Acquiring Interaction Rule Reflecting User's Evaluation Tendency

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Abstract: Research on human interaction is done actively recently. We believe that mutual understanding between user and system has effective improvement in intimacy to system. In this paper, we propose the system which can promote mutual understanding by acquiring and reflecting user's evaluation tendency from interaction of a user and the system. User and the system expresses a simple symbol by turns, and user evaluates interaction at every evaluation phase. The proposal system learns the relation of interaction sequence and user's evaluation. We propose method of learning interaction sequence using All-Combinatorial N-grams. Thereby, the system gains interaction rule which raises user's evaluation. We believe that the intimacy to the system improves by offering a better interaction for a user using the gained interaction rule. The validity of the proposal system was shown by sensitivity evaluation.

Key words: ***interaction, n-gram, user's evaluation tendency***

1 Introduction

Research on human interaction is done actively recently [1–3], and activity of robot is expected in various scenes. For example, robot which guides facilities while regarding communication as a human being or the robot is intended to play with a child. A trial to improve the impression that a user has towards a robot in that attracts attention [4–6]. We think that it is necessary that user should have a good impression toward a robot for performing a good interaction. Ono points out the possibility that users can perform better interaction for robots when they feel an affinity [7]. In this paper, we paid our attention to the interaction for purpose of enjoying turn-taking. For example, a impromptu jazz session or a turn-taking play [8]. We believe that it is necessary to reflect the preference of the user for an interaction so that a user has a positive impression for the system through such an interaction more. This research aims at the development of the human interaction system which a impression for the system of a user improves by the system reflect a preference of the user, and emergence does a better interaction for the user. The user gives an evaluation to the interaction that the user and the system performed, and the system learns it dynamically. The system carries out emergence of better interactions to users. This paper pays attention to beads pattern play as simple interaction by visual sense, and inspects effectiveness of the proposal method in interaction by using simpler symbol.

2 Interaction Model

In this paper, we use extremely simple interaction model. The system which we build by making an interaction model simple will become general-purpose. Thus, we can use this system to other interaction model.

Fig. 1 shows the interaction model used in this paper. In addition, in this paper, CU_t is the input of user's tth dialogue, and CS_t is the system's output, M and S_{max} are arbitrary non-negative integers. The interaction model

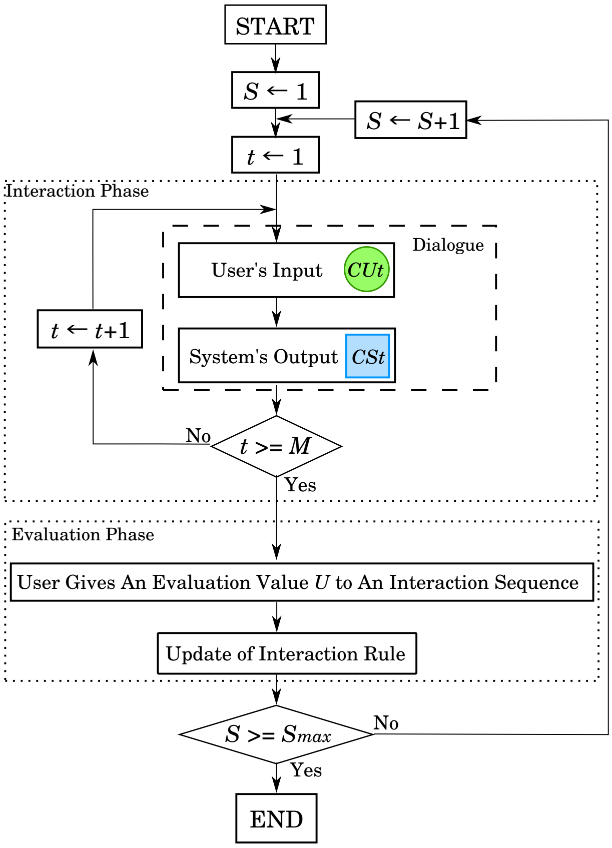
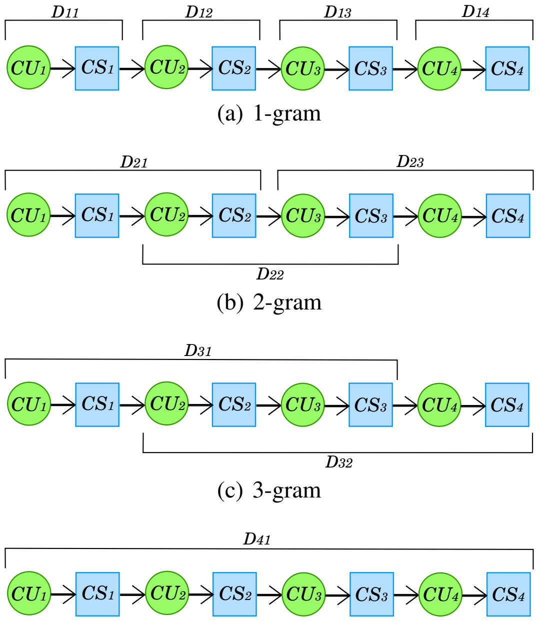


Fig. 1. Interaction model.

consists of interaction phase and evaluation phase. In interaction phase, user and the system perform interaction. In addition, we set the following limitations for interaction in this paper.

– Both user and the system can only choose symbols from the symbols we prepared.
– User and the system output a symbol by turns.
– User and the system output symbols for same times.

In evaluation phase which is after the interaction phase, user evaluates the interaction output by the interaction phase previously. In this paper, user evaluates a pattern in the symbol sequence which did emergence. If the pattern which user regards as good is contained in the sequence which the system emergences, user will give a high evaluation value to the system. Evaluation value U $(-X \leq U \leq X)$ is an integer, and good evaluation is meant if the value of U is high. In addition, X is an arbitrary non-negative integer, the concrete value and the evaluation method will be introduced in Chapter 4. By this way, the system gains the interaction rule that reflected user's evaluation tendency by repeating interaction phase and evaluation phase. The interaction rule is updated at every evaluation phase and gains user's evaluation tendency dynamically. Therefore the system can support in the change of the user's evaluation tendency and the unlearned symbol dynamically. In addition, in this paper, we define that user and the system output by once in turn as "one dialogue", a sequence of symbols in a dialogue as "dialogue sequence", M dialogues as "one interaction", and a sequence of symbols in one interaction as "interaction sequence". Thus, dialogue sequence is subsequence of interaction sequence. Output CS_t of the system is determined probable in inputting into the interaction rule which acquired the subsequence $(CU_1, CS_1, \cdots, CU_t)$ to CS_t. We believe it when



(a) 1-gram

(b) 2-gram

(c) 3-gram

(d) 4-gram

Fig. 2. Division example by ACN (M=4).

we can expect that emergence does the interaction that reflected user's evaluation tendency while not only memorizing interaction sequence that merely user appreciated, and outputting it, but also leaving room for unlikelihood by using probability.

3 Acquiring User's Evaluation Tendency

3.1 All-Combinatorial N-gram

User gives evaluation to the system according to liking of self for every M dialogs. If the evaluation value which the user gave is regarded only as evaluation to the whole interaction, the system cannot grasp which dialogue sequence was given the evaluation and the intention of the evaluation which the user gave. Thus, we suggest All-Combinatorial N-gram (ACN) as technique to get user's evaluation tendency in detail. ACN is a method to divide an interaction sequence into based on N-gram. The study which is using N-gram often fixes the value of N, such as bi-gram and tri-gram [9]. In this paper, minimum unit is one dialogue, and the value of N changes from 1 to M and divides one interaction in each to output all the combinations that the system can generate by N-gram expression. Therefore, a maximum of $M(M+1)/2$ patterns of dialogue sequence are outputted. Fig. 2(a)-2(d) is a division example when $M=4$. However, this example does not consider the case that dialogue sequence D repeats. We are dividing one interaction in this way, and think that a user's evaluation tendency can be acquired in detail.

3.2 Update of Interaction Rule

In this paper, an universal set of generated N-gram model is called interaction rule $\boldsymbol{R}$. $\boldsymbol{R}$ holds all of the past experiences and is updated at each evaluation phase. The overview of $\boldsymbol{R}$ is shown in Fig. 3. Moreover, we define the evaluation value history of each dialogue rule in an N-gram model is updated as "update of $\boldsymbol{R}$". Dialogue rule R_{ij}

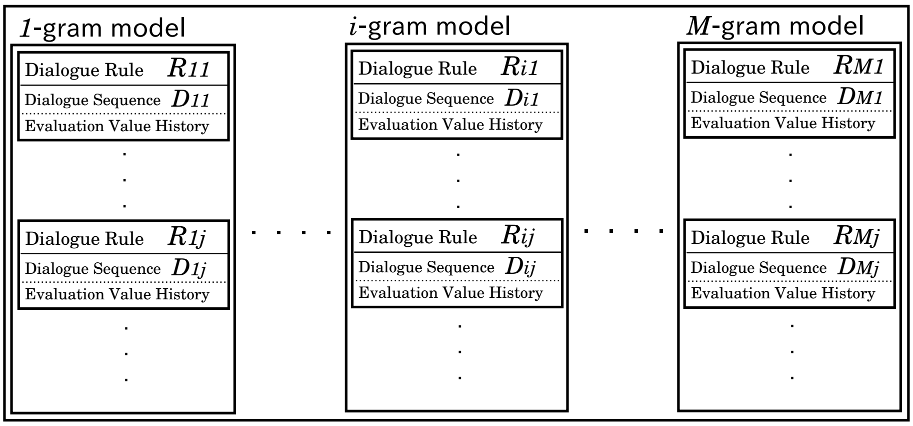


Fig. 3. Interaction rule $\boldsymbol{R}$.

consist of that dialogue sequence D_{ij} was outputted ACN and history in evaluation value of a D_{ij}, N-gram model is a set of dialogue rule. The evaluation value P of dialog sequence D_{ij} can be computed by Formula (1).

$$P = \frac{U \times A_{ij}}{M - ||D_{ij}|| + 1} \tag{1}$$

In addition, i expresses the value of N, j is an identifier of D in a i-gram model, U is a evaluation value which user gave, A_{ij} is number of times that D_{ij} appeared in one interaction, M is the number of regulation dialogues, and $||D_{ij}||$ expresses the length of the dialogue sequence of D_{ij}.

When user's evaluation is direct given to dialogue sequence D_{ij}, the swing of evaluation of a dialogue sequence becomes large from the characteristic which tends to be evaluated by the shorter dialogue sequence repeatedly, user's evaluation tendency cannot be caught correctly. Therefore Formula (1) is defined so that absolute value of the evaluation to dialogue sequence is discounted by shortness of the dialogue sequence ($M - ||D||$). Thereby, swing of evaluation value by difference in dialogue sequence length becomes small, and we think that user's evaluation tendency can be caught more correctly.

3.3 System Output

The output CS_t of the system is determined by the gained interaction rule $\boldsymbol{R}$ and the dialogue sequence ($CU_1, CS_1, \cdots, CU_t$) to CS_t. The system chooses an output symbol which maximizes evaluation from a user in evaluation phase.

A set of the output symbol of user and the system is expressed as $\boldsymbol{\alpha}$, the candidate of output CS_t is expressed as $\alpha_k \in \boldsymbol{\alpha}$, the system determines total evaluation predicted value E_{α_k} over α_k in the following procedures.

1. The system searches the set $R_{\{\alpha_k\}}$ which fills the following formula.

$$\begin{aligned} R_{\{\alpha_k\}} &= \{\forall R_{ij} \in \boldsymbol{R} \,|\, t - ||D_{ij}|| \geq 0 \ \wedge (CU_{t-||D_{ij}||}, CS_{t-||D_{ij}||}, \cdots, CU_t, \alpha_k) = D_{ij}\} \\ &\cup \{\forall R_{ij} \in \boldsymbol{R} \,|\, t - ||D_{ij}|| < 0 \ \wedge (CU_1, CS_1, \cdots, CU_t, \alpha_k, *, \cdots, *) = D_{ij}\} \end{aligned} \tag{2}$$

In addition, D_{ij} expresses the dialog series which the dialog rule R_{ij} has, and $*$ expresses arbitrary output signs.

Fig. 4. GUI which used for the experiment.

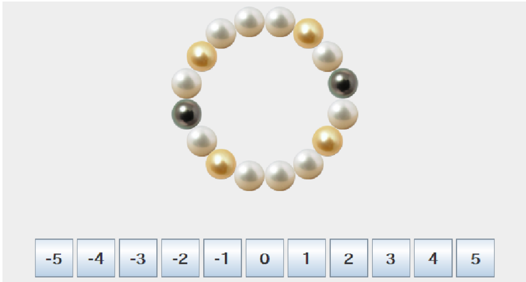


Fig. 5. Screen of evaluation.

2. The total evaluation predicted value E_{α_k} of output sign α_k is calculated by the following formula.

$$E_{\alpha_k} = \sum_{R \in R_{\{\alpha_k\}}} F(R)$$
$$F(R) = \begin{cases} \mu(R) \times \frac{1}{\sqrt{2\pi}\sigma(R)} & (\sigma(R) \neq 0) \\ \mu(R) & (\sigma(R) = 0) \end{cases} \tag{3}$$

$\mu(R)$ is average value of evaluation value included in evaluation value history which R has, $\sigma(R)$ is standard deviation, and $\#R_{\{\alpha_k\}}$ is the number of elements of $R_{\{\alpha_k\}}$. In addition, Formula (3) refers to the frequency function (Formula (4)) of a normal distribution, it integrated to $\mu(R)$ by making probability density $f(\mu(R))$ of the average value into a likelihood.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{4}$$

The occurrence probability OP_k of α_k is relatively computed from the output sign candidate's α_k general comment value predicted value E_{α_k} computed at the above two steps, and the system output CS_t stochastically based on OP_k.

$$OP_k = \frac{E_{\alpha_k}}{\sum\limits_{\alpha_k \in \boldsymbol{\alpha}} E_{\alpha_k}} \times 100 \tag{5}$$

Thereby, CS_t becomes a sign with high probability that high evaluation will be obtained from a user. By the way, when there is no extracted dialogue rule($R_{\{\alpha_k\}} = \phi$ for $\forall \alpha_k \in \boldsymbol{\alpha}$), CS_t is outputted at random.

4 System Evaluation

We performed sensitivity evaluation experiment to confirm effectiveness of the system which we suggested in this paper. First, it is verified whether emergence of interaction of pattern which user likes by sensitivity evaluation can be carried out. Next, it is checked whether user's individuality can be acquired through interaction by verification of user's evaluation tendency.

We used GUI for interaction of a user and the system. Fig. 4 is GUI used in this experiment. In interaction phase, user outputs a sign by clicking on icon drawn on the GUI lower berth, the system outputs after a definite period of time from user's output. An output history is drawn by the GUI upper part when user and the system outputted. Moreover, one interaction is completed in M dialogue of regulation count, and it shifts to an evaluation screen. Fig.

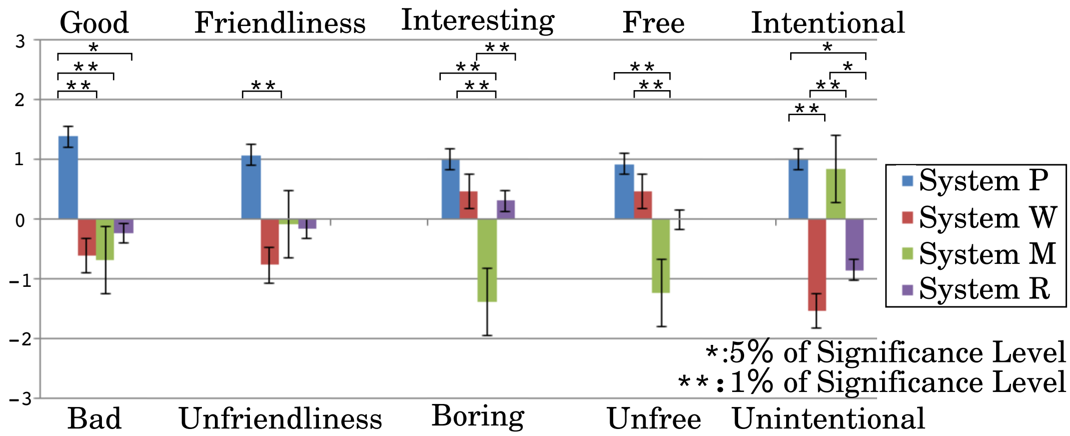


Fig. 6. Evaluation of sensitivity.

5 is the evaluation screen displayed. Evaluation value U from a user could be 11 steps ($X = 5$) between -5 (very bad) and +5 (very good). In this paper, In order to treat subjective evaluation to pattern within an interaction as user's evaluation tendency, We directed evaluation standard not to consider tempo and rhythm to subject beforehand.

In this experiment, the output sign set of user and the system is taken as the set which consists of round figure of 3 colors which imitated the beads, and one interaction is four dialogues ($M = 4$). The examinee is 13 men in twenties. Incidentally, originally the proposal system is learned dynamically. However, since what cannot be dynamically learned as candidate for comparison in this experiment was included, the experiment was conducted in static environment. That is, each examinee does communicate to unlearned proposal system beforehand, making the proposal system gain each examinee's interaction rule, we experimented. Learning was performed until it repeated the interaction phase and the evaluation phase 20 times ($S_{max} = 20$).

4.1 Sensitivity Evaluation

We let examinee communicate with four systems and had them evaluate sensitivity after the communicate. The system used for the evaluation experiment is shown below.

- Proposal System (System.P) : The system which learned user's evaluation tendency by the proposal method.
- Whole Tendency System (System.W) : The system which learned all examinee's evaluation tendency.
- Mirroring System (System.M) : The system which carries out the completely same output as a user's output.
- Random System (System.R) : The system outputted at random.

As for sensitivity evaluation, the semantic differential method [10] was used and It carried out by seven-step evaluation about five adjective pairs. The adjective pair used for evaluation is shown below.

1. Good-Bad
2. Friendliness-Unfriendliness
3. Interesting-Boring
4. Free-Unfree
5. Intentional-Unintentional

Table 1. Interaction Sequence of Examinee A

The interaction sequence D_A which obtained the highest evaluation at time of learning.	When the same user output as D_A is given, it is an interaction sequence with the highest emergence probability.	
	Proposal System	Whole Tendency System
b,**w**,y,**b**,b,**y**,w,**b**	b,**w**,y,**b**,b,**y**,w,**b**	b,**b**,y,**y**,b,**b**,w,**b**

Table 2. Sensitivity Evaluation Result of Examinee A

Evaluation Item	Proposal System	Whole Tendency System	Mirroring System	Random System
Good-Bad	1	-1	-1	-1
Friendliness-Unfriendliness	1	-1	1	-1
Interesting-Boring	1	1	-2	-1
Free-Unfree	1	1	-2	1
Intentional-Unintentional	1	-1	-1	-2

Fig. 6 is a result of the sensitivity evaluation experiment. This bar graph is average of a user's sensitivity evaluation, and error bar is standard error. We see from Fig. 6 that the proposal system is having obtained evaluation higher than other systems as for all items of sensitivity evaluation. Moreover, we performed the test of significance by multiple comparison official approval of Tukey to evaluation of each system. Result of official approval, the proposal system was evaluated "good" significantly by 1% of significance level to the whole tendency system and the mirroring system, and It was evaluated "good" significantly by 5% of significance level to the random system. Thereby, it is thought that the proposal system can learn evaluation tendency of "Good-Bad" which the user gave, and can be reflecting it in interaction. Moreover, it was evaluated "Friendliness" significantly by 1% of significance level to the whole tendency system, and it was evaluated "interesting" significantly by 5% of the significance level. Thus, it is concluded that the system which performed study by the proposal method carries out emergence of interaction which gives impression more positive than other systems to user. By the way, the mirroring system has obtained high evaluation along with the proposal system about the item "Intentional-Unintentional", however, the proposal system is evaluated "Free" significantly by 1% of the significance level to the mirroring system. Thus, the proposal system can carry out emergence of beads pattern "Free" and "Intentional" for user, however, the mirroring system can carry out emergence of beads pattern "Intentional" and "Unfree" for user. It is likely that user can predict output of the mirroring system easily.

4.2 Verification of User's Evaluation Tendency

We turn now to an account of reflection of user's evaluation tendency by the proposal system. We take up the examinee A who gave the nearest sensitivity evaluation to the evaluation average of Fig. 6 as a representative example. Table 1 shows interaction sequence D_A which the examinee A gave the highest evaluation at the time of study, and it shows interaction sequence with the highest emergence probability when the user's output of D_A is given to the proposal system and the whole tendency system. Table 2 shows the examinee A's sensitivity evaluation result. Table 3 and Table 4 show interaction rule set which the proposal system and the whole tendency system got each. "w" in a list expresses "a white circle" that is an output symbol, likewise, "y" expresses "a yellow circle" and "b" expresses "a black circle". Moreover, portion which is an output of system is written with boldface. $F(R)$ is value which integrated a likelihood to an average value of evaluation value included in evaluation value history

Table 3. Interaction rule Set of the Proposal System $\boldsymbol{R}$（The portion which has relation in the sequence of Table 1）

Interaction rule$\boldsymbol{R}$							
1-gram Model		2-gram Model		3-gram Model		4-gram Model	
Dialogue Sequence	$F(R)$	Dialogue Sequence	$F(R)$	Dialogue Sequence	$F(R)$	Dialogue Sequence	$F(R)$
b,**w**	0.6649	b,**w**,y,**b**	1.5958	b,**w**,y,**b**,b,**y**	0.9575	b,**w**,y,**b**,b,**y**,w,**b**	5
y,**b**	1.5032	y,**b**,b,**y**	1.4361	y,**b**,b,**y**,w,**b**	2.5	b,**b**,y,**y**,b,**b**,w,**b**	ϕ
b,**y**	0.1794	b,**y**,w,**b**	0.6678	b,**b**,y,**y**,b,**b**	ϕ		
w,**b**	0.6258	b,**b**,y,**y**	ϕ	y,**y**,b,**b**,w,**b**	ϕ		
b,**b**	-0.2261	y,**y**,b,**b**	ϕ				
y,**y**	ϕ	b,**b**,w,**b**	-0.3333				

Table 4. Interaction rule Set of the Whole Tendency System $\boldsymbol{R}$（The portion which has relation in the sequence of Table 1）

Interaction rule $\boldsymbol{R}$							
1-gram Model		2-gram Model		3-gram Model		4-gram Model	
Dialogue Sequence	$F(R)$	Dialogue Sequence	$F(R)$	Dialogue Sequence	$F(R)$	Dialogue Sequence	$F(R)$
b,**w**	0.1710	b,**w**,y,**b**	0.2713	b,**w**,y,**b**,b,**y**	0.9575	b,**w**,y,**b**,b,**y**,w,**b**	5
y,**b**	0.1026	y,**b**,b,**y**	0.3025	y,**b**,b,**y**,w,**b**	3.1915	b,**b**,y,**y**,b,**b**,w,**b**	3
b,**y**	0.1838	b,**y**,w,**b**	0.7658	b,**b**,y,**y**,b,**b**	0.1995		
w,**b**	0.2384	b,**b**,y,**y**	0.2736	y,**y**,b,**b**,w,**b**	0.0278		
b,**b**	0.2356	y,**y**,b,**b**	0.1407				
y,**y**	-0.1268	b,**b**,w,**b**	0.4091				

which dialogue rule R has like Formula (3), however, $F(R)$ of the dialogue rule in which evaluation value history does not exist is written as ϕ. We see from Table 1 that interaction sequence with the highest probability in which the proposal system carries out emergence is the same as that of D_A when user's output is the same as that of D_A. On the other hand, in the whole tendency system, although user's output is the same as that of D_A, interaction sequence with the highest probability that carries out emergence differs from D_A. Moreover, in the case of the proposal system, emergence probability of D_A (b,**w**,y,**b**,b,**y**,w,**b**) is approximately 27% and, in the case of the whole tendency system, is approximately 19% and, in the case of the random system, is approximately 1.2%. Thus, it is reasonable to suppose that the proposal system can be carrying out emergence of interaction reflecting examinee A's tendency, having the unpredictability by probability.

By the way, when Table 3 is compared with Table 4, it turns out that $F(R)$ of 1-gram model and 2-gram model differs greatly. Moreover, although it exists in interaction rule of the whole tendency system, it turns out that the dialogue rule in which evaluation value history does not exist is in the examinee A's interaction rule. Since the emergence probability of interaction sequence is computed by Formula (2)-(5), it is safe to say that it is decided by $F(R)$ of dialogue rule R which involves. In the case of the examinee A, $F(R)$ of (y,**b**) and (b,**w**,y,**b**) and (y,**b**,b,**y**) of Table 4 greatly increases in Table 3, we think that these differences induced the difference in interaction sequence by which emergence was carried out as examinee A's evaluation tendency.

We think that user's tendency is expressed as tendency of $F(R)$ computed from the dialogue rule R in interaction rule. We calculated $F(R)$ of dialogue rule R to participate in emergence of affiliation given evaluation from examinee at time of learning, and performed correlation analysis with evaluation value U that examinee gave. We demanded rank correlation of Spearman from every examinee using learning data of all examinees in analysis. As a result of analysis, the correlation coefficient in the proposal system is over 0.6 by all examinees, and user evaluation value U and high correlation of $F(R)$ were checked. On the other hand, when same analysis was conducted to the whole tendency system, there were six examinees exceeding 0.6 and the correlation coefficient of the correlation coefficient was clearly low compared with the proposal system. Thus, it turns out that the proposal system was able to generate high interaction rule of user evaluation value and correlation.

5 Conclusion and Future Work

In this paper, we proposed method of learning dynamically user's evaluation tendency for offering interaction which user likes, moreover, we proposed division of interaction sequence using All-Combinatorial N-gram (ACN) as method to acquire user's evaluation tendency in detail. It was found sensitivity evaluation experiment using GUI that the proposal system carries out emergence of interaction which gives user positive impression compared with other systems. This method is learning of the appearance pattern, however can handle only simple interaction that user and the system only output a symbol by turns. We would now like to go on to devise a system which can treat more advanced interaction. To take an example of application to music expression, we think that the construction of the system which can perform a musical session is possible by which it allows you to output a symbol in timing when user and system are free, or the interaction model is changed into what can permit a continuous sound. Moreover, by handling an act as a symbol and considering physical limitation, we think that construction of the interaction system — as for example child can play like turn-taking play or adult can use as child-rearing practice — is possible.

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