Error-related potential during cooperative exploration by humans and robots in a large-scale maze and the effect of boredom on it

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***Abstract*— In future, humans live with autonomous robot, and cooperate with it. In this study an autonomous robot and a human were asked to cooperate in an exploration task to reach a goal in a large-scale maze. While they were doing a task, electroencephalogram (EEG) was measured from the human. The human was asked to choose the direction of travel at intersections, and 30% of the choose, the robot traveled in a different direction from that specified by the human. Error-related potentials (ErrPs) occurred in the human brain at the time, and that was consistent with that reported in the previous studies. Time-frequency analysis of EEG revealed an increase in θ-frequency power and a decrease in β-frequency power. Some participants felt "bored" during the task. As if to reflect this, in the second half of the task, the amplitude of ErrPs decreased and θ-frequency power also decreased. When the ErrPs of the first and second halves were discriminated using a convolutional neural network, the accuracy rate of the correct responses decreased in the second half compared to the first half. These results suggest that ErrP changes with boredom, and there is a possibility to detect the boredom using EEG.**

Keywords— Human-robot cooperative behavior, error-related potentials, time-frequency domain, boredom

I. INTRODUCTION

The number of elderly people is expected to continue to increase in the future of Japan. The quality of life (QOL) of bedridden elderly people is greatly reduced due to their monotonous daily life. To improve their QOL's, we have proposed an exploration system outside of the room cooperatively with an autonomous robot controlled remotely [1]. The system uses brain-machine interface (BMI) technology to operate the robot for the disabled person. However, the robot may operate against the human's will due to errors or noise induced in the system. Human's brain induces one of the electroencephalogram Error-related potentials (ErrPs) when they have an error by themselves or when some agents and robots commit the errors. ErrPs can be originated from the anterior cingulate cortex (ACC) based on signal source estimation [3]. If the system malfunctions can be detected using ErrP induced in humans, it is expected that the system performance can be improved through the reinforce learning [4, 5]. Based on this idea, in a previous study [1], we conducted a search task in a simulated small maze (12m x 16m) with seven three-way intersections, using a teleoperable autonomous robot. During the task, when the robot approached an intersection in the maze, the user instructed the robot which direction to go, but the robot sometimes did not follow the instructions. When the robot did not follow the instructions, ErrP was observed from the participants. However, the maze in the previous study was so small and had only intersections with three paths. If the system is to be put into practical use, it needs to be tested in a more complex and larger maze. There is also a possibility that participants may become bored with the task of the larger maze, because they had to instruct the robot how to go many times. It has not yet been clarified how ErrP changes during such a boring situation. In this study, we aimed to clarify whether ErrP occurs during human-robot cooperative maze search task in a large-scale maze, if so, what kind of EEG features are measured, and how ErrP changes when the participants feel boredom. We also examined Convolutional Neural Networks (CNN) for detecting ErrPs.

II. METHOD

This study was approved by the Committee on Experiments on Human Subjects of the Kyushu Institute of Technology (Approval No. 23-06). Four male graduate students (age: 22.8 ± 0.83 (mean ± SD) years) participated in the experiment. Consent was obtained from all participants to participate in the experiment.

In the experiment, the participants and the robot cooperated to explore a maze created in the Gazebo simulator from the start to the goal. The maze was presented in a PC monitor (Horizontal visual angle: 54.9 deg, and vertical visual angle: 32.9 deg) in front of a participant. The maze was approximately 25 m × 25 m with 32 to 33 intersections including 24 to 25 three-way and 8 four-way intersections, and was explored the maze for approximately 30 minutes. In the straight path, the robot ran autonomously, but at the intersections, it stopped and asked the participants for the moving direction. The participants instructed the direction using gaming pad. The robot usually followed the instruction, however, the robot was programmed to go in a different direction from that of the participant's instruction a the rate of 30%. This simulates the robot's erroneous behavior. In addition, two types of search maze tasks were prepared. One was with a mini-map and the other as without a mini-map. In the case of the maze with mini-map, the current position and the goal position were known to the participants.

After the task, the participants had to answer the Multidimensional State Boredom Scale (MSBS) [6]. The

Scale was used to determine whether participants became bored during the task.

EEG was measured from the participants during the maze search task. EEG was based on the extended 10-20 method and was measured with silver plate electrodes attached to scalp positions Fz, F3, F4, FCz, Cz, C3, and Pz. EEG signals were low-pass filtered at 10 Hz for time-domain analysis and 30 Hz for frequency-domain analysis, with blink components removed by EEGLAB [7]. The EEG epochs from -500 to 1000 milliseconds (the start of robot motion was set at 0 millisecond) were then extracted as the EEG epochs. The EEG epochs in which the robot moved in the same direction as instructed by the participant were defined as Correct epochs, and those in which the robot moved in a different direction contrary to the instruction were defined as Error epochs. In the feature extraction analysis, we performed an additive average for each epoch in the time domain and the time-frequency domain to examine the EEG features specific to the Error epoch. Wavelet analysis was used for the time-frequency domain analysis, in which the Morlet wavelet function was used.

For the detection of error epochs in a single trial using CNN, a CNN was trained with time-domain and time/frequency-domain features of an epoch in single trials as input signals for Error and Correct epochs. The input signals were 7*100 (electrode x time) dimensions in the time domain and 30*100 (frequency x time) dimensions with one electrode in the time-frequency domain. Since both were compared, they were adjusted to be of equivalent dimensions. The layer structure of CNN was kept the same in the analyses of time and time/frequency domains. Fig. 1 shows the structure of the CNN for time-domain signals. The Relu function was used for the activation function of the units in the convolutional layer, and the Sigmoid function was used for the output units of the all-connected layer. Adam was used to optimize the network, and the network was trained 100 iteration times. The accuracy rate was obtained by leave-one- out cross-validation method.

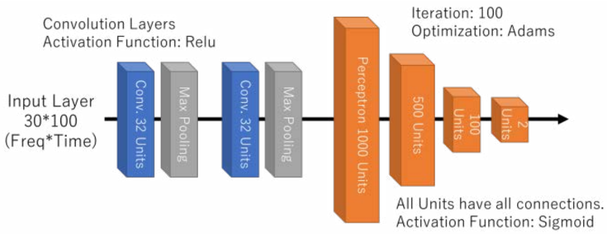

Fig. 1. The structure of time/frequency domain CNN.

III. RESULTS AND DISCUSSIONS

A. ErrP in cooperative exploration by humans and robots in large-scale maze

A positive potential at 200 ms, a negative potential at 500 ms, and a positive potential at 600 ms were time domain features with significant differences between Error/Correct epochs (Fig. 2). Since these potentials occurred at latencies close to ErrP of previous studies [2], they could be considered ErrP. There are several kinds of ErrP. The measured ErrP can correspond to the interaction ErrP, because it can be recorded in the task where the cursor moved in the different direction which the participants pointed out [8]. The latencies were longer than in the small-scale maze exploration [1] and the cursor movement task [2]. This may be due to the increased complexity of the Error information processing in the large-scale maze task intersection in this study, as the number of options for correcting the direction of movement increased compared to that in the previous study. The obtained results were consistent with the result that latency was longer for more complex tasks [9].

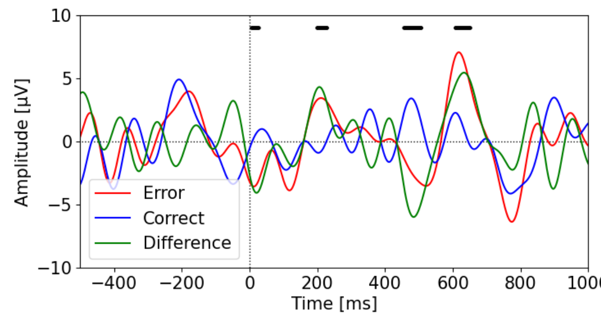

Fig. 2. Examples of time-domain ErrP features at front-central FCz. The red and blue lines are the EEGs for the Error and Correct epochs, respectively. The green line is the difference between them. The upper black bars indicate that the time when there are the significant differences between the Error and Correct epochs ($p < 0.05$). The time zero indicates the onset of the robot moving.

Next, we examined the time-frequency features of ErrP. In the front-central region, there was an increase in θ power from 200 to 1000 ms (Fig. 3A, black rectangle) and a decrease in β power from 600 to 900 msec (white rectangle). The time-frequency features of ErrP caused by the robot malfunction were in the θ frequency range. On the other hand, θ frequency powers increased from 400 to 1000 msec and β frequency powers also increased around 800 msec in the Correct epoch (Fig. 3B). θ frequency powers significantly increase from 200 to 400 msec, and β frequency powers decreased significantly decreased in Error trials (Fig. 3C and D).

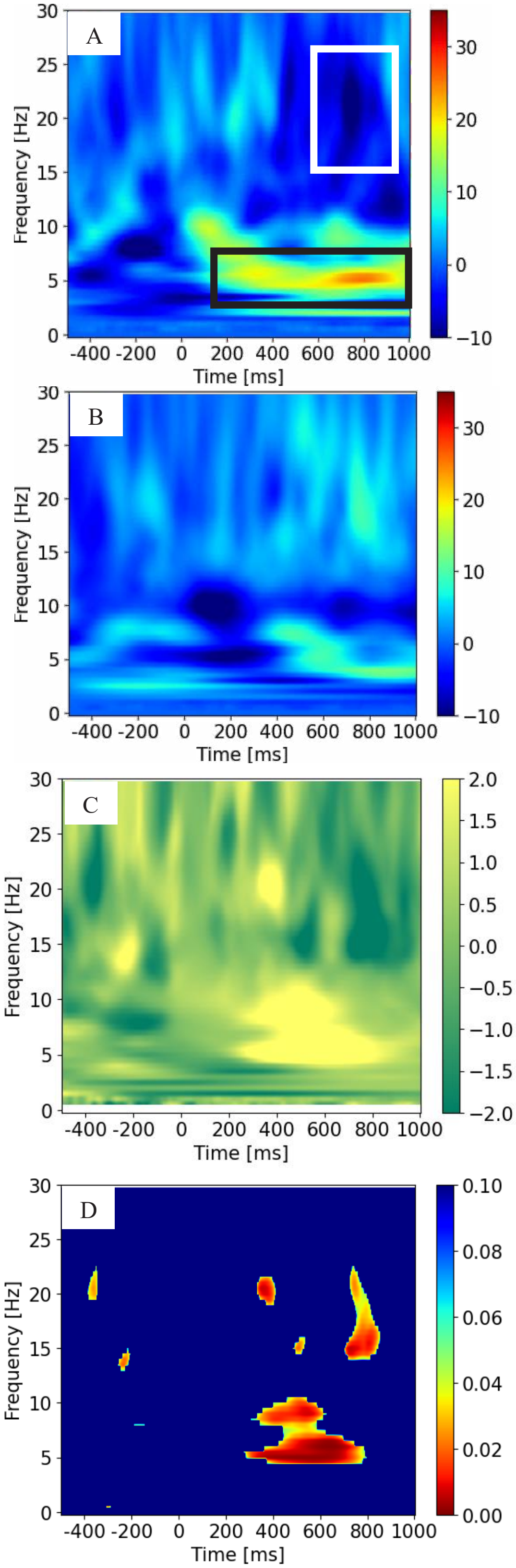

Fig. 3. An example of time-frequency features of ErrP. From the top, A: the spectrogram of potential in an Error epoch, B: the spectrogram of potential in a Correct epoch, C: t-values of the averaged potentials of all participants in the time-frequency domain, and D: p-values, the probability of significance, comparing of EEGs between in Error and Correct epochs are shown. T-values in yellow indicate increased activity in Error trials, and in green, decreased activity in Error trials. The p-value is below 0.05. The closer the p-value is to 0, the warmer the color is.

B. The detection of Error Epochs and Boring.

The detection of the Error epoch by CNN had an average accuracy rate of 82% for time-domain features and 86% for frequency-domain features (Fig. 4). This is higher than those in the smaller-scale maze exploration [1], and the robot malfunction detection was possible even in long-time exploration of larger-scale mazes. The accuracy rate is comparable with the other reports of the interactive ErrP [10]. Error epoch detection using time-frequency-domain features had a higher accurate response than time-domain features. This may be because the appearance of powers in the θ and β bands around 800 msec of the Error epoch showed less variation than the time-domain features. In the larger maze, the number of epochs were also larger. Therefore, the number of the training data was larger, and the accuracy rate can be higher.

Based on the results of this study, we believe that it is possible to learn the user's preferred route using ErrP in a remote robot exploration system. In the unexplored area, the robot can construct a map using Simultaneous Localization and Mapping under the instruction of the human, and because a system follows the same path in the map, it can learn the user's preferred path by reinforcement learning based on ErrP. As a result, the burden on the user can be reduced by sharing control between the robot and the human.

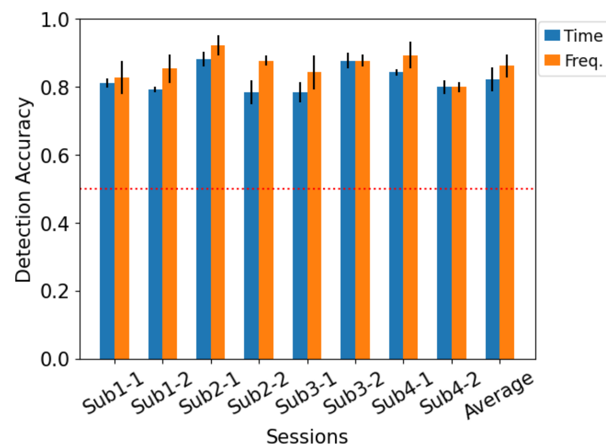

Fig. 4. Percentages of the detection of Error epochs by CNN using time-domain features (blue bars) and time-frequency domain features (red bars). Horizontal red dotted lines indicate the chance levels. “SubX-1” indicates the percentage of the accuracy rates for the error epochs for tasks with mini-map, and “SubX-2” does the percentage for tasks without map (X=1, 2, 3, 4).

The participants do the cooperation with the robot for a long time, there is a possibility that they are bored. Actually in the exploration task of the larger maze in the present study, all participants except Sub3 felt boredom with the mini-mapped task, but none with the unmapped task. Sub3 did not become bored in both mini-mapped and unmapped tasks. Boredom would be induced in the latter half of the task. ErrP was compared between the first half and the second half of the task in which boredom occurred. The results showed that negative potential of ErrP around 500 msec was smaller in the second half of the task than that in the first half (Fig. 5). In the time-frequency domain, θ frequency power from 500 to 1000 msec decreased (Fig. 6).

Those time-domain and time-frequency domain features were input to the CNN and subjected to discriminative learning in four classes: ErrPs before and after the boredom, and Correct EEG before and after the boredom. The results showed that the percentage of accuracy rate was higher when time-frequency features were used than when time-domain features were used. Using the time-domain features, there was no difference in the accuracy rates between with and without mini-maps (averaged accuracy rates with and without mini-maps were 27% and 26%, respectively), but the accuracy rates using the time-frequency features was higher with mini-map task than that without mini-maps (averaged accuracy rates with and without mini-maps were 35% and 27%, respectively). Thus, the time-frequency feature of ErrP may be better at detecting the participant boredom. Actually measuring EEGs, you can detect the boredom in the exploration task of the large maze with the robot.

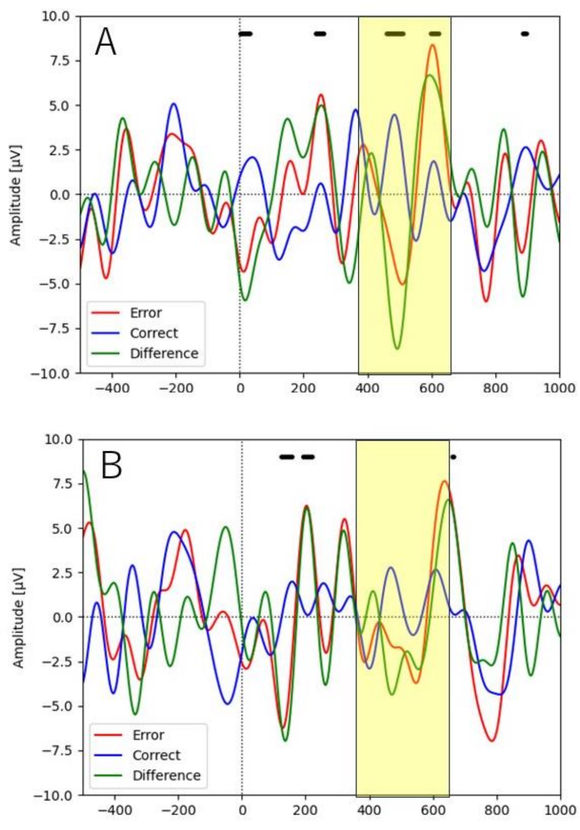

Fig. 5. ErrP in the first half (A) and the second half (B) of the mapped task, with smaller ErrP around 400 msec (yellow shaded rectangle areas).

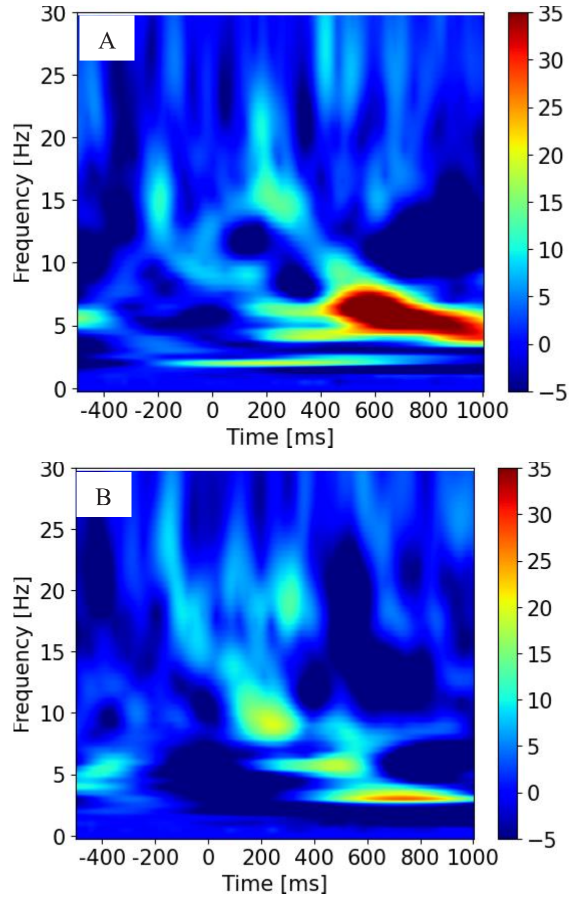

Fig. 6. Spectrogram of ErrPs before (A) and after (B) the induced boredom in the mapped task. Signal measured at FCz. Theta frequency powers between 500 and 1000 msec were smaller after the induction of boredom.

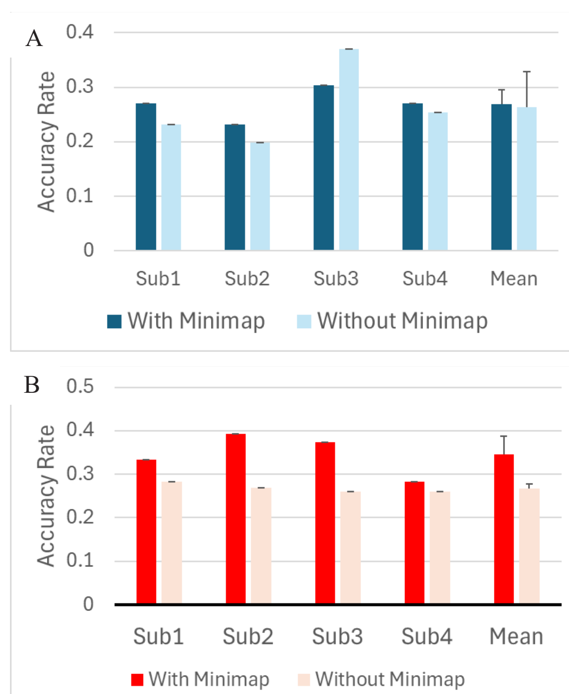

Fig. 7. Results of detecting boredom using ErrP. Fig. A shows the accuracy rate using the time domain as the input

feature and the bottom Fig. B shows the time-frequency feature. Dark and light colored bars are the results of the with-map and without-map tasks, respectively.

IV. CONCLUSIONS

During the human-robot cooperative exploration for a large-scale maze, it was found that the EEG produced by the robot's malfunction had ErrP features of positive potentials at 400 msec, negative potentials at 500 msec, and positive potentials at 700 msec. Theta frequency band power from 400 to 800 msec and beta frequency band power around 800 msec were decreased. Compared to ErrP reported in the small-scale maze in the previous study, ErrP found in the large-scale maze in this study revealed long latency.

In the detection of the robot errors using CNN, we achieved an accuracy rate of more than 80%, and the rate was better for time-frequency-domain features than for time-domain features. The θ power increased and β power decreased in the time-frequency domain were considered stable features for the higher accuracy rate. The rate was also higher than that reported in the smaller maze in the previous study. That is because the number of the training data will be larger in the large-maze task.

The participant also felt bored during the exploration task with a mini-map, and when bored, the component of ErrP at a latency of about 500 msec became smaller, and the θ power between 500 and 1000 msec decreased. Using this EEG feature, the accuracy rate for the induced boredom was higher for the time-frequency feature than for the time-domain feature. Therefore, the time-frequency features of ErrP may be useful for detecting robot errors and task performers' boredom.

V. FUTUIRE WORK

In this experiment, we conducted a exploration task using a robot in the simulation space. In the future, we would like to verify whether similar ErrP features can be measured from the participants when using actual robots and in the actual environment. In this study, we also conducted a boredom questionnaire by asking participants to recall after the offset of all exploration sessions. In this case, the time of occurrence of boredom can only be roughly captured. Therefore, we would like to investigate the effect of boredom on ErrP in more detail by using a method in which participants report sequentially when they feel bored.

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