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Self-Efficacy using Fuzzy Control for Long-term Communication in Robot-Assisted Language Learning

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Abstract—**Recently, language education has a great demand from elementary school to adults. Robots are used as teaching assistants in Robot-Assisted Language Learning. It is very effective to use robots for language education. However, the robots may have some problems. One of the problems is to get bored when interacting with robots. This paper deals with this issue by using a method based on social cognitive theory. We discuss the role of robots based on mutual learning in language education. Next, we explain the concept of self-efficacy for evaluating the learning condition of robots. We propose a method to express self-efficacy using fuzzy control. The essence of the proposed method is to adapt to human's state. The experimental results show the effectiveness of the proposed method for long-term communication between a human and a robot.**

I. Introduction

There has never been greater enthusiasm and interest in English education. In order to acquire English, we need to have opportunities to use English language. In general, the communicative approach is important in the second language education [1], hence we need to have conversation partner in daily life to practice the communication. Therefore, we can apply intelligent robots and practice the conversation with these robots like with humans.

In robot-assisted language learning (RALL) shown in Table I [2-7], a humanoid robot named Robovie has taught English at an elementary school for two weeks [2]. It is an effective way to motivate students learning English, although it is less effective than educational software. In Korea, RALL has been studied actively. It is also called r-learning. The robot helps human teachers and does role-playing with the students. Robot IROBI is used as a home robot and teaching assistant in a classroom [3]. The robot was used to examine the learning effect on children. The application of robots in learning is good compared with using books, tapes, or computers. Robots are also used as native teachers in rural areas [4]. As the teachers prefer not to leave big cities, the students have few opportunities to take classes by them. In [5], there is no significant difference in the listening skill, but the speaking skills are improved. In [6], the authors report the design and testing of five instruction scenarios for teaching second language. Tanaka et al. use a care-receiving robot (CRR) at an English learning school and accelerate the children's spontaneous active learning by teaching [7]. However, these robots are not autonomous, therefore it is difficult to communicate with them for long time.

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In the research of long-term communication, the robot was used for three months, however it was not completely autonomous. Furthermore, the robot was located in a classroom, and had to communicate always to certain people [8]. Pseudo-development and confidential personal matters enable the robot to do long-term interaction. In this case the robot changed interaction patterns along with each child's experience, and the robot seems as if it learns something from the interaction. It means that the robot needs the capabilities of acquiring new information and adapting to personal preferences. Suga et al. realized a user-adaptive communication robot [9]. Through the interaction, the subjects evaluated the robot and the robot learned appropriate combinations between input and output. For continual and autonomous learning, Kawamoto et al. proposed a mechanism of self-regulated learning. It guided an agent's learning process and applied it for a maze exploration [10].

Previous researches on language acquisition although carried out the acquisition method, however they did not verify how the obtained language was used for subsequent communication [11,12].

We proposed a method where the robot learns words by associative learning [13]. The robot can learn and adapt to a partner by composing user-adaptive learning. However, it is not decided when these learning are performed. In this paper we propose self-regulated learning based on self-efficacy for the robot to decide which type of learning the robot should apply. Self-regulated learning has focused on how a student controls his academic ability cognitively, motivationally, and aggressively [14].

Bandura explained that self-efficacy refers to an individual's assessment of his or her ability to cope satisfactory with particular situations [15,16]. It arises from the relation between efficacy expectation and outcome expectation of its behavior.

II. Robot Partner

We have developed a PC-type physical robot partner called MOBiMac (Fig.1) in order to realize human-friendly communication and interaction. This robot has two CPUs and many sensors such as CMOS camera, microphone, and ultrasonic sensors. Furthermore, the information perceived by a robot is shared with other robots by wireless communication. Therefore, the robots can easily perform formation behaviors. We have applied steady-state genetic algorithm (SSGA) [17], spiking neural networks (SNN) [18],

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TABLE I. ROBOT-ASSISTED LANGUAGE LEARNING

Type	Teaching Assistant				Learning Companion	
Robots	IROBI [3]	Telepresense robot [4]	Mero and Engkey [5]	Humanoid robot [6]	Robovie [2]	Nao [7]
Aim	Interest	Interest	Listening	Cheering	Motivation	Care-Receiving
	Concentration	Confidence	Speaking	Conversation practice	Long-term Interaction	Learning by teaching
	Achievement	Motivation				
Situation	In class				Recreation hour	English learning school
Country	Korea			Taiwan	Japan	

self-organizing map (SOM) [19], and other methods for human detection, motion extraction, gesture recognition, and shape recognition based on image processing [20]. Furthermore, the robot can learn the relationship between the numerical information as a result of image processing and the symbolic information as a result of voice recognition [13]. MOBiMac can be also used as a standard personal computer.

We have used Apple Inc.'s iPad as pocket robot partners, because it is easy to use the touch interface and accelerometer in the development. In this paper, we use iPad as a face of the robot to interact with learners. Figure 2 illustrates the overview of the interfaces used in iPad. Human can interact with the robot by touching the robot's mouth or using a software keyboard.

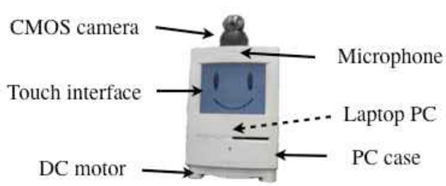

Figure 1. Human-friendly robot partner: MOBiMac

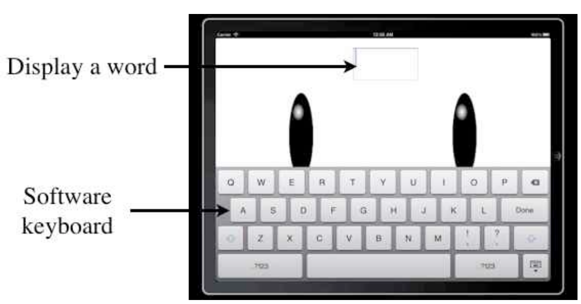

Figure 2. The screenshot of inputting a word to the robot

III. LEARNING

Three types of learning are discussed in this Section. The first one is mutual learning, which is performed between a robot and a human, where both the human and the robot also learn. The second one is associative learning, where relationships between different forms of inputs are learned. The last one is user adaptive learning, where the human's preferences, the human's attitude towards a set of objects, are also considered.

Figure 3 illustrates the architecture of our applied system. Humans can provide four kinds of information to the robot. The "Word" in Fig. 3 is what the user wants to teach for the robot. It is a word that the robot has to learn like an exam. The "Image" can refer to the human face or any objects. It is the information that relates an object or situation with the word. The "Reply" means what the human speaks and the robot recognizes by voice recognition. The "Evaluation" is used for evaluating the robot's speech using touchpad. The evaluation can be either good or bad.

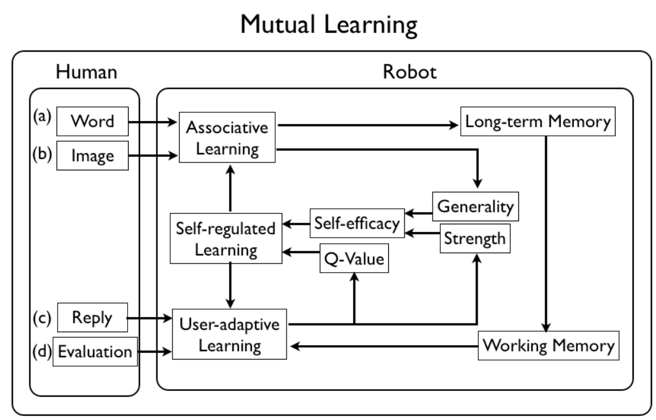

Figure 3. System configuration

A. Mutual learning

Mutual learning was proposed as a framework for long-term communication [21]. During the mutual learning the robot can learn and the human can learn as well. The robots learn words from human and humans learn conversation with robots. Since humans will get bored if they experienced all the patterns that the robot has, it is difficult to continue the communication. The purpose of mutual learning is to mutually improve. The human and the robot learn and become partners and they keep learning in this way. By this method, the robot continues acquiring new information and it will be possible to attain long-term communication as long as the student has motivation to study English. The situation is depicted in Fig. 4. The applied procedure is as follows:

1. A learner touches the robot's face and inputs an English word by using a software keyboard (Fig.5 (a)).
2. The robot learns the relationship between the word and the object seen by the camera (Fig.5 (b)). The robot increases the pattern of conversation.
3. The robot utters a sentence containing the learned words. After that the learner replies to the robot (Fig.5 (c)).

4. The learner can do English conversation. Finally, he evaluates the conversation. He strokes the robot's face as a reward or sticks the cheek as a punishment (Fig.5 (d)).

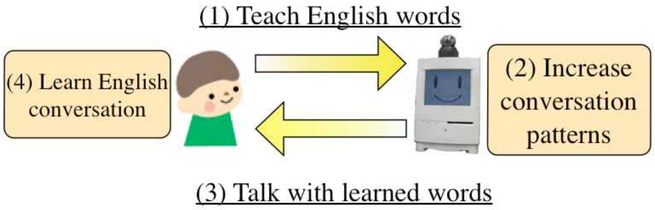

Figure 4. Mutual learning

Figure 5 illustrates the actual use of the robot.

(a) Teaching a word

(b) Showing an object

(c) Replying to robot

(d) Evaluating conversation

Figure 5. The appearance of human-robot communication

B. Associative learning

For a long-term memory, we use a simple spike response model of a neural network to reduce the computational cost [18]. Spiking neural networks are used for memorizing spatiotemporal information.

First of all, the internal state $h_i(t)$ is calculated as follows:

$$h_i(t) = \tanh\left(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t)\right). \quad (1)$$

The hyperbolic tangent is used to avoid the bursting of neuronal fires, $h_i^{ext}(t)$ is the input to the ith neuron from the external environment, and $h_i^{syn}(t)$ including the output pulses from other neurons is calculated by

$$h_i^{syn}(t) = \gamma^{syn} \cdot h_i(t-1) + \sum_{j=1, j\neq i}^{N} w_{j,i} \cdot h_j^{EPSP}(t). \quad (2)$$

Furthermore, $h_i^{ref}(t)$ indicates the refractoriness factor of the neuron, $w_{j,i}$ is a weight coefficient from the jth to the ith neuron, $h_j^{EPSP}(t)$ is the excitatory postsynaptic potential (EPSP) that is approximately transmitted from the jth neuron at the discrete time t, N is the number of neurons, and γ^{syn} is the temporal discount rate. The presynaptic spike output is transmitted to the connected neuron according to the EPSP, which is calculated as follows:

$$h_i^{EPSP}(t) = \sum_{n=0}^{T} \kappa^n p_i(t-n), \quad (3)$$

where κ is the discount rate ($0<\kappa<1.0$), $p_i(t)$ is the output of the ith neuron at the discrete time t, and T is the time sequence to be considered. If the neuron is fired, R is subtracted from the refractoriness value as follows:

$$h_i^{ref}(t) = \begin{cases} \gamma^{ref} \cdot h_i^{ref}(t-1) - R & if \;\; p_i(t-1) = 1 \\ \gamma^{ref} \cdot h_i^{ref}(t-1) & otherwise \end{cases} \quad (4)$$

where γ^{ref} is the discount rate. When the internal potential of the ith neuron is larger than the predefined threshold, a pulse is outputted as follows:

$$p_i(t) = \begin{cases} 1 & if \;\; h_i(t) \geq q_i \\ 0 & otherwise \end{cases} \quad (5)$$

where q_i is the threshold for firing. The weight parameters are trained based on the temporal Hebbian learning rule as follows:

$$w_{j,i} \leftarrow \tanh\left(\gamma^{wgt} \cdot w_{j,i} + \xi^{wgt} \cdot h_j^{EPSP}(t-1) \cdot h_i^{EPSP}(t)\right), \quad (6)$$

where ξ^{wgt} is the learning rate and γ^{wgt} is the discount rate.

Figure 6 depicts a situation where the robot performs associative learning [13]. The robot learns relationship between words from touch interface and attributes from image processing. In Fig. 6(a) the original image (a photograph) is displayed. Figure 6(b) shows differential extraction, while Fig. 6(c) illustrates the reference vectors of SOM corresponding to gestures. The object recognition results and the human detection results by SSGA are shown in Fig. 6(d) and (e), respectively. The green box indicates the candidates for human face position produced by SSGA, the red box indicates the face position produced by human tracking, and the pink box indicates the hand position. Figure 6(f) illustrates the EPSP of the spiking neurons, which indicates the spatiotemporal pattern captured from the subject's hand motion. The red rectangle is EPSP, and it gradually diminishes, turns blue, and becomes smaller.

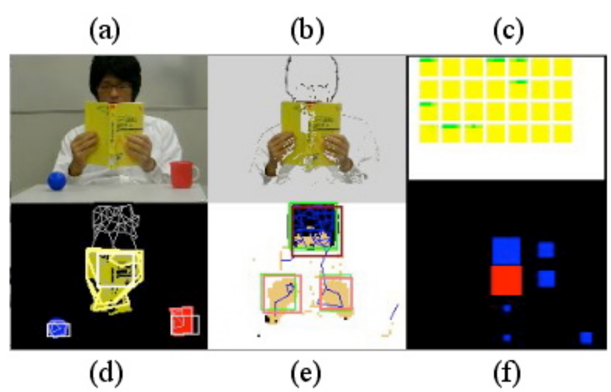

Figure 6. The robot performs associative learning interacting with the person

C. User-adaptive learning

Human can perform long-term communication to learn others' preferences in a conversation. By associative learning, the robot can learn a language, however the robot does not consider human preferences. In order to learn human preference as well, user-adaptive learning is applied.

Although the robot can easily recollect what was learned repeatedly, but what is being learned only once may be important as well. Kitano proposed the hormonal modulation learning which combined a genetic algorithm and reinforcement learning for this problem [22]. Furthermore, Suga et al. applied this method to communication of human and robot. We are arranging the method by interactive evolutionary computing which Suga et al. [9] proposed for conversation.

The flowchart of user-adaptive learning is depicted in Fig. 7.

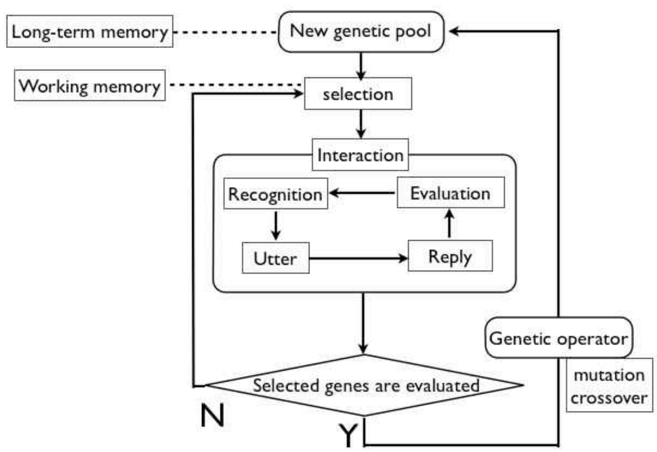

Figure 7. The flowchart of user-adaptive learning

1. ε-greedy selection chooses an action at random by a certain probability epsilon, and the rest chooses the action with the greatest Q-value [23]. By ε-greedy selection, the robot chooses the contents of the conversation from the long-term memory to the working memory. Working memory is selected from long-term memory and it decides the next utterance in the conversation.

2. The robot performs a conversation with human using the selected utterance, and the human evaluates the utterance. The robot sets the selection probability of the selected utterance to 0 as a lethal gene if the evaluation is punished. If the evaluation is rewarded, the selection probability is set to half. Here, the Q-value is the selection probability of the utterances. If the Q-value is low, we judge the user having no interests in the conversation because the average of Q-value is decreasing if the human gives punishment. Reversely, if the human gives reward, the average of Q-value is big. It estimates that the human is satisfied with the conversation. So the average of Q-value is taken as desire to utterance. For the evaluation, we use a touch interface for the input to evaluate the robot's utterance.

3. Genetic operation will be performed if the selected genes are evaluated. Mutation randomly increases the selection probability of the contents of the selected utterance. It is applied in order to make the conversation content not to consist of only those contents, which has similar attributes. Crossover increases the selection probability of that utterance that has similar attributes with the selected utterance. This can lead to choose that utterance that the human is interested in.

In the crossover, the selection probability of the contents close to the selected utterance is updated by the following formula:

$$Q_{t+1}(s,a') = (1-\alpha)Q_t(s,a) + \alpha[r + \gamma Q_t(s,a)] \tag{7}$$

where s expresses a state and it is chosen from small, medium, or big value of self-efficacy. Self-efficacy will be explained in the next Section. In Eq. (7) a is the contents of utterance, r is the reward/punishment. In case of reward r is 1, in case of punishment r is -1. α is learning rate and γ is discount rate. a' is decided by the smallest distance among the attribute of utterances:

$$a' = \arg\min_i (w_{j,a} - w_{j,i}) \tag{8}$$

Reinforcement learning updates the last behavior, but it is meaningless to utter the same content repeatedly during the communication. By the cognitive principle of the relevance in relevance theory, information processing of humans pays attention to the information, which has relation for himself or herself [24]. Minewaki et al. proposed an interpretation method of utterances using relevance theory [25]. They define the cognitive effect and the processing effort, and apply those to multi-objective optimization. We use the distance of the attributes as fitness function. We assume that the robot selects the utterance of the smallest distance of the attributes since the processing effort is small, and the robot chooses it as utterance at t+1.

IV. Self-efficacy and Self-regulated Learning using Fuzzy Control

A. Self-efficacy of the robot

Generally, the self-efficacy is expressed by the extent with three dimensions of Level, Strength, and Generality in efficacy expectation (Fig.8).

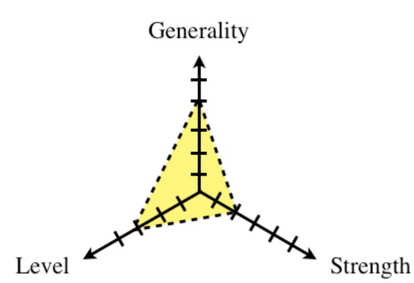

Figure 8. The dimensions of self-efficacy

In this paper, we use Strength and Generality. The robot makes an utterance suited for the human's capability. The value of self-efficacy has three states, small, medium, and big. Self-efficacy is used to evaluate the robot's own learning state.

S_S refers the strength of confidence that executes how much possibility is in each action. It is determined by the number of replies, that the robot gets when the robot speaks to humans:

$$S_S = \frac{n_R}{n_I} \tag{9}$$

n_R is the number of replies from human, and n_I is the number of interaction. There are 3 rules. If the robot talked to a person in Japanese and the person answered in Japanese, n_R increases. If the robot talked in English and the person answered in English, n_R increases. If the person answered in Japanese, n_R does not increase.

S_G means the generality of contents adapting to similar circumstances. Generality is defined by how much knowledge is utilized. It is decided by how much relevance of the robot's word has:

$$S_G = \frac{\sum_{j=1}\sum_{i=1} w_{j,i}}{N} \tag{10}$$

where N is the number of connections, $w_{j,i}$ is the connection weight between the jth and the ith neurons in the neural network.

We apply simplified fuzzy inference to express self-efficacy because the fuzziness and self-efficacy may be different to individuals. We used fuzzy system to control mobile robot in our previous research [26], because fuzzy rules can be easily designed. In general, a fuzzy if-then rule is described as follows,

If S_1 is $A_{i,1}$ and ... and S_m is $A_{i,m}$ **Then** S_{total} is B_i

where $A_{i,j}$ and B_i are the membership function for the jth input and the singleton for the output of the ith rule, and m is the number of inputs. The fuzzy inference is described by,

$$\mu_{A_{i,j}}(S_j) = \left(1 - \frac{|a_{i,j} - S_j|}{b_{i,j}}\right) \tag{11}$$

$$\mu_i = \prod_{j=1}^{m} \mu_{A_{i,j}}(S_j) \tag{12}$$

$$S^*_{total} = \frac{\sum_{i=1}^{n} \mu_i B_i}{\sum_{j=1}^{n} \mu_j} \tag{13}$$

where $a_{i,j}$ and $b_{i,j}$ are the central value and the width of the membership function $A_{i,j}$. In our case the fuzzy system has two inputs, S_S and S_G, and one output for deciding the total value of self-efficacy, S_{total}. Table II illustrates the fuzzy rule base, where the membership function PS means a=0, b=1; PM means a=0.5, b=0.5; and PB means a=1, b=1.

TABLE II. FUZZY RULE BASE

		S_S		
		PS	PM	PB
S_G	PS	0.25	0.25	0.5
	PM	0.25	0.5	0.75
	PB	0.5	0.75	0.75

By enhancing self-efficacy, the robot tries to speak English positively if the robot thinks it can get replies. When self-efficacy is big, we are willing to communicate [27]. The robot estimates the English skills of humans, which will be improved in this way. Self-efficacy is used as a criterion for judgment to speak English or Japanese. Moreover, S_{total} has three states. When S_{total} is small, the robot utters one word. When S_{total} is medium, the robot asks an easy question. When S_{total} is big, the robot asks a question which contains idiom or composed by a long sentence.

For example, when the word "dream" is selected, if self-efficacy is small, the robot utters only "dream" and the human utters the Japanese translation of "dream". If self-efficacy is medium, the robot utters "Do you often see dreams?" and the human answers "yes" or "no". If self-efficacy is big, the robot utters "What types of dream do you have often?" and the human answers what type of dream he or she had. Figure 9 shows the complete conversation examples.

Who talks	Conversation contents
Human	Hello.
MOBiMac	Dream?
Human	Yume (It means "dream" in Japanese).
MOBiMac	That's right.

(a) Self-efficacy is small

Who talks	Conversation contents
Human	Hello.
MOBiMac	Do you often see dreams?
Human	Yes.
MOBiMac	You can see good dream.

(b) Self-efficacy is medium

Who talks	Conversation contents
Human	Hello.
MOBiMac	What types of dream do you have often?
Human	Happy.
MOBiMac	That's great.

(c) Self-efficacy is big

Figure 9. Conversation examples

Figure 10 shows the concept of self-efficacy in a conversation. An outcome expectation is defined as a person's estimate that a given behavior will lead to certain outcomes. An efficacy expectation is the conviction that one can successfully execute the behavior required to produce the outcomes.

Outcome expectation shows the degree whether the robot can get a reply or not, and efficacy expectation decides if the robot speaks English or Japanese (Fig. 10.).

In existing dialogue systems, it was not measured whether the dialog have succeeded or not. Therefore, it is thought that a dialog does not continue for a long time. It is because the robot does not know whether the human understands the robot's contents of utterance. Then, self-efficacy is used in order to carry out conversation made consistent with the degree of comprehension in order to show whether the conversation has succeeded. If the self-efficacy increases, it will be thought that the robot can talk well. Self-efficacy shows whether the robot can talk with human well.

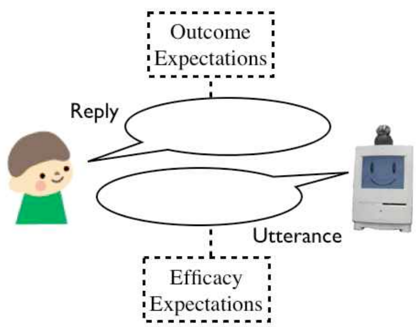

Figure 10. Representation of self-efficacy in a conversation

B. The content of self-regulated learning

It is important to raise a student's self-evaluation in education. However, the robot does not have the evaluation to itself. If the robot has self-evaluation, the robot will be able to choose behavior appropriately according to it.

Self-regulated learning has focused on how a student controls his academic ability cognitively, motivationally, and aggressively [14]. Since a robot is for education, it is set up to have the intention to make the human to learn. Therefore, it aims at assuming that a robot has desire of enhancing self-efficacy, the robot should choose suitable learning. The learning strategies chosen here are as follows.

(1) User-adaptive learning mode

The robot selects that utterance which is easy to obtain replies for.

(2) Associative learning mode

The robot asks a learner to teach a new word. Then the robot learns the relationship.

Usually the robot selects user-adaptive learning. When self-efficacy is increased, it thinks that the level of desire goes up like in Maslow's need-hierarchy theory [28], and the robot selects associative learning. Since the robot's conversation contents do not change if a new word is not taught, a learner will get bored. In order to get a new conversation pattern, associative learning is performed. We propose that the robot gets bored with conversation when the self-efficacy of the robot is big and the average of Q-value is small.

V. EXPERIMENTAL RESULTS

This section presents experimental results of the proposed method for language education. In the experiment a human and a robot perform conversation. By showing that the three types of learning are effective, we demonstrate that mutual learning is possible. Associative learning is performed first. The result is presented here.

The initial value of the Q-value is set randomly. The value of self-efficacy is set to 0. We taught words to the robot and made the robot learn relationship between words and images beforehand (associative learning mode). In this paper, although the learning process is not described, the robot learns the relation of a word with color, shape and gesture by image processing (Fig.11). Here, the information is acquired from image processing in a situation when learning the word without having any information about the word itself. The number of words to learn is 30 (see Table III), the number of colors is 4, the number of shapes is 3 (round, triangle, rectangle), and the gestures are classified according to self-organizing maps automatically.

The intermediate progress is detailed here. The result of the user-adaptive learning enables the robot to do conversation by using Interactive Evolutionary Computation (IEC) [29]. It can select relevant words. Table IV shows the Q-values corresponding to the words in Table III. First, these are given at random, but as interactions are performed repeatedly the robot learns the user's preference. The red zone indicates values over 0.5. By giving rewards to the robot, it recognized the user's preference.

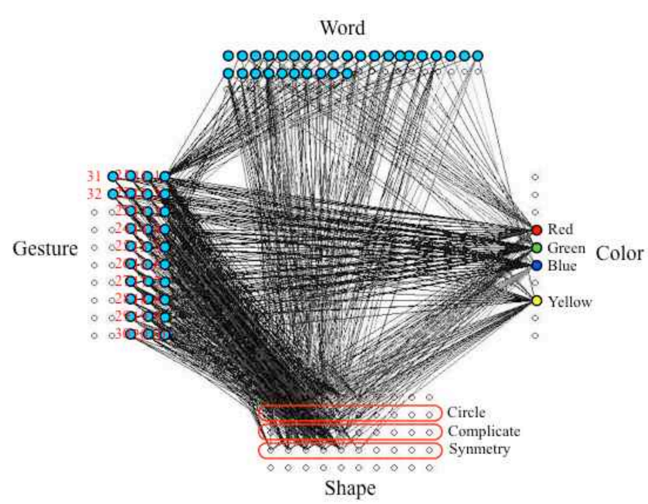

Figure 11. The relationship between words and perceptual information. This presents long-term memory.

TABLE III. 30 WORDS HAVE BEEN TAUGHT TO THE ROBOT AND 10 ADDITIONAL WORDS (RIGHT MOST)

hello	trouble	English	tall
exercise	fine	grade	weight
sleepy	day	family	weather
teeth	hair	hobby	egg
dust	what	baseball	bag
today	fat	soccer	have
dream	thin	sport	do
free	study	interest	be
meet	long	abroad	say
again	business	old	go

TABLE IV. THE Q-VALUES OF UTTERANCE WORDS CORRESPONDING TO TABLE III

0.84	0.88	0.08	
0.39	0.12	0.00	
0.73	0.79	0.19	
0.77	0.75	0.95	
0.59	0.76	0.96	
0.42	0.16	0.60	
0.01	0.51	0.05	
0.42	0.01	0.00	
0.00	-0.41	0.00	
0.89	0.00	0.42	

Next, we present the result of self-regulated learning. Here, since the user experienced all the patterns that the robot has, the user gave punishments. After that the average of the Q-values was gradually decreasing.

We show an experimental result without fuzzy control in Figure 12 (Left). The generality is about 0.83, and the strength becomes about 0.5. Accordingly, the total value of the self-efficacy becomes about 0.4. Therefore, the utterance level is medium. In this case, the effect of one variable is high. If one variable has small value, the total value is small even if the other input is big. Thus, the learning mode is not changed even if the Q-value is small.

Thereafter, we applied fuzzy control to calculate the self-efficacy. First, we had triangle membership functions in the fuzzy control, and we optimized the membership functions using user's training data by bacterial algorithm [30]. The training data were made by estimating self-efficacy based on strength and generality. In this way, the users can set up preferences for the way of communication. If a user makes self-efficacy big regarding to strength and generality, the self-efficacy becomes big faster. This is for those, who want to finish the study earlier. Otherwise, if a user sets the self-efficacy to small, it increases gradually and the user can go through the learning carefully. In our case, we set up the self-efficacy high as a training data.

Next, we show the change of self-efficacy after tuning the membership functions (Fig.12, Right). In this case, the strength is medium and the generality is big, the total value of self-efficacy is big. We always used punishments and the conversation contents are changed every time. Moreover, the decrease of the Q-value is quick. Because of this, the time to change from user-adaptive learning to associative learning is shortened. The number of conversations is 15. When *time* is 530, the learning mode changed to associative learning. Therefore the mutual learning continues.

After associate learning, we performed user-adaptive learning again. The robot was taught 10 new words shown in the right most part of Table III. The robot gained a new utterance pattern, and the desire to utterance increased again. The human and the robot talked using the pattern.

In the past, it was not able to distinguish utterances learned before and after. Therefore, it was not the conversation, which reflects the user's preference to learn only the word itself that the user wants to learn. However, by user-adaptive learning, we can learn new words intensively and the words relevant to them (Table V).

It indicated that the robot has the ability to repeat associative learning and adaptive learning for long-term communication, and therefore the robot and the person could acquire English words and practice conversation.

The experimental subject is a man who is a graduate student. Because of this, the English words that used in this experiment are easy for him. Since it was difficult to use these words in conversation even if he knew the meaning of the word, we were dared to use the easy words. This time the words are for beginners, it is possible to adapt to various learners because they can select the words that they want to learn.

The most advantageous point of this method is that the autonomous robot can communicate and adapt in the conversation. Robot-assisted language learning mainly uses robots as a teacher giving a lecture or as a teaching assistant. In addition, a care-receiving robot has a role of a friend though it uses a Wizard-of-Oz method. As compared to Kawamoto's self-regulated learning [10], although it shares similarity with our approach in changing a learning strategy, however its purpose is the interaction with the environment. Since our method differs from the research on human-robot communication, the self-efficacy for carrying out communication adapting to the person's condition is effective. By contrast, if the person decreased his motivation for learning, the communication way of the robot will not change because the robot cannot learn the new words. Consequently, the term they can communicate depends on the learner's motivation for learning.

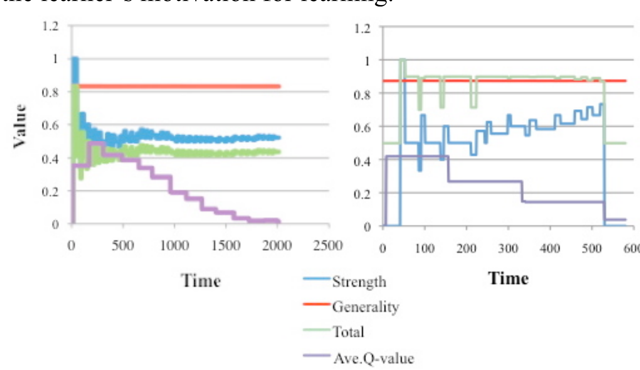

Figure 12. Change of the value of self-efficacy and average Q-value without fuzzy control (Left) and with fuzzy control (Right)

TABLE V. THE Q-VALUES OF UTTERANCE WORDS AFTER THE SECOND USER-ADAPTIVE LEARNING

0.68	0.00	0.00	0.04
0.27	0.00	0.00	0.08
0.00	0.00	0.32	0.04
0.00	0.31	0.12	1.35
0.00	0.00	0.00	0.04
0.00	0.29	0.06	0.05
0.00	0.00	0.00	0.05
0.00	0.00	0.00	0.05
0.00	-0.88	0.00	0.05
0.00	0.00	0.00	1.00

VI. CONCLUSION

In this paper, we discussed long-term communication as an example of language learning. First, we explained a dialogue system and conversational robot. Next, we discussed how to interact and communicate between human and robot in the language education. We proposed learning conversation system of physical robot partners. The essence of the proposed method is how humans and robots will improve each other's communication ability. Although the problem of long-term communication has not been solved yet, since it was actually omitted from this experiment, the integration of multiple learning methods showed the possibility of enabling long-term communication.

As future works, we will produce several utterances in the conversation system. Along with doing conversation experiment for long-term communication and we will clarify the educational effect of this system.

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