigate the role of imitation in the process of forming a new communication system. Furthermore, we compare the constructed model against a human experiment. The results of this comparison reveal the cognitive mechanism involved in the formation of a human communication system. Before presenting our model, we will provide an overview of our previous experiment.

Experiment

The present study simulates the experiment reported in Konno, Morita, and Hashimoto (in press), where we modified and used a coordination game taken from Galantucci (2005). As in Galantucci's study, the game environment contained two characters, each controlled by a players, and four intercommunicating rooms. The game was composed of several repeated rounds. At the beginning of a round, characters were randomly placed in two different rooms. Players were unaware of the location of each other and aimed to bring their characters to the same room. The characters could not move to rooms that were located diagonally. Owing to this constraint, players need to communicate before moving their characters.

Figure 1 presents the flow of each round consisting of three steps: step 1 for exchanging messages; step 2 for moving characters; and step 3 for confirming the result of the movement. Among these steps, step 1 is the most crucial for the success of this task. In this step, the two players construct their own messages composed of two figures such as "▲□" using six available figures: ■, ▰, ▼, ◆, ▲, and □. The meanings and usage of the figures were not shared among

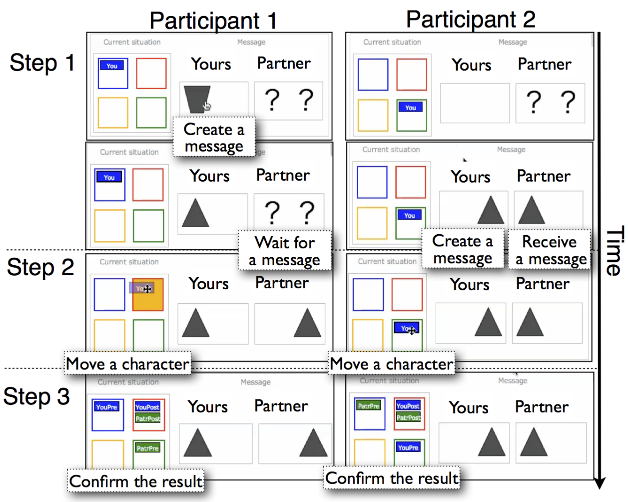

Figure 1: A round of the coordination game consists of three steps. In step 1, to create a message, participants select figures by clicking the segments indicated by "Yours". Each time a participant clicks a segment, a figure appears in the order of □, ■, ▰, ▼, ◆, and ▲. In step 2, a character (blue boxes indicated by "You") is moved by drag-and-drop. In step 3, the result of the movement are shown to the participants. Blue boxes ("You-Pre" and "You-Post") and green boxes ("Pat-Pre" and "Pat-Post") represent a movement made by the participant and the partner, respectively. In the case of this figure, they succeeded in moving to the same room (the upper-right room).

the participants in advance. Each player could send only one message per round, but they could take turns in exchanging messages. A message sent by the first sender instantly appeared on the screen of the other player. The second sender could compose her/his message after observing the message of her/his partner (see the participant 2 in Figure 1). By this turn-taking approach (role-settings), the first sender could transmit her/his current room location, and the second sender could transmit the destination while taking into account the current room location of her/his partner. Importantly, the participants were not assigned their roles by the experimenter. They were required to assign their roles by themselves.

The experimental procedure consisted of one trial session and three test sessions. In the trial session, the participants (21 pairs) attempted to develop a communication system within one hour time limit. When characters moved to the same room, players received two points, otherwise they lost one point, but the scores did not drop below zero. The trial session was terminated when the score reached 50 points.

Test sessions were conducted subsequently. The T_{NM} (Test with No Message exchanges) did not allow message exchanges. In the T_{SM} (Test with Simultaneous Message exchanges), messages were displayed on the screen of each player after both players had sent their messages. Thus, taking turns in sending messages was prevented in this test session. The T_{IM} (Test with Immediate Message exchanges) was conducted under the same conditions as in the trial session. Each test had 12 rounds that contained all possible room combinations for two characters. The order of appearances was set at random.

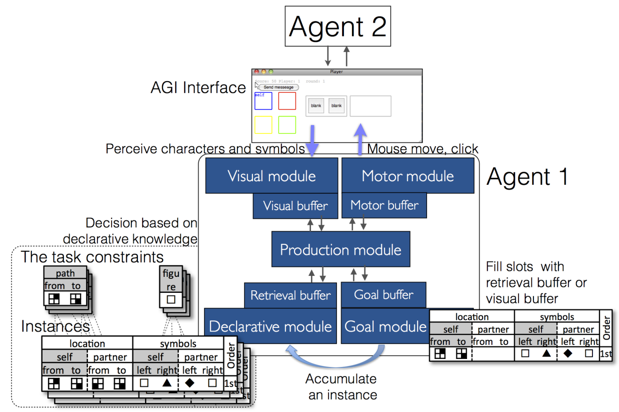

Figure 2: Schema of the model.

The results of the experiment confirmed the success of forming a shared symbol communication system, indicating the differences of the performance between the three tests. The detailed results are shown in a latter section.

Model

Architecture

The task presented in the previous section requires symbolic learning for constructing a new symbol system. In addition, according to Galantucci (2005)'s report, implicit learning, which is not present in symbolic systems, possibly plays a role in this task. In this study, we construct a model using ACT-R (Adaptive Control of Thought-Rational: Anderson, 2007), which integrates symbolic and subsymbolic learning mechanisms.

ACT-R is composed of several independent modules. The modules used in this study are presented in Figure 2. Except for the production module, each module has a buffer to temporarily store information called a chunk (a set of slot-value pairs). The production module integrates the other modules using production rules, which consist of a condition-action pair that is used in sequence with other productions to perform a task. The conditions and actions in production rules are specified along with buffer contents of each module.

In our model, two independent agents interact through a simulated task environment developed in the ACT-R graphical user interface (AGI). AGI provides screens that hold visual information as chunks. In this study, the locations of the characters and messages associated with each agent are displayed on the screen. An agent's visual module searches for a character and stores its location (room) into a visual buffer. The visual buffer also stores the symbols that compose a message, attending to the screen locations where the figures appear. The simulated task environment also provides a virtual mouse to change the figures and move the characters on the screen.

Visual information stored in the visual buffer are transferred to the goal buffer through the production module. The goal buffer holds the goal of the current task and other task-related information. Specifically, our model has nine slots for

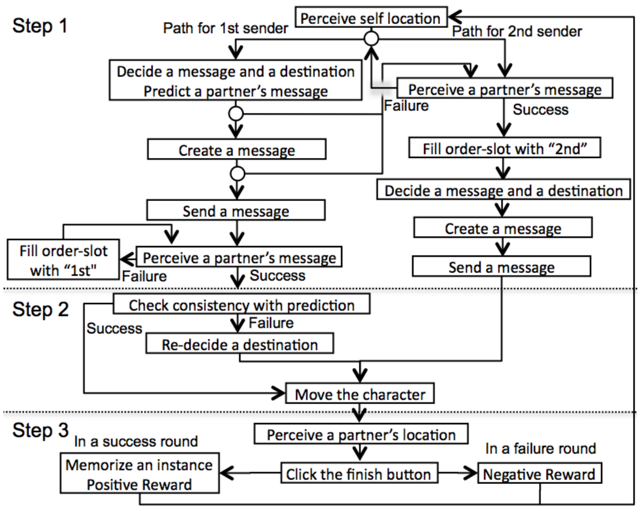

Figure 3: Process of the model. Circles indicate decisions based on conflict resolution.

the goal buffer: four slots for storing room locations (initial (from)-destination (to) × self-partner), four slots for storing the symbols (left-right × self-partner), and a slot for encoding the order for exchanging messages.

The declarative module stores past states of the goal buffer as instances. It also stores chunks representing task constraints such as path information indicating a room the characters can move to (e.g., *from*_*to*_*isa_path*) or figures the agent can use to construct a message (e.g., _*isa_figure*). An agent uses these chunks (i.e., declarative knowledge) to chose its destination and construct a message.

Process of the model

Overview We prepared 169 productions that construct the process presented in Figure 3. This process is divided into three steps just as in the original experiment (Figure 1).

In addition, the operation of taking turns to send a message is autonomously managed by this process. There are two paths in this process. The left path is for the first sender and the right path is for the second sender. The choice of path is made by conflict resolution, which is a comparison of two conflicting productions with noise added utilities. In each phase of the path of the first sender, there is a conflict (indicated by circles) between keeping the path of the first sender and changing to the path of the second sender. If in any of these the agent selects the path of the second sender, the agent tries to perceive the message of her/his partner from the screen. When the agent obtains the message of her/his partner, s/he realizes that s/he is the second sender (fills the order slot with "2nd"). Otherwise, s/he resolves a conflict by waiting for the message of her/his partner and changing to the path of the first sender. This conflict loop continues until one of the agents sends a message.

Decision making In step 1, regardless of the contents of the order slot, both agents make decisions about their destinations

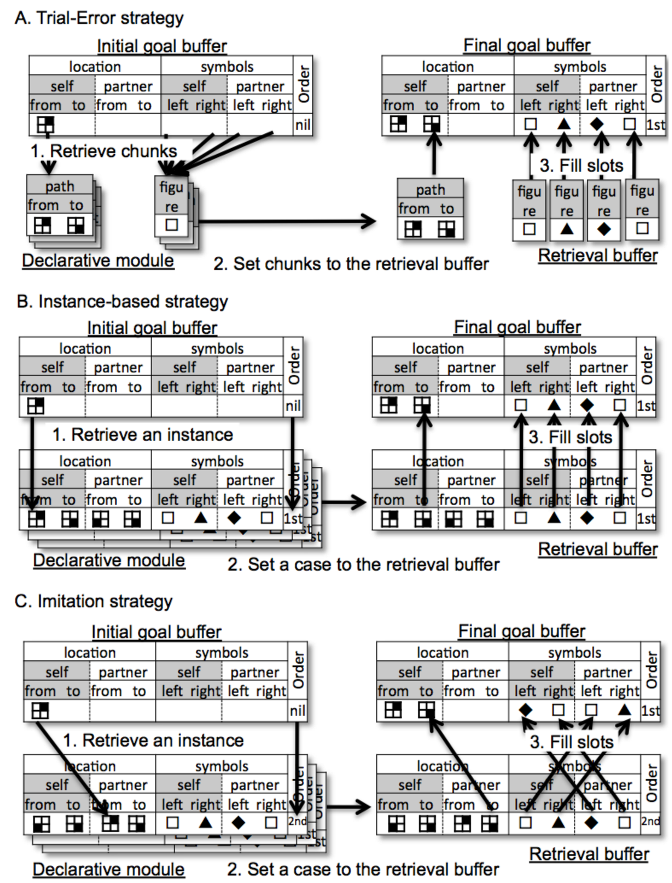

Figure 4: Three types of decision strategies.

and their messages. Concurrently, the first sender predicts the message that s/he will receive from her/his partner. The predicted message is checked against the message received in step 2. When the received message is inconsistent with the predicted message, the agent makes a new decision about her/his destination.

Summarizing, there are three situations where agents make decisions. In these situations, agents apply one of the three decision strategies shown in Figure 4[1]. Every decision strategy begins by retrieving chunks from the declarative module by using the current goal buffer as a cue. In the trial-error strategy, chunks concerning task constraints (chunks representing a path and symbols) are retrieved, and are used to fill in the blank goal slots. In the instance-based strategy, the agent retrieves an instance that is consistent with the current goal buffer. The retrieved instance is used to fill slots concerning a destination and symbols. The imitation strategy also uses an instance, but the roles of an agent and her/his partner are reversed when retrieving and filling slots.

The implementation of the trial-error and instance-based strategies follow a past study on decision making using ACT-

[1] Figure 4 explains each strategy by using an example of the first sender in step 1. In the case of the second sender in step 1, a partner's message is added to the retrieval cue. The first sender in step 2 uses a message as a cue to retrieve an instance and make a new decision about the destination.

R (Lebiere, Gonzalez, & Martin, 2007; Reitter & Lebiere, 2011). The imitation strategy is constructed according to the role-reversal imitation described by Tomasello (1999).

Learning The decision making strategy implemented in this model changes through a learning process. This model uses the standard symbolic and subsymbolic learning mechanisms of ACT-R. Symbolic learning includes instance-based learning and production compilation. Subsymbolic learning includes utility learning and activation updating.

Instance-based learning and utility learning occur at the end of each round (see Figure 3). In a success round (two characters meet in the same room), the agent stores a state of the goal buffer into the declarative module. Conversely, in a failure round (two characters move to different rooms), the agents do not store an instance. Regardless of the results of the movement, the utilities, which are used in conflict resolution, are updated by the following formula.

$$U_i(n) = U_i(n-1) + \alpha[R_i(n) - U_i(n-1)]) \qquad (1)$$

where α is the learning rate and $R_i(n)$ is the reward value given to production i at time n. In a success round, productions used in the round receive positive rewards ($Ri(n) = 10$). Otherwise, productions used in the round receive negative rewards ($Ri(n) = 0$).

As instances are accumulated, the chance to retrieve an instance increases, but utility learning does not directly affect decision making. In each decision strategy, there are no conflicting productions. Instead, each decision strategy needs to select declarative chunks because a single state of the goal buffer usually matches several chunks. The selection of chunks is controlled by the activation values of the chunks[2]. In ACT-R, an activation value is updated by the following formula.

$$B_i = ln(\sum_{j=1}^{n} t_j^{-d}) + \beta_i \qquad (2)$$

where n is the number of presentations of chunk i, t_j is the time since the jth presentation, and d is the decay parameter[3]. This value is determined by the frequency and recency of a particular chunk. Therefore, an agent usually retrieves a chunk that has been frequently observed or retrieved in the past round.

Even though utility learning does not directly affect decision strategies, there is a possible effect that occurs through production compilation. Production compilation is a mechanism that creates a new production integrating sequentially firing two productions. It typically occurs when the first production requests a retrieval and the second harvests it. The resulting production is specialized to include the retrieved information. In other words, the declarative knowledge is proceduralized into the production. Because compiled productions receive rewards, it is possible to change behavior through production compilation and utility learning.

[2]The simulation uses a summation of this base-level activation and the spreading activation values

[3]In this study, we use $d = 0.50$ and $\beta = 0.00$

Table 1: The performance in the trial session. The numbers in parentheses indicate standard deviation.

	Data	Trial-error	Instance	Imitation
Success rates	0.66	0.00	1.00	1.00
Round	48.42	NA	72.08	54.50
	(13.36)	(NA)	(16.95)	(15.93)

Simulation

Simulation conditions

To explore the cognitive process behind forming a communication system, we set up the following three models controlling the decision strategies presented in Figure 4.

- Trial-Error model: This model does not have a decision strategy other than the trial-error strategy. The agent tries to construct a communication system from subsymbolic learning and production compilation.
- Instance model: This model, in addition to the trial-error strategy, also has the instance-based strategy. The agent first tries the instance-based strategy. If the instance-based strategy fails, the agent chooses her/his destination and message based on the trial-error strategy.
- Imitation model: This model extends the instance model by adding the imitation strategy. The agent first tries to chose her/his destination and message using the instance-based strategy. If the agent fails to retrieve an instance, the imitation strategy is applied. When all other decision strategies fail, the agent uses the trial-error strategy.

By comparing the imitation model with the other two models, we can identify the role of imitation in forming a shared communication system. We also identify the required learning mechanism from the difference between the trial-error model and the other models. Furthermore, by comparing the experimental data, we reveal the features of human communication systems.

In this simulation, each model runs 100 times. In each run, the model continued the trial session for 3,600 sec[4] or until the scores reached 50 points. Following the trial session, the model was engaged in three test sessions similar to the experiment presented in the section 2.

Results

Performance of trial session Table 1 shows the proportion of runs/pairs whose scores reached 50 points, which is a termination condition for the trial session. It also presents the numbers of rounds required to reach the termination condition. All runs with the trial-error models failed to form a communication system whereas all runs with the instance and imitation models succeeded in completing the session. Even though there were some pairs that did not reach the termination condition, the number of rounds required to complete the session in the experiment (data) was smaller than that in the instance and imitation models. Compared to the instance model, the imitation model finished the session in less number of rounds, and the difference in the number of rounds

[4]We used the simulation time estimated by ACT-R.

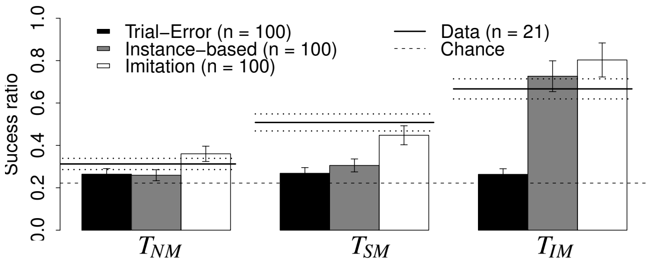

Figure 5: Performance of three test sessions. Solid lines in the graph indicate the results of the experiment. Error bars and dashed thin lines represent the standard error of means. The dashed thick line indicates chance-level performance (2/9).

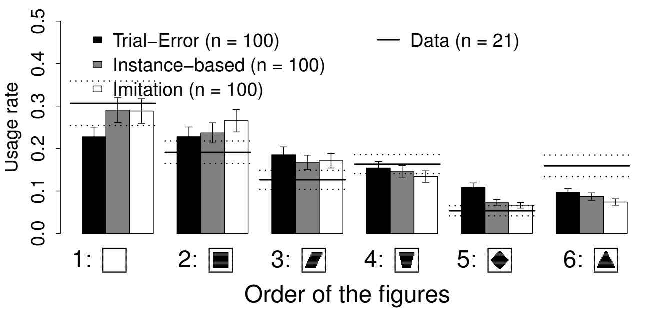

Figure 6: Rate of using each symbol. Solid lines in the graph indicate the data obtained in the experiment. Error bars and dashed thin lines represent the standard error of means.

between the experimental data and the imitation model is quite small (i.e., 48.42 and 54.50 respectively, compared with 72.08 in the instance model).

Performance of tests sessions Figure 5 presents the results of the three tests. The experimental data reveals significant differences between the three tests. The imitation and the instance models reproduced these differences well. From the difference between T_{NM} and T_{IM}, we confirmed that the pairs/models formed effective symbol communication systems. In addition, from the difference between T_{SM} and T_{IM}, we confirmed that the pairs/models take turns in transmitting messages. In contrast to the other models/data, we did not observe the differences of the three tests in the trial-error model.

Messages constructed in the trial session To examine the messages created in each model/experiment, we first computed the frequency of using each symbol in the trial session. From Figure 6, we can observe the decrease in the frequencies with respect to the order of the figures (see the caption of Figure 1). Using the symbols listed in the earlier order is considered as an adaptive behavior that reduces the time to construct a message. The three models reproduced this behavior. We postulate that this behavior is derived from the activation updating mechanism. As shown in formula 2, activation values are influenced by the frequencies of observing/retrieving chunks. Hence, symbols listed in the earlier order usually receive higher activation values.

We examined this distribution for each participant/agent

Table 2: Indices of sharing when using symbols.

	Data	Trial-error	Instance	Imitation
Single	0.80	0.92	0.76	0.94
	(0.25)	(0.04)	(0.14)	(0.07)
Combination	0.63	0.52	0.28	0.84
	(0.31)	(0.19)	(0.19)	(0.11)

Table 3: Bias of using symbols.

	Data	Trial-error	Instance	Imitation
Single	0.48	0.07	0.31	0.33
	(0.22)	(0.02)	(0.12)	(0.17)
Combination	1.81	0.43	1.43	1.57
	(0.48)	(0.07)	(0.26)	(0.30)

and computed symbol sharing indices within pairs. The indices were computed as the dot-product of two unit-vectors that consisted of the frequencies of using each symbol. These indices were computed not only for single symbols (e.g., ■, ▰) but also for combinations of symbols (e.g., ▼◆).

Table 2 shows the computed indices of symbol sharing. The imitation model has the highest indices for both the single symbol and combination of symbols. Conversely, the indices in the instance model are the lowest. This suggests that an agent in the imitation model created an isomorphic symbol system with a partner. The values obtained in the experiment are between those of the instance and imitation model, implying that imitation certainly occurred in the experiment.

The other explanation of the high indices of sharing symbols is that agents/participants chose symbols according to a uniform-distribution. To exclude this possibility, we computed a bias index using the geometric mean of two Kullback-Leibler divergences of the probability distributions P and E.

$$B = \sqrt{D_{\mathrm{KL}}(P_1||E) \cdot D_{\mathrm{KL}}(P_2||E)} \,,$$
$$D_{\mathrm{KL}}(P_i||E) = \sum_{n=1}^{N} P_i(n) \log \frac{P_i(n)}{E} \,, \quad (3)$$

where P_i is the probability distribution of the use of symbols of agent/participant i, E is the uniform distribution, and N is the number of bins of the probability distributions[5]. If the distribution P deviated from the uniform distribution, the index would increase.

The results are presented in Table 3. The trial-error model, which had the high symbol sharing indices, has the lowest values for both the single symbol and combination of symbols, indicating that the choice made in the trial-error model was less biased. Contrary to the trial-error model, the other two models and the experiment were biased towards using specific symbols, indicating that they communicated with a small number of symbols.

Discussion and Conclusions

This study constructed a model that forms a new communication system through interactive coordination. To date, many

[5]For the distribution of using a single symbol, $E = 1/6$ and $N = 6$. For the distribution of using a combination of symbols, E = 1/36 and N = 36

models for language evolution have been developed (for a review Steels, 2011). In addition, there exists a research work that uses ACT-R to simulate experiments of forming a communication system (Reitter & Lebiere, 2011). However, these researchers did not deal with a situation with spontaneous turn-taking or role-setting operations. Most of the previous models assign roles to agents, such as director or matcher, using simulation parameters.

Unlike the previous studies, we dealt with a situation where roles are autonomously assigned. In such a situation, agents efficiently develop a shared communication system through a two-way imitation, which uses a single instance in two ways by reversing roles. It reduces trial-errors, and results in a faster forming process as presented in Table 1. In addition, differently from the instance model, the imitation model create an isomorphic symbol system as indicated by Table 2. Summarizing these results, we conclude that with few interactions, imitation can create an isomorphic symbol system.

Moreover, the comparison of the models with the experiment revealed the existence of imitation in the formation of a human communication system. Table 2 showed the apparent difference in the sharing index between the instance model and the experimental data. This result is consistent with previous laboratory experiments, in which participants used similar symbols in pairs through interactions (Fay, Garrod, Roberts, & Swoboda, 2010; Garrod, Fay, Lee, & Oberlander, 2007).

An additional finding was observed from the trial-error model. Unlike the imitation and the instance models, the trial-error model failed to construct a communication system. All models possess a common subsymbolic learning that updates activations of chunks and utilities of compiled productions. Therefore, this difference indicates an advantage of symbolic learning. Our results suggest that subsymbolic learning by itself have a limitation in constructing a communication system. Rather, subsymbolic learning are used to adapt to the structure of the environment as shown in Figure 6. We consider that this adaptivity provides a scaffold for forming a new symbolic communication system (Konno et al., in press).

There are several limitations in this study. We could examine neither the syntax (combination rules of symbols) nor the symbol-meanings mappings. These important features of human communication systems, namely language, are difficult to be captured by simple statistics. We need analysis methods to understand how a new language emerges in an experiment or computer simulation.

To extend our model to more complex situations, the goal buffer of the model should be hierarchically decomposed. The current design of the goal buffer cannot be applied to a complex situation where many symbols are combined. Imitation strategy also needs to include more detailed processes. We believe that the theory of analogical reasoning (Gentner, 1983) can be applied to a model of a complex imitation strategy. There is some previous research that point out that imitation is a type of analogical mapping (Barnes & Thagard, 1997; Thagard, 2001). It is a big challenge for the broad cognitive science community to examine how analogical mapping is changed through symbolic and subsymbolic learning when forming a new language.

Acknowledgment

This work was supported by a Grant-in-Aid for Scientific Research on Innovative Areas "The study on the neural dynamics for understanding communication in terms of complex hetero systems (No.4103)" (21120011) of The Ministry of Education, Culture, Sports, Science, and Technology, Japan.

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