Learning the meaning of action commands based on "No News Is Good News" Criterion

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ABSTRACT

In the future, robots will become common in our daily life. For using the robot more efficiently, it is desirable that the robot would have learning ability. However, a human teaching process for robot learning in the real environment usually takes a very long period of time. We hence believe that the robot should learn from implicit information which is included in human natural behavior. We direct our attention to the lack of utterance as a kind of implicit information, and insist that the lack of utterance should be interpreted as a positive evaluation of the ongoing action, which we call No News Criterion, in a robot navigation context. In this paper, we propose an efficient command learning algorithm based on the No News Criterion, and demonstrate its effectiveness by a human-robot interaction experiment in the real environment.

Categories and Subject Descriptors

I.2.6 [Artificial Intelligence]: Learning—language acquisition

General Terms

Algorithms

Keywords

human-robot interaction, implicit information, action command learning, Q-learning

1. INTRODUCTION

In the future, robots will become common in our daily life. We believe that robots should have an ability to adapt to its environment, and should learn desirable behavior without instructions of every move. Although reinforcement learning enables learning from not instructions but rewards, it is not

practical for humans to explicitly evaluate every action of a robot. It hence is important that robots can use implicit information that is unconsciously given by humans.

Recently there have been several attempts to design a robot or an agent that acquires the meaning of words [1, 4, 5, 6, 7, 8]. The learning makes progress based basically on the co-occurrence of a word or a phrase with a situation, and additionally on other pieces of information. Among them Iwahashi [1], Komatsu and others [4], and Steels and Kaplan [6] utilize rewards for learning. While Iwahashi [1] and Steels and Kaplan [6] only use explicit rewards given by a human, Komatsu and others [4] also use implicit rewards unconsciously generated by a human. They noticed a rapid rise in pitch, and regarded it as a warning signal that means the ongoing action is inappropriate.

We also believe that the utilization of implicit information is essential for a robot or an agent to learn from interaction with a human. In this paper, we direct our attention to the lack of utterance as a kind of implicit information, and propose that the lack of utterance, that is, "no news", should be interpreted as "a good news", which we call "No News Criterion" hereafter, in a robot navigation context.

In Section 2 we give an account of a preliminary experiment in which we found that a certain duration of no utterance often means that the ongoing action is appropriate. We then propose an efficient command learning algorithm that utilize the No News Criterion in Section 3. An experiment into the properties of the learning algorithm is described in Section 4, the experimental results are shown in Section 5, and the discussion is made in Section 6. The final section is devoted to conclusion and future work.

2. PRELIMINARY EXPERIMENT

In this section, we describe a preliminary experiment in which we collect and analyze the interaction data between a robot and a human in a navigation context.

2.1 Experimental method

Thirteen participants, who were the students of our institute, were asked to guide AIBO, SONY's four-legged robot, to a goal by means of voice. The instruction shown to the participants was the following:

> Please show AIBO a way to the goal. AIBO does not understand well what you say, and will produce wrong actions, but please be patient with AIBO.

There were some obstacles that prevent AIBO from walking straight to the goal. Five kinds of actions were implemented in AIBO. They were <forward>, <backward>, <left-turn>, <right-turn>, and <stop>, and <stop> interrupts all other actions.

In the experiment, we used the Wizard of Oz method [3] in which participants interacted with AIBO that participants believed to be autonomous, but which was actually being operated by an unseen human operator. The operator manipulated AIBO according to two methods: one is random operation that corresponds to AIBO in the before-learning phase, and the other is 80% correct operation that mimics AIBO in a during-learning phase.

2.2 Experimental result

We analyzed the video that recorded the human-robot interaction in the navigation experiment, and found the following:

- There were mainly two types of utterances: one is the instruction that specifies an action AIBO should take, and the other is the evaluation of an ongoing or the last action. The instruction amounted to 68 % of all utterances, the evaluation 26 %, and the rest 6 % were utterances with ambiguous meaning such as "Umm". We confirmed that the participants do not evaluate every action of the robot explicitly.

- The action instructions consisted primarily of five groups each of which has different meaning. They were <forward>, <backward>, <left-turn>, <right-turn>, and <stop>. The evaluation meant either <good> or <bad>. Multiple expressions were observed for each meaning, for example, "SUSUME. (March!)", "MASSUGU. (Go straight!)", "MAE. (Forward!)", and so on were used to mean <forward>. We use the following notation hereafter: "UTTERANCE IN JAPANESE (Its English translation)", and <its meaning>.

- We can say AIBO took a correct action with 99% reliability if there has been no utterance for five seconds since AIBO began to move after received an action instruction.

3. ACTION COMMAND LEARNING BASED ON THE NO NEWS CRITERION

We aim to build a system that learns the meaning of action instructions based on rewards given by a human. Although the target actions are restricted to built-in actions of the robot, <forward>, <backward>, <left-turn>, and <right-turn> in this study, and the target instructions are also restricted to registered ones of the voice recognition system, we do not assume a one-to-one correspondence between actions and instructions.

We employ Q-learning [9], one of the reinforcement learning algorithm, for learning the meaning of action commands. In Q-learning, the action value $Q(s, a)$ which is the value of an action a in a state s is updated based on rewards r, and the best action in each state is found by trial and error.

In this work, we consider a state in which an instruction has been given as a state in Q-learning, and hence the number of states is equal to the number of different instructions. We furthermore consider the values of actions in the state
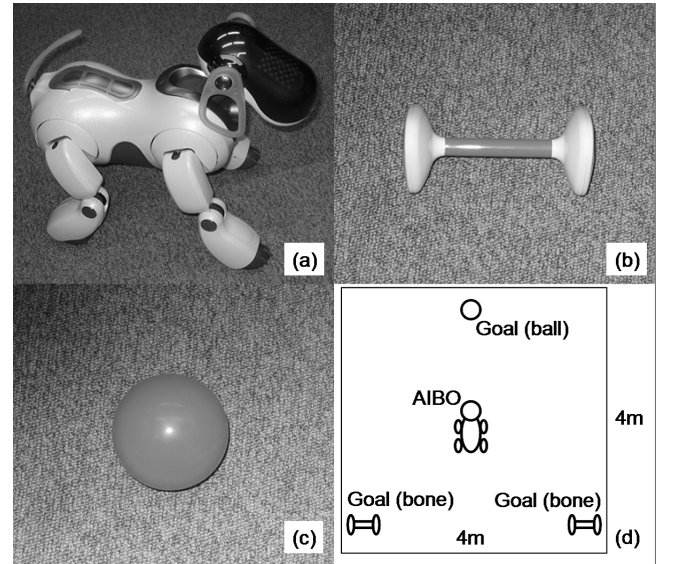

Figure 1: Experimental apparatuses
(a) AIBO ERS-7 (b) Goal (bone)
(c) Goal (ball) (d) The position and the distance
between AIBO and each goal

as the meaning of the instruction, that is, the meaning of an instruction is the amount of rewards expected when actions are taken receiving the instruction.

In this study, we take account of rewards only from humans, and suppose that they are given without delay, that is, for simplicity, we do not consider delayed rewards given when AIBO reaches a goal. In this case, the expression that update the action value Q becomes simple as below:

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha r \quad (1)$$

where α is the learning rate.

The central idea of this paper, which is based on the finding described in Section 2, is the following:

No News Criterion (hereafter NNC): If there has been a certain duration of no utterance since the robot began to move after received an action instruction, it is a sign that the ongoing action is appropriate, and a reward is hence given to the robot.

As a result, the robot receives not only explicit evaluations such as "Good!" or "No!" but implicit evaluations based on the NNC.

4. PERFORMANCE ASSESSMENT EXPERIMENT

This section describes an experiment into the properties of the learning algorithm utilizing NNC. Participants were told to guide AIBO ERS-7 (Figure 1 (a)) to the goals by means of voice, in a similar manner to the preliminary experiment. Two bones (Figure 1 (b)) and a ball (Figure 1 (c)) were used as goals. Figure 1 (d) shows the initial position of AIBO and the goals, and Figure 2 shows a snapshot taken during the experiment.
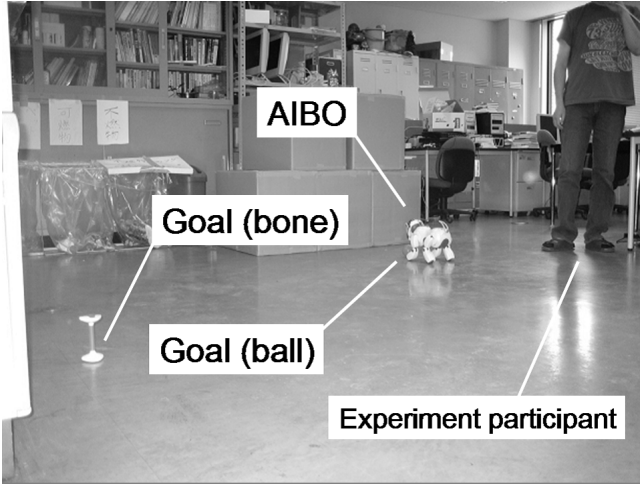
Figure 2: Experimental setup

4.1 Target algorithms of evaluation

We evaluated the learning performance of the following algorithms in this experiment:

Algorithm 1: We suppose that the robot understands the meaning of evaluative expressions such as "Good!" or "No!", and it thereby learns action commands by using explicit evaluations as rewards, but it does not use implicit rewards based on the NNC.

Algorithm 2: We suppose that the robot understands the meaning of evaluative expressions, and also utilizes the NNC. It thereby learns action commands by using both explicit and implicit evaluations.

Algorithm 3: We suppose that the robot does not understand the meaning of evaluative expressions, but utilizes the NNC. It thereby learns action commands by only using implicit evaluations.

4.2 Target words for learning and voice recognition

We aim to build a system that learns the meaning of action-instructions each of which correspond to one of the built-in actions of the robot, that is, <forward>, <backward>, <left-turn>, and <right-turn>.

Julius [2] is an open-source speech recognition engine, and we used it as a grammar-based recognition parser of small vocabulary. We thus pre-registered words that participants of the preliminary experiment used during the navigation.

In the preliminary experiment, we observed that multiple kinds of expressions were used to indicate a particular action. This fact slows down the learning speed of action commands because the number of times that the robot receives a particular expression decreases as the variation of the expression increases. We therefore decided to give participants an instruction table (See the upper half of Table 1) in order to restrict the variation of the expression as small as possible and facilitate the progress of learning. This leads to clear differentiation of the performance of target algorithms by a relatively short experiment.

Table 1: Instruction table
If you want to move the robot, use the following words:
"MAE. (Forward!)"
"USHIRO. (Backward!)"
"HIDARI. (Turn left!)"
"MIGI. (Turn right!)"
If you want to judge the action of the robot, use the following words:
"SOSO. (Good!)"
"CHIGAU. (No!)"

However, it is not always true that participants only use the words in the table even if the instruction table is presented. We hence registered not only listed words but unlisted words to Julius, the speech recognition engine (see Appendix A).

Although our algorithm has ability to learn the meaning of expressions unrelated to whether an expression is listed or not, the learning of the unlisted words did not sufficiently progress in the experiment, because the frequency of the unlisted words were not sufficient for learning. We therefore show and discuss only the learning result of listed words hereafter.

The lower half of Table 1 shows the listed words for evaluation use, which were commonly used words in the preliminary experiment. We also registered unlisted words to Julius here again.

4.3 The definition of states

As we already described in Section 3, we consider a state in which an instruction has been given as a state in Q-learning, and consider the values of actions in the state as the meaning of the instruction, that is, the meaning of an instruction is the amount of rewards expected when actions are taken receiving the instruction.

We use the following labels to refer to the states in which the four listed command words has been given:

s1: the state in which the action instruction "MAE. (Forward!)" has been recognized

s2: the state in which the action instruction "USHIRO. (Backward!)" has been recognized

s3: the state in which the action instruction "HIDARI. (Turn left!)" has been recognized

s4: the state in which the action instruction "MIGI. (Turn right!)" has been recognized

4.4 Experimental method

Six participants were asked to guide AIBO that has three different learning programs described in Section 4.1. The order of the algorithms used in the experiment were varied among participants. The experiment lasts one hour per participant in total (20 minutes per one algorithm).

We showed participants an instruction sheet and an instruction table that are shown in Section 4.2. Each of them was written on a A4 paper. The instruction sheet says:

Please show AIBO a way to the goal. AIBO does not understand well what you say at the beginning. However, as you praise and blame AIBO while you are guiding, it comes to understand you gradually. Use the listed words in the instruction table.

The explanation of four kinds of actions <forward>, <backward>, <left-turn>, and <right-turn> implemented on AIBO was also written in the explanation sheet. In this experiment, we defined <left-turn> and <right-turn> as movements of going forward after turning 45 degrees.

We set the learning rate α at 0.1, the explicit positive reward at +0.2, the explicit negative reward at −0.2, and the reward from NNC at +0.2. The Boltzmann selection was used for selecting actions, and the Boltzmann temperature was set to 0.06.

5. EXPERIMENTAL RESULT

Figure 3 (a)-(d) show the progress of action value learning in each state, that is, the progress of meaning acquisition of each command. The horizontal axis represents the number of action instructions that have been given by a participant. The vertical axis represents the probability that the correct action is selected. The points plotted on figures are averages of the result of the six participants.

6. DISCUSSION

6.1 Performance comparison between algorithms 1 and 2

We drew a comparison between the probabilities of correct action selection of algorithm 1 and algorithm 2 by the paired t-test. The results are shown in figure 3 (a)-(d), they show that the pairs of points that are circled with dotted line have significant tendencies at the 10% level, circled pairs with full line have a significant differences at the 5% level, and circled pairs with double line have a significant differences at the 1% level.

In the state S1 (i.e. meaning acquisition of "Forward!"), there were significant tendencies at the 10% level at the 3rd ($t(5) = 2.50$), 9th ($t(5) = 2.37$), 10th ($t(5) = 2.56$), and 12th instructions ($t(5) = 2.17$), significant differences at the 5% level at the 6th ($t(5) = 3.38$), 7th ($t(5) = 2.92$), 8th ($t(5) = 2.80$), and 11th instructions ($t(5) = 2.70$), and a significant difference at the 1% level at the 5th instruction ($t(5) = 6.14$).

In the state S2 (i.e. meaning acquisition of "Backward!"), there were significant tendencies at the 10% level at the 9th ($t(5) = 2.22$), and 10th instructions ($t(5) = 2.26$) and a significant difference at the 5% level at the 3rd instruction ($t(5) = 2.28$).

In learning the meaning of action commands of "Forward!" and "Backward", it was shown that the learning by both the explicit evaluation and the NNC (algorithm 2) is faster than the learning by only the explicit evaluation (algorithm 1). However, in learning the meaning of action commands of "Turn left!" and "Turn right!", there were no significant differences between the probabilities of correct action selection of algorithms 1 and 2.

We consider that the difference between the two groups of commands came from a difference in the property of actions.

AIBO's action pattern <left turn> and <right turn> were designed to go straight after turning 45 degrees, thereby there were many cases that the traveling direction after turning was different from the direction that a participant wanted, even if AIBO successfully turned according to the instruction. In these cases, participants often gave next instruction without waiting 5 seconds, which is the standard for applying the NNC. Consequently, there might be no significant difference between algorithms 1 and 2 in the learning results of <left turn> and <right turn>.

6.2 Performance of algorithm 3

In algorithm 3, AIBO learned only from NNC under the setting of not understanding the meaning of the explicit evaluations. Figure 3 (a)-(d) show that the learning were advanced to some extent though the probabilities of correct action selection tend to be lower than algorithms 1 and 2.

We drew a comparison between the probabilities of correct action selection of algorithm 3 and the initial state before learning, that is, the state in which the selection probability of each action is 25% because there are four candidate actions, by the paired t-test. The results of the t-test are shown in figure 3 (a)-(d) in which a pair of points framed with dotted line represents that there is significant tendency at the 10% level, a frame of full line represents a significant difference at the 5% level, and a frame of double line represents a significant difference at the 1% level.

In the state S1 (i.e. meaning acquisition of "Forward!"), there were significant tendencies at the 10% level at the 4th ($t(5) = 2.29$) and 5th instructions ($t(5) = 2.29$), significant differences at the 5% level at the 6th ($t(5) = 3.25$), 7th ($t(5) = 3.25$), 8th ($t(5) = 3.36$), 9th ($t(5) = 3.27$) and 10th instructions ($t(5) = 3.27$).

In the state S2 (i.e. meaning acquisition of "Backward!"), there was a significant tendency at the 10% level at the 4th instruction ($t(5) = 2.22$), significant differences at the 5% level at the 5th ($t(5) = 2.28$), 6th ($t(5) = 2.89$), and 7th instructions ($t(5) = 2.94$), significant differences at the 1% level at the 8th ($t(5) = 4.83$), 9th ($t(5) = 4.46$), 10th ($t(5) = 5.36$), and 11th instructions ($t(5) = 6.97$).

In the state S4 (i.e. meaning acquisition of "Turn right!"), there were significant tendencies at the 10% level in the 3rd ($t(5) = 2.24$), 7th ($t(5) = 2.23$), 8th ($t(5) = 2.23$), 9th ($t(5) = 2.23$), 10th ($t(5) = 2.23$) and 11th instructions ($t(5) = 2.45$).

In learning the meaning of action commands of "Forward!" and "Backward", it was shown that there were significant differences between algorithm 3 and the initial state at many points, that is, the action command learning can be advanced only using NNC. However, in learning the meaning of action commands of "Turn left!" and "Turn right!", there was no significant difference between algorithm 3 and the initial state, although there were significant tendencies. We consider that the difference between the two groups of commands came from the same cause as discussed in Section 6.1.

6.3 Standards for applying NNC

The experiment demonstrated that the NNC significantly accelerate the learning of "Forward!" and "Backward!", but there is no significant acceleration in the learning of "Turn left!" and "Turn right!". As already discussed, this difference between the two groups of commands depends on the standards for applying the NNC, the period of 5 seconds.

(a) Meaning acquisition of "Forward!" (Action value learning for S1)

(b) Meaning acquisition of "Backward!" (Action value learning for S2)

(c) Meaning acquisition of "Turn left!" (Action value learning for S3)

(d) Meaning acquisition of "Turn right!" (Action value learning for S4)

− ● − Algorithm 1 (without NNC, and evaluation instructions available)
── ◆ ── Algorithm 2 (with NNC, and evaluation instructions available)
· · ▲ · · Algorithm 3 (with NNC, and evaluation instructions not available)
− ■ − Initial state

Comparison between algorithm 1 and 2
a significant tendency at the 10% level
a significant difference at the 5% level
a significant difference at the 1% level

Comparison between initial state and algorithm 3
a significant tendency at the 10% level
a significant difference at the 5% level
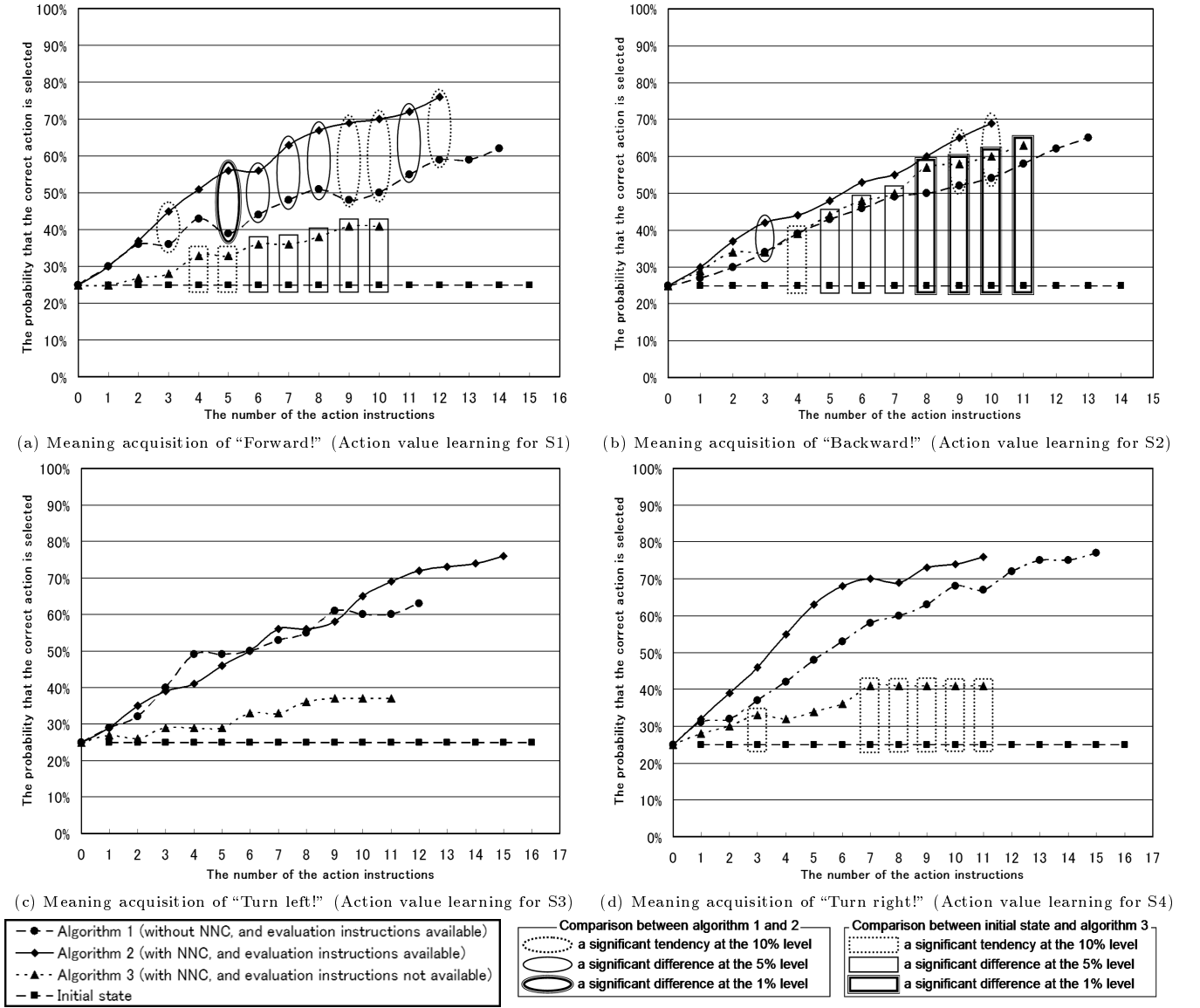a significant difference at the 1% level

Figure 3: The learning curves of the command meaning acquisition

Figure 4 shows the relation between the standards for applying the NNC, and the precision and the recall of NNC. The precision is the proportion of actually correct actions, out of all the actions that fit the NNC, and the recall is the proportion of actions that satisfy the NNC, out of all correct actions produced.

We first examine the recall plot at the time of 5 seconds, which was the interval adopted in the experiment. There is a remarkable difference between the plotted points of "Forward!" and "Backward!", and those of "Turn left!" and "Turn right!". The difference affects the frequency of the NNC application and changes the effectiveness of the NNC.

Similarly, there is a considerable difference also in precision at the time of 5 seconds, however, we consider the influence of the difference in the precision to be much smaller than that in the recall. The reason is that the recall is the proportion of correct actions that satisfy the NNC and are given rewards, it has a direct influence to the action value Q of correct actions. On the other hand, the precision does not have a direct influence to the action value Q of correct actions, but has dispersed influence to the other three incorrect actions. Consequently, the influence of the recall is three times larger than that of the precision in average.

The precision and the recall are in the trade-off relation, and the interval of 5 seconds, which was the standard adopted in the experiment, seems to be a balanced point at first glance. However, as already discussed, considering that the influence of the precision on the learning is only about one-third of that of the recall, it is estimated that setting the standard interval of the NNC to 4 seconds is more desirable for efficient learning, because the influence of the precision is less than that of the recall.

6.4 Additional Experiment

As already discussed, we believe that the reason why the effect of NNC was unsatisfactory in the meaning acquisition of "Turn left!" and "Turn right!" were as follows:

- AIBO's action pattern of <left-turn> and <right-turn>
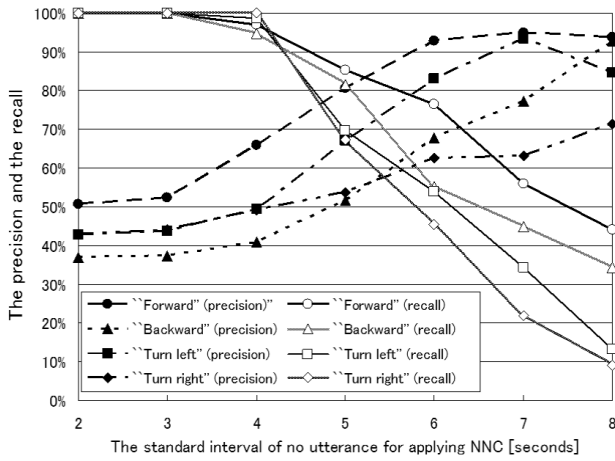
Figure 4: The relation between standards for applying NNC, and the precision and the recall of NNC

differed from that of <forward> and <backward>, and were designed to go straight after turning 45 degrees, thereby there were many cases in which the traveling direction after turning was different from the direction that a participant wanted, and the next utterance was given before the NNC was applied, even if AIBO successfully turned according to the instruction.

- The chance of applying NNC decreased because the interval of standards for applying NNC were too long.

We thus decided to change the setting of the experiment as follows, and are conducting an additional experiment:

1. AIBO's action pattern of <left-turn> and <right-turn>: AIBO does not go straight after turn, but keep on turning.

2. the standard interval of the NNC: the NNC is applied after 4, and not 5, seconds of silence.

In this section, we report the interim result of the additional experiment. The experimental method is similar to the one described in Section 4.4, and we have done the experiment with five participants by now. Figures 5 (a)-(d) show the result of the experiment.

The graph demonstrates that the NNC significantly accelerates the learning of all the four commands including "Turn left!" and "Turn right!", which was brought by the two changes of the experimental setting described above.

On the other hand, there was no significant difference between the performance of algorithm 3 and that of the initial state in the learning of "Turn left!" and "Turn right!". One reason of it may be that the number of participants was not enough; however, more important cause should be that the influence of rewards given to incorrect actions was beyond our expectation. As described in Section 6.3, when the NNC is accidentally applied to wrong actions, the rewards are split into three kinds of actions, and it is expected that there is no bias to a specific wrong action under normal conditions; however, when the explicit evaluations are not available as in algorithm 3, if a reward was given to a wrong action in the initial stage of learning, the selection probability of the

action increases and it is possible that the successive rewards are concentratedly given to the action.

The following is a list of current topics of research:

1. The method of automatically setting the standard interval for applying NNC: A duration period of silence differs among different people and among different actions of the robot. Some people can quickly identify actions of the robot at the initial short period, while others carefully identify actions after considerable period of observation; some actions are easy to identify, and others are not. For example, <forward>, <left-turn>, and <right-turn> have similar initial movement, and it is difficult to identify each other from the initial movement, while <backward> is easy to identify because it has a distinctive initial movement. It consequently is desirable to automatically set appropriate NNC intervals according to human partners and according to actions of the robot.

2. The method for deciding the amount of reward given by the NNC: It is not reasonable to give the same amount of reward when the NNC is satisfied in compare with the reward from explicit evaluation commands, which might be one reason for insufficient performance of Algorithm 3 in the additional experiment. If the amount of reward can be decided in accordance with the certainty of the judgment of giving the reward, the biased accumulation of rewards to an accidentally rewarded action will be reduced. In order to realize this, we must study the way to compute the certainty of the judgment, and the way to transform the certainty into the amount of reward.

7. CONCLUDING REMARKS

We believe that robots should use implicit information that is unconsciously given by humans in order to learn from interaction with humans, and hence proposed the No News Criterion (NNC) for improving the efficiency of command learning. Based on the NNC, the lack of utterance, that is, no news, can be interpreted as a good news, and the implicit evaluation accelerate learning.

We conducted an experiment on human-robot interaction in a navigation context, and demonstrated that the NNC significantly improved the performance of command learning in many cases. We also analyzed the relation between the standard interval of no utterance for applying the NNC, and the performance of the leaning. The standard should be set adequately to get a full effect of the NNC.

Our future plan includes:

- We will study the method of automatically setting the standard interval of the NNC, and the method of deciding the amount of rewards given by NNC.

- We will develop the method of articulating continuous speech signal into the phrase candidates, and attach meaning to the candidates using the learning algorithm proposed in this paper, with which we will dispense with pre-registered words of a speech recognition system.

- We also plan to make an algorithm that can learn the meaning of other kinds of words than action commands.

(a) Meaning acquisition of "Forward!" (Action value learning for S1)

(b) Meaning acquisition of "Backward!" (Action value learning for S2)

(c) Meaning acquisition of "Turn left!" (Action value learning for S3)

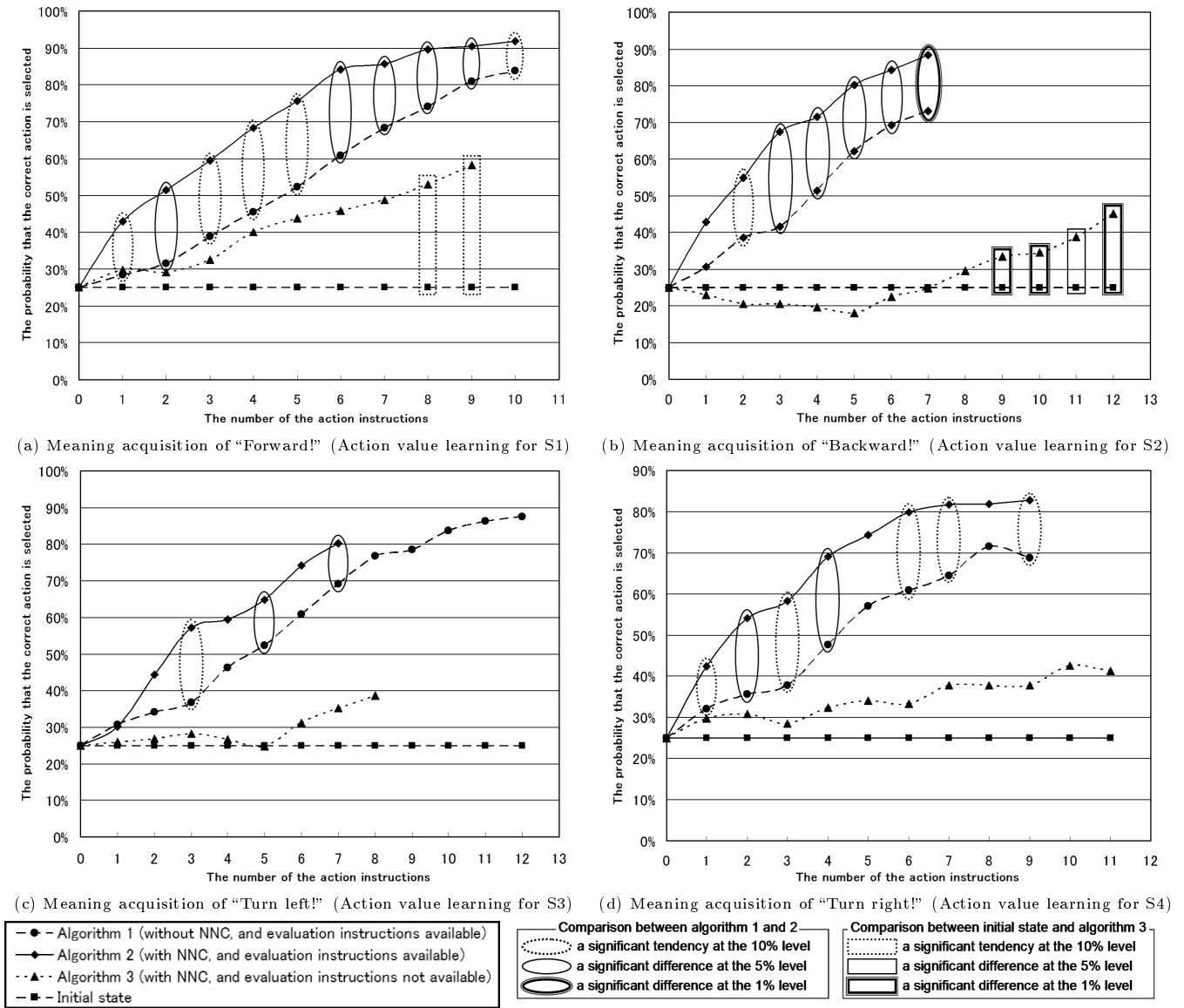(d) Meaning acquisition of "Turn right!" (Action value learning for S4)

Figure 5: The interim results of the additional experiment: the learning curves of the command meaning acquisition. The standard interval of the NNC and the action pattern of <left-turn> and <right-turn> differ from those of the previous experiment.

8. ACKNOWLEDGMENTS

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APPENDIX

A. THE REGISTERED WORDS ON JULIUS

Table 2: The registered action instructions

Meaning of instructions	Registered words
"Forward!"	"MAE"
	"SUSUME"
	"MASSUGU"
	"ZENSHIN"
	"SUSUNDE"
	"MAE NI SUSUNDE"
"Backward!"	"USHIRO"
	"MODORE"
	"SAGATTE"
	"USHIRO E SAGATTE"
"Turn left!"	"HIDARI"
	"HIDARI MUITE"
	"HIDARI DAYO"
	"MŌCHOTTO HIDARI"
	"HIDARI MUKE"
"Turn right!"	"MIGI"
	"MIGI DAYO"
	"MŌCHOTTO MIGI"
	"MIGI MUITE"
	"MIGI MAWATTE"
	"CHOTTO MIGI"
	"MIGI MAWARE"
	"MAWARE MIGI"

Table 3: The registered evaluation instructions

Meaning of instructions	Registered words
"Good!"	"SŌ SŌ"
	"SONOMAMA"
	"YŌSHI"
	"YOSHI YOSHI"
	"OK"
	"SUGOI"
	"DOTCHI DEMO EEWA"
	"YATTĀ"
	"ITTA"
	"IIZO"
"No!"	"DAME"
	"AKAN"
	"YOKU NAI"
	"CHIGAU"
	"KORA"
	"DAME DAME"
	"SHIPPAI"
	"MIGI IKAHEN"
	"MISU"
	"ARE"
	"YŪKOTO KIKAHEN"
	"MIGI CHIGAUDE"
	"IYA IYA"
	"HAZUSHITA"

Table 4: The registered noises

Registered noises
"ETTO"
"Ū"
"FŪN"
"HAHAHA"
"OMOSHIROI"
"Ā"