Paper No: SE-02 **Systems Engineering**

Contribution of reflection in language emergence with an under-restricted situation

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***Abstract*: Owing to language emergence, human beings have been able to understand the intentions of others, generate common concepts, and extend new concepts. Artificial intelligence researchers have not only predicted words and sentences statistically in machine learning but also created a language system by communicating with the machine itself. However, strong constraints are exhibited in current studies. Models dependent on task settings, or supervisor signals and rewards exist, thus hindering the emergence of languages like the real-world. In this study, we improved Batali and Choi et al.'s research and attempted language emergence under conditions of low constraints such as human language generation. We developed a new language emergence agent that combines a language module and a visual module and included the bias that exists in humans as a "reflection function" into the new emergence algorithm. We used the MNIST dataset for language emergence. Irrespective of the function, messages corresponding to the label of MNIST could be generated. However, through qualitative and quantitative analysis, we confirmed that the reflection function caused pattern structuring in the message. This result suggested that the reflection function performed effectively in creating a grounding language from raw images with an under-restricted situation like the human language generation.**

Keywords: *Cognitive bias, Conceptual grounding, Language emergence, Multi agent description game, Reflection*

I. Introduction

Humans, as well as animals, have emerged information and concepts through the exchange of languages [1],[2]. Languages enable the understanding of the intentions of others and a socially common system to be built [3]-[5]. In addition, languages can be used to recursively construct concepts and create new ones [6],[7]. The intelligence needs to formulate and systematize a language from contexts and situations. For artificial intelligence studies, it is important to build machines that can handle words and concepts[8],[9]. Deep learning, especially the attention mechanism, has improved the success of various natural language processing tasks [10]-[12]. Furthermore, studies on multi-modal information are progressing. Supervised learning based on large datasets regards languages as statistical pattern processing with discrete symbols.

Introducing the language system using the current datasets has been difficult in machine learning [13], [14]. Language intelligence involves more than statistically predicting words and sentences. Therefore, Researchers have built neural network agents to create the language system by communicating with each agent instead of language processing using statistical information [9],[15]. Complex tasks could be solved using these generated messages. Constructed rules and messages that emerge owing to this communication are a system that differs from that of a human.

However, current language emergence studies have not achieved the autonomous grounding of mental images as those of humans and animals [16],[17]. Two issues remain: (1) The correspondence of generated messages to concepts is mediated by the architecture. Messages are not directly grounded to concepts. In some cases, a meaningless message was generated, and in other cases, a meaningful message was assigned to random noise images. (2) The "supervisor" role is essential because emergence agents do not gain a language system unless they are rewarded for communication. The supervisor method provided implicit indices such as "direction of correct communication for task resolutions" and "direction of a correct language system corresponding to a concept."

These issues occur because conventional language emergence models were considered based on "machine learning." "Machine learning" requires a "strong-restricted situation" such as a supervisor and uniquely defined concepts. On the other hand, the language emergence and learning of humans are different from the language emergence model of machine. Humans have prior knowledge of the concept [18,19]. Such the concept is not uniquely fixed. Humans can create language systems independently from the supervisor [20]. These mean that humans can make language emergence in an under-restricted situation. Little has been reported on language emergence under these conditions in which the agent possesses individual prior knowledge and is independent of the supervisor. Therefore, the need to introduce a human cognitive model is being discussed[21]-[23].

The purpose of this study is to confirm a compositional language emergence method, in which machines autonomously ground concepts to multiple agents in an under-restricted situation. We developed a method and architecture that can generate a language from discrete symbols. Using Description Game, agents must autonomously generate messages corresponding to cluster images that are not fixed at one point. To create compositional rules within these under-restricted situations, we introduce human cognitive bias into agents. Using the generated messages and the reconstructed images, we compared the characteristics of the agreed compositional rules by bias and discovered the emergent parameters necessary for the rules.

II. Related Work

Artificial life studies of language emergence have discovered the dynamism of the generated language and the condition under which language systematization and formality have emerged [24],[25]. Recently, a neural network model has been used to generate a complex language using reinforcement learning or supervised learning. It is classified into the task solution type and the concept correspondence type. In the task solution type, multiple agents are prepared, and the tasks, such as VQA problems, are solved by communicating each other's situations and behaviors [26]-[28]. The agents materialize words (instructions) through communication to generate appropriate behaviors and generate answers to specific questions. On the other hand, the concept correspondence type generate messages corresponding to objects recognized through a reinforcement learning(RL)-based approach [29]-[31]. This approach comprises different modules for generating and learning messages. It converges on a common language because the reward is transmitted to each module. However, the RL-based approach suffers from internal consistency [17],[32] [33].

Our study is inspired by the studies of Batali [34] and Choi et al [33]. Batali and Choi et al proposed the 'obverter technique' to generate compositional languages. The obverter technique is a commonly used message generation method [35]. A speaker cannot know the state of mind of a listener. Therefore, in the obverter technique, the speaker is assumed to have a similar mind as the listener. The speaker generates a message that maximizes his own understanding. Based on this assumption, the technique attempts to solve the problem of mutual communication. It can solve the problem of the RL-based approach "the problem of internal consistency in languages" and enables language emergence based on "the theory of mind [36]." However, in Batali's study, experiments were conducted under strong constraints that allowed the corresponding concepts to be uniquely determined[34]. In Choi et al.'s study, the supervised signal was required for generation[33].

The formation process and concept correspondence of human communication are useful as reference. Supervisors are not required for the process of human language acquisition. Furthermore, it is characterized by not learning concepts and words simultaneously [18],[19]. The emergence of sign languages in Africa [20] and the formation of languages such as the Pidgin and Creole languages demonstrate the unsupervised and asynchronous nature in language systems. Additionally, it is known that animals acquire different formal language depending on the species [37]. In this study, we refer to the above-mentioned studies to allow multiple agents to autonomously generate messages corresponding to concepts without a human supervisor.

We herein propose the multi-agent description game to establish a language system for multiple agents without a human supervisor. The description game consists of a teacher agent (speaker) that generates messages and a student agent (listener) that receives and learns the messages [30],[33]. The student agent receives the messages from the teacher agent and associates them with the presented image. Repeating this process creates a common language with messages corresponding to concepts between agents.

III. Method

A. Multi-Agent description game

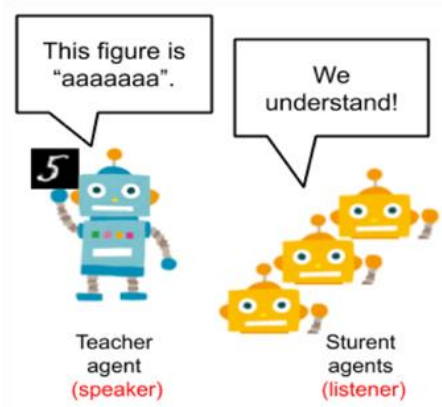

Fig 1. Multi-agent description game schema

The game proceeds as follows for each epoch. (1) One teacher agent is randomly selected from all agents. (2) The teacher agent randomly selects one image from a list and generates the message corresponding to the image. (3) The teacher agent sends the image and the message to the student agent, and the student agent associates the message with the image (Learning process). (4) (1) to (3) are performed a specified number of times. No image labels are presented between in-game agents. Therefore, the agent must associate the message with the representation read from the image. There is no guarantee that a message will completely correspond to a label. It is noted that "image" means raw pixel data that are provided to the agent, and "label" means "numbers (common concepts understood by humans)" written to the image.

In this study, one hundred agents were prepared and the image object used was the MNIST dataset. A training dataset was used during learning and generation, and a test dataset was used to evaluate the messages.

B. Model architecture and Obverter technique

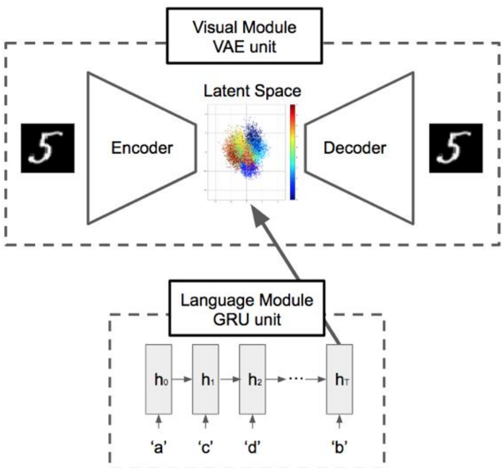

Fig 2. Agent model architecture (The visual module consists of the VAE unit. The language module consists of the GRU units. The VAE unit is composed of an encoder and a decoder. The encoder output is mapped to the latent space. Entering a message in the GRU units outputs a value corresponding to a point in the latent space.)

We herein propose an agent architecture for the multi-agent description game. An agent comprises a language module for reading and generating a message, and a visual module for processing an image and associating the image with the messages.

The visual module uses a variational autoencoder (VAE) [38] and the language module uses a gated recurrent unit (GRU) [39]. The visual module is given prior knowledge of MNIST. The language module outputs a numerical value corresponding to the latent space by inputting an arbitrary message that has been converted into a one-hot vector. This structure enables the generation of messages corresponding to the image and reconstruction of an image that corresponds to the messages. This module architecture differs from the pre-existing architecture in terms of some characteristics: (1) The proposed architecture enables language emergence by agent interaction without using human-prepared supervised signals and rewards. (2) The reconstructed image corresponding to the generated message can be directly confirmed.

An agent learns and generates a language using the obverter technique [34]. The below-mentioned procedure corresponds to self-supervised learning from the viewpoint of one agent. An agent set takes an emergent behavior that forms a conceptual pact without supervised signals.

1) Generate messages: In the teacher agent, the GRU model parameters are fixed. When a target image is input, the vision module encoder outputs a latent space value z corresponding to the image. After initializing the GRU hidden layer, the language module evaluates the output of all possible symbols. During this evaluation, the symbol with the minimum value between latent space z and the output of the language module is selected. The GRU hidden vector derived by the selected symbol is used by the next GRU unit. This procedure is repeated until the minimal value between z and the output value of the language module becomes less than a predefined threshold or until the max message length is attained. This procedure generates a message corresponding to the image.

2) Learning message: The student agent performs the learning so that the received message corresponds to the image. In the student agent, the GRU model parameters are updated. The GRU parameters are updated by backpropagating the mean square error loss between the value of the GRU unit output by inputting the message generated by the teacher agent and the latent space value z corresponding to the target image.

The details of the model architecture and parameter are described in Table 1. In this study, we used the same visual module agent group in each trial for comparison. Each agent in the agent group was learning a different latent space. The initial value of the language module was specified to be different for each agent.

TABLE I. PARAMETER LIST

Parameter	Value
Number of agents	100
Number of learnings in one Epoch	100
VAE structure	782(ReLu)-512-4-512(ReLu)-782(sigmoid)
VAE Optimization function	Adam(Lr=1e-3)
GRU structure	Hiddden128-Output4(Tanh)
GRU Optimization function	SGD(Lr=0.005)
Available symbols(Alphabet)	a,b,c,d
Maximum message length	10
Generation definition threshold	0.005

C. *Reflection function*

We introduced cognitive bias to the agents. In conceptual pacts, in some cases, humans may not agree with all the concepts presented [40]. Thus, human learning generally includes introspective elements. We improve and introduce this function so that the student agent compares messages generated by the teacher agent and rejects the message if it is significantly different from the self-concept. In this study, we defined this function as the "reflection function.".

The reflection function is realized by the student agent checking the message received from the teacher agent before updating the parameters. (1) The student agent receives a target image that the teacher agent used to generate a message. Each student agent self-generates its own message using an image by the method shown in § 3.2. (2) Each student agent calculates a degree of comparison similarity between the message received from the teacher agent and the self-generated message using gestalt pattern matching [41]. The degree of comparison similarity by gestalt pattern matching is output in the range of 0-1. The value of 1 means an exact match. (3-A) When the degree of comparison similarity is lower than the threshold value, the received message is regarded as an error and the learning process is not performed. (3-B) When the degree of comparison similarity is higher than the threshold value, the received message is regarded as correct and the learning process is performed.

In this experiment, three types were prepared for comparison. The first type was NORMAL: do not use reflection function. The second type was REFLECTION: the reflection function was incorporated from the beginning of the game. The threshold degree of comparison similarity was set to 0.4. The third type was SWITCH: to verify the strength of the constraints of the reflection function, we activated the reflection function during the game. SWITCH required parameters for the threshold degree and the activated point for the reflection function. The parameter used is the threshold value of 0.6/activated point at epoch = 600. We tested each type five times and evaluated the results.

D. *Evaluation indices*

We analyzed the language generation characteristics of each learning method. In particular, we investigated the correct answer rate of the image which the agent reconstructed from the messages, and the systematic rules of the messages. These points are necessary for the compositional properties of the emergence language.

1) Basic information evaluation: The first analysis was to confirm that learning has converged and to examine the similarity of messages between labels. We verified the mean square error loss between the output of the GRU unit and the latent space z. We also confirmed the reconstructed image using the generated messages.

In addition, a quantitative evaluation of the reconstructed images was performed. The message for evaluation was obtained by the following method: Three arbitrary agents were selected from each agent set. 200 messages per agent were generated by the method proposed in §3.B. The breakdown of 200 messages is as follows:100 messages were generated using a common image among the agents. Another 100 messages were generated using independent images for each agent. These messages allow duplicates. We entered the messages into the agents to generate the reconstructed image. The accuracy was finally calculated for each label by putting the image into the evaluators. The evaluators utilized five MNIST classifiers with over 98% accuracy. This evaluation method was based on Vedantam et al. [42].

2) *Compositional evaluation of lead symbols*: In the second analysis, we evaluated the characteristics of the relationship between the generated message and the label (concept) [43]. Specifically, the relationship between lead symbols and labels were quantitatively compared using lead symbol configuration for each label and usage rate of head symbol. Hereinafter, when the first symbol in the message is indicated or when a general concept is used, it is referred to as "Lead symbol". The first two-digit symbol, which is frequently used in analysis, is referred to as "Head symbol". We analyzed 600 messages generated in the above assessment. In lead symbol configuration for each label, the composition ratio of the lead symbol to one label was confirmed. If one label 's lead symbol consisted of only one or a few symbols, it is likely to be a clear ownership relationship between the symbol and the label. However, if it was composed of a plurality of lead symbols, it is likely that there is no clear symbol corresponding to the label. Specifically, the number of labels whose lead symbol constituted more than 70% of each label was counted.

In usage rate of head symbol, whether the expressed head symbol is biased to a specific symbol is evaluated as a variance. If the head symbol was generated without bias (i.e., using various symbols for the head), the variance became small and the symbol is considered to have a unique meaning. However, if a specific head symbol was mainly used (i.e., using only a single symbol), the variance became large and the symbol is considered to have multiple meanings. The variance formula is expressed as follows.

$$var = \frac{1}{n}\sum_{i}^{n}(x_i - \mu) \tag{1}$$

Where xi represents the number of uses of a certain head symbol and n represents the number of head symbol types.

3) *Attempts to formalize messages*: The third analysis confirmed the compositional rule for the message corresponding to reconstructed image. Language structure by recursion and multiple symbols is the basic element of "Compositionality" in language emergent research [44]. We entered a message to each agent set and confirmed the conditions of the message under which the image of each label was reconstructed. Therefore, we enumerated repeated patterns that appeared in the message by label as compositional rules.

Next, we simplified the compositional rules and analyzed whether a specific syntax appeared in the simple rules. Parentheses and repetitions have been omitted for simplicity. We analyzed the existence of overlap symbols in the structure of the simple rule's sequence and first two-digit (head) symbols in simple rules. The comparison was based on the lead symbol. Using these indices, we can be confirmed of the basic symbol composition for reconstructing a certain label.

IV. Results

A. *Basic information evaluation*

We confirmed the characteristics of the reflection types in the description game phases and the message generation. First, the distance between the message and target image was analyzed using the MSE. The loss tended to decrease during the description game in all reflection types (Fig. 3). SWITCH and NORMAL showed the same decreasing trend because they had no reflection function at the beginning of learning. In REFLECTION, a gradual decrease was shown compared with others. NORMAL showed an upward trend from epoch = 850. On the other hand, in REFLECTION and SWITCH, this tendency was not observed until epoch = 1100.

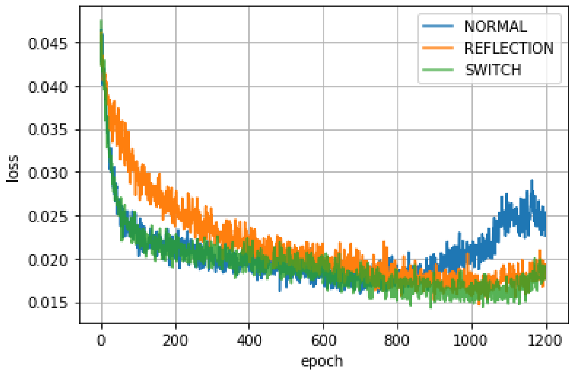

Fig 3. Transition of teacher's loss function (The average of five trials is presented. Averages from epoch = 700 to epoch = 900 were 0.018, 0.017 and 0.016 for NORMAL,REFLECTION and SWITCH, respectively. Meanwhile, averages from epoch = 1100 to epoch = 1200 were 0.023 and 0.017 for NORMAL and INTERNAL, respectively. IN SWITCH, Averages from epoch = 1100 to epoch = 1200 were 0.017. A clear increase in loss function was observed only in NORMAL.)

Thus, these results exhibited different loss function transitions depending on the reflection types. Subsequently, we attempted to analyze epoch points that have a smaller loss function value for each reflection type. (NORMAL = 810, REFLECTION and SWITCH = 1200. For the analysis with NORMAL = 810, we created five new verification agent sets at epoch = 810. The decrease in loss function showed a similar trend.)

Fig. 4 shows the result of the reconstructed image of one agent group in each reflection type. As shown, all reflection types have the same ability to the reconstructed image. Some labels have low agent sharing for the messages. For example, labels "6," "8" for NORMAL, label "6" for REFLECTION, and labels "2," "6" for SWITCH showed this tendency. However, we confirmed that all the same messages reconstructed the images corresponding to the label.

Next, we confirmed the accuracy of the reconstructed image corresponding to the generated message (Fig. 5). The average accuracy was 0.49 (NORMAL), 0.47

(REFLECTION), and 0.47 (SWITCH). Statistically significant differences in the accuracy were not observed.

The clustering accuracy average of the VAE latent space for all agents was approximately 0.65 using the v-score. Therefore, the accuracy of the reconstructed image is lower than the clustering accuracy but did not present a significant decrease.

B. Compositional Evaluation of Lead Symbols

From the lead symbol configuration for each label and usage rate of head symbol analyses, the characteristics of the relationship between the generated message and the label are compared. The lead symbol configuration analysis for each label (Table II) showed almost the same value at the end of the description game in the reflection types. No statistically significant difference was observed. Meanwhile, in the usage rate of head symbol analysis, each reflection type showed different trends.

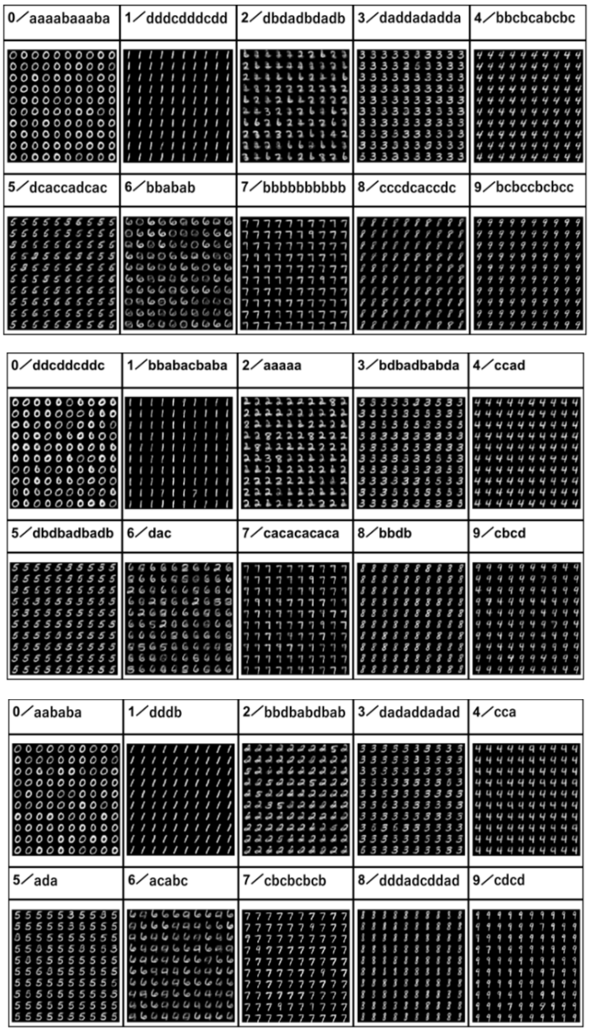

Fig 4. An example of the reconstructed image from messages (NORMAL, REFLECTION, and SWITCH, respectively, from top to bottom. The text above each figure is the message entered into the agents. The numbers in each figure represent the corresponding label numbers.)

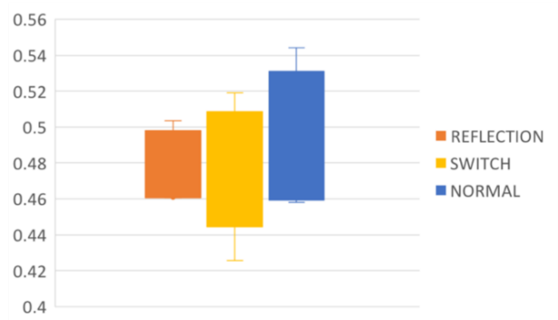

Fig 5. The accuracy of the reconstructed image in each reflection type (*The vertical axis indicates accuracy*.)

TABLE II. COMPOSITIONAL EVALUATION OF LEAD SYMBOLS.

	Reflection Type		
	NORMAL	***REFLECTION***	***SWITCH***
Lead symbol configuration	5.8	6	4.8
Usage rate of head symbol	1041.4	559.0	464.9

At epoch = 210, the variance was almost equal in all reflection types. As the game progressed, in NORMAL, the variance remained almost constant. REFLECTION showed a downward trend at the game progressed. SWITCH showed the same value as NORMAL before the reflection function was applied. At the end of the description game, a statistically significant difference ($p < 0.01$ in t-test) appeared in the value of the head symbol variance between NORMAL and the reflection function such as REFLECTION and SWITCH. The existence or nonexistence of the reflection function caused the lead symbol to exhibit a quantitatively different structure.

C. Attempts to formalize messages

1) *Decoding from human viewpoint of symbol compositional rule*: One agent group (Same group as Fig. 4) was extracted from each reflection type. We confirmed the compositional rules for messages according to Method 3.D.3 The compositional rules for each label are shown in Table III.

TABLE III. COMPARISON OF COMPOSITIONAL RULES.
WE ANALYZED THE MESSAGE IN WHICH THE RECONSTRUCTED IMAGE IS GUARANTEED FOR EACH LABEL. ONE AGENT GROUP WAS EXTRACTED FROM EACH REFLECTION TYPE. [XXX]* MEANS THAT THE XXX SYMBOL IS REPEATED. "Y" SYMBOL OF [XXX]*Y MEANS AN UNREPEATED SYMBOL. (Z) MEANS THE SYMBOL THAT MAY BE REQUIRED DEPENDING ON THE REPETITION STATE OF THE MESSAGES. "WITHOUT S" MEANS AN EXCLUSIVE SYMBOL THAT CANNOT BE RECONSTRUCTED IF "S" SYMBOL EXISTS.

Label	Reflection Type		
	NORMAL	***REFLECTION***	***SWITCH***
0	[aaa]*[aab]* (a>=2)	[dda]*, [da]*	[a]*, [a(b)a]*
1	d>=5	(a)[bba]*b	[bd]*, [db]* (without"a")
2	[dcab]*,[dacb]*	(db)[aaa]*	bbd(a)(b)b (without"c")
3	[dad]*,[dda]*	(aa)[bdb]*a	d[ad]*, [dda]*
4	[bbc]*a	[cad]*, [ca]*d	[cca]*
5	(d)cccacca	d[bd]*	[aadd]*, [aad]*
6	[bba]*	d[aaa]*d,a[aaa]*d	[acb]*
7	b>=6	[cc(c)a] * (without "d")	[cb]*

Label	Reflection Type		
	NORMAL	***REFLECTION***	***SWITCH***
8	Ccd	[bbcd]*, [bbd]*	[dda]*(d)c
9	[bcbbc]*	[ccb]*,[cbc]*	[ccd]*,[cd]*

In all reflection types, each agent set formed its own compositional rule. A key symbol was created to generate each label's reconstructed image. A compositional rule having repeated patterns including the order and combination of symbols emerged in REFLECTION and SWITCH. Additionally, REFLECTION and SWITCH identified the presence of exclusive symbols that prevented the label from being reconstructed. Meanwhile, NORMAL had few labels with such a compositional rule. NORMAL did not show a clear repeated pattern on some labels and could reconstruct the reconstructed image by the minimum necessary key symbol.

2) *Parsing of simple rules*: After simplifying the compositional rule shown in Section 4.C.1, the syntax of the generated rule was analyzed (Table IV).

TABLE IV. SIMPLE RULES ALIGNED FOR EACH LEADING SYMBOL. THE ONLY NON-OVERLAPPING SYMBOL IN THE SIMPLE RULE OF THE SAME LEAD SYMBOL IS SHOWN IN ITALICS. IN ADDITION, THE PART WHERE THE COMBINATION OF THE FIRST TWO DIGITS (HEAD) OF THE SYMBOL DO NOT OVERLAP IS UNDERLINED.

NORMAL			
"a" series	***"b" series***	***"c" series***	***"d" series***
aaa/aab	bbbbb	ccc*a*	dad/dda
	bba	cc*d*	da*cb*/dc*ab*
	bbca		ddddd
	bcbbc		

REFLECTION			
"a" series	***"b" series***	***"c" series***	***"d" series***
aaa	bbab	ca*d*	daaad
aaaa*d*	bb*cd*/bbd	cca	d*b*d
	bdba	cc*b*/ c*b*c	dda/da

SWITCH			
"a" series	***"b" series***	***"c" series***	***"d" series***
a/aa	bd	cc*a*	dad/dda
aa*d* /aa*dd*	bbdb	c*b*	dda*c*
a*cb*		cc*d*/c*d*	d*b*

- NORMAL: the use of the leading symbol was biased. The "b" series was especially used in the lead symbol. Three of the four were composed of the same head symbol. In addition, no unique symbol existed for each simple rule. The head symbol in the "c" series was the same. The unique symbol existed for each simple rules. In the "d" series, the unique symbol and the head symbol appeared on the same simple rule.
- REFLECTION: The lead symbol was allocated almost evenly. In the "b" series, a distinctive head symbol appeared, while the unique symbol appeared in one simple rule. In the "c" series, a distinctive head symbol appeared in two simple rules, while the unique symbol appeared in two simple rules. In the "d" series, a distinctive head symbol appeared in two simple rules, while the unique symbol appeared in one simple rule.
- SWITCH: SWITCH has a symbol syntax trend similar to that of REFLECTION. In "a" series, unique symbols appeared in two simple rules. A distinctive head symbol appeared in one simple rule. In the "b" series, although the symbols were similar, different head symbols appeared. In the "c" series, a unique symbol existed for every simple rule. In the "d" series, a distinctive head symbol appeared in two simple rules.

In REFLECTION and SWITCH, head symbol duplications were less than in NORMAL. The number of unique symbols appeared was slightly higher in types that had the reflection function.

In NORMAL, even in the "b" series, which requires a clear division, only one simple rule appeared clearly independent. Meanwhile, in REFLECTION and SWITCH, distinctive head symbols and unique symbols appeared in a balanced manner in each rule. Each rule had a proprietary tendency. It was confirmed that even simple rules not having a unique symbol exhibited a different pattern. Therefore, the tendency to form a unique symbol combination was confirmed in REFLECTION and SWITCH.

V. DISCUSSION

In this study, we proposed a multi-agent description game with 100 agents and a model architecture. The obverter technique was used for message generation. In addition, the reflection function, which imitates human language acquisition, was introduced.

As described in Sections 4.A, messages corresponding to the label were successfully generated, and we confirmed the reconstructed image from the message. It was found that by the proposed method, messages that correspond to concepts and allow an agreement between agents emerged without any human supervisor. However, as reported in Section 4.A, the decreasing tendency of the loss function was different between reflection types. As described in Sections 4.B and 4.C, the compositional rule between reflection types differed.

In NORMAL, the usage rate of head symbol showed a large value, it was considered that there was a bias in the use of lead symbols. On the other hand, in REFLECTION and SWITCH, the usage rate of head symbol showed a relatively small value, and it was considered that various lead symbols were used.

In NORMAL, a pattern with only one symbol or a label without clear repetition appeared. From the simple rules, the relationship between symbol patterns and labels was not clear. On the other hand, in REFLECTION and SWITCH, a label expression using a plurality of symbols mainly appeared, and a relationship between the specific pattern and the symbol was clear.

For SWITCH, the description game start point was NORMAL, and after some learning steps, the reflection function was activated. Notwithstanding, SWITCH showed the same results as REFLECTION. The reflection function seems to have broken the language structure at the time of NORMAL and generate a new structure. Thus, it was found that the compositional rules of messages that could be conceptually agreed by reflections were structured differently. It suggested that this characteristic difference was due to the reflection function.

We consider the features of the reflection function. NORMAL allowed students to learn all the messages generated by the teacher as a “positive example.” In this situation, the “this and that” symbol was learned. Even a major difference was absorbed as a "correct" message. Therefore, the results of the loss function indicated that learning converged quickly. However, at the same time, it also indicated that this situation produced “over-learning [45]."

Meanwhile, in the reflection function, a learning constraint based on the agent’s similarity evaluation existed. Because of this constraint, it is presumed that each agent creates a “negative example” in a pseudo manner by comparing itself with others. The positive and negative examples might have constructed a pseudo boundary among the labels. Therefore, it is assumed that the language generation has been constructed conservative. Consequently, a whole agent tends to a generate message having a common symbol for the same label. This situation, in which only common-term messages are generated, could be regarded as a bottleneck in information transmission between agent groups. Several studies have reported that bottlenecks produced syntactic structures [46], [47].

The bottleneck resulting from the reflection function is considered to have resulted in the build of the compositional rule having a pattern structure. This result suggests the existence of qualitatively different compositional trends is caused by the reflection function. Therefore, the reflection function can be expressed as an emergent parameter of a language system.

VI. Conclusion

In this study, we established a method for the emergence of a language system, in which consensus could be achieved in a group without a human supervisor. We proposed an emergence parameter, i.e., the “reflection function,” which acquired structuring compositional rules; additionally, we confirmed its effectiveness. This suggests that it performs effectively under restricted situations similar to human language generation. Further studies are required to generalize the relationship between formalization and concept. An extension to a general data set in which a plurality of concepts such as a color, a shape, and a place are integrated can be considered. We will confirm the laws of systematization generated by machines using extended dataset and having “different concepts” in each agent.

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