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Improvement of human error prediction accuracy in single-trial analysis of electroencephalogram

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Abstract— **The prevention of human error is an important task that has already been researched. Previous studies have shown that EEG signals can predict the occurrence of human errors. However, high accuracy has not yet been achieved in a single-trial analysis. This study is aimed to improve the accuracy of single-trial analysis, and propose a method for anomaly detection with auto encoder(AE). In the experiment, we conducted "Press the button(Go)" or "Do nothing(No-Go)" according to the visual stimulus and analyzed the EEG signal from -1000 ms to 0 ms when the stimulus was displayed. We prepared two types of inputs, time series data and frequency spectrum, and an AE was trained to reconstruct the inputs. We then calculated the difference between the reconstructed data and input data and predicted human error by its largeness. In the prediction using Support Vector Machine (SVM) based on the frequency spectrum, some over-fitting occurred and the average accuracy was 43 %. In the prediction using anomaly detection with frequency spectrum was 53 % and could not be classified. The time series data was 63 % which improved the accuracy. A previous study has shown frequency-dependent features such as -band activity and rhythm, as precursors of human error. However, in single-trial analysis, we obtained a higher accuracy by time series data than when by using the frequency spectrum. However, there was no noticeable difference between SVM and anomaly detection methods other than over-fitting. Therefore, in this case, the improvement in accuracy by the anomaly detection method could not be confirmed. However, the result suggests that it is more effective to use the frequency spectrum than the time series data in the single-trial analysis in the future.**

I. INTRODUCTION

Human error is possibly connected to fatal accidents; thus, preventing human error is a very important task. Research aimed at predicting the occurring of human error has been conducted. Brain activity becomes active in a specific frequency band before human error occurs [1], [2]. However, to realize a realistic prediction, it is necessary to make a prediction based on single-trial data. Contrastingly, the accuracy of such predictions is not high [3]. Machine learning methods are effective in detecting abnormal EEG signals in the analysis of highly nonlinear EEG [4], [5]. The drawback of machine learning is that the accuracy depends on the amount of data to be prepared. Therefore, in this study, we proposed the prediction of human error by anomaly detection. The biggest advantage of anomaly detection is that it does not require test data. In general, human error is rare, and normal data are obtained in most cases. Therefore, it is possible to prepare a sufficient amount of data using anomaly detection. In this study, we interpreted brain activity that occurs immediately before human error as an abnormal EEG signal and examined the prediction of human error by anomaly detection. Specifically, the input was reconstructed using an AE, and normal (without human error) brain waves and abnormal (with human error) brain waves were discriminated from the reconstruction error. We used the EEG signal of the Go/No-Go task that was used previously [3].

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II. EXPERIMENT

This section describes the details of the data acquisition experiment conducted in [3].

A. Participants

Seven right-handed men aged 20-23 years participated in the study. The content of the experiment was explained to them in advance, and the experiment was conducted after they filled out a consent form. The experiment was approved by the Ethics Committee of Nagaoka University of Technology.

B. Equipment

We measured EEG signals using a digital electroencephalograph (ActiveTwo, Biosemi, Amsterdam, the Netherlands) with 64 electrodes attached to the subjects scalps and using "fieldtrip"[6] that's MATLAB toolbox. The data were digitized at 2048 Hz. The electrodes were placed in accordance with the international 10-20 system, and a reference electrode was attached to each earlobe. Artifacts were monitored using a pair of bipolar electrodes located below the eyes.

C. Experiment content

Participants were instructed to perform "Go"(press a button) or "No-Go"(do nothing) in response to a visual stimulus. Participants were presented the cross in the center on the display and were instructed to focus on the cross to reduce eye movement. The visual stimulus with numbers "1-9" was given on the bottom-left of the screen. Since each number appears with the same probability, the ratio of Go / No-Go tasks was 8 vs 1. When the stimulus "5" was presented, the participant was instructed to enact the "No-Go" task, and the other stimulus was given for the participant to enact the "Go" task. The trial wherein the participant pushed the button in the "Go" task was defined as "hit", the trial wherein the participant did nothing in the "No-Go" task was defined as "correct", the trial wherein the participant pushed the button in the “No-Go” task was defined as “false”. The experiment of the protocol for a session and an example of a visual stimulus are shown in Figure 1. Each session include 151 trials, with each trial construct by 200 ms “task displayed” and 1500 ms “interval”. The participants conducted 12 sessions while resting between each session. The resulting data are shown in TABLE I.

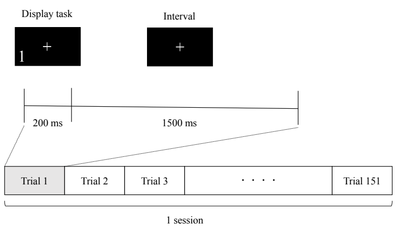

Fig. 1. Experiment protocol and example of visual stimulus.

TABLE I
NUMBER OF DATA FOR EACH CLASS FOR EACH PARTICIPANT

Sub No.	Correct	False
1	60	152
2	67	137
3	100	113
4	61	151
5	157	55
6	147	65
7	62	150

III. PRE-PROCESSING

This section describes the pre-processing. Conducted pre-processing is shown in Figure 2.

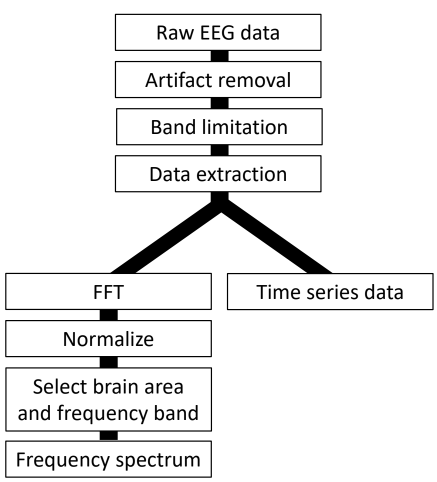

Fig. 2. Flow chart for pre-processing of each input.

A. Artifact removal

The data acquired from the experiment included artifacts caused by eye movement and blinking. Artifacts were removed using Electro-OculoGram(EOG) obtained from both eyes of the participant. Compared to brain activity, the change in potential caused by eye movements is very large. Therefore, trials containing signals with an absolute amplitude of EOG exceeding 70 μV were excluded from the analysis, and if the excluded trials exceeded 30 % of the total, they were also excluded.

B. Band-pass filtering

Convoluted LPF with a cutoff frequency of 30 Hz and HPF with a cutoff frequency of 1 Hz were used to reject high wave noise and trends.

C. Data extraction , Fast Fourier Translation and normalization

We set the timing of the visual stimulus to 0 ms, and extracted the EEG signal from -1000 ms to 0 ms. This was the time series data used as the input. The calculated frequency spectrum by FFT and normalized max value become 1 between 0 and 30 Hz in each channel [3].

D. Selection of brain area and frequency

We used three frequency bands: α band (8-12 Hz), β band (18-24 Hz) and θ band (3-5 Hz).

We also used the three brain areas that confirmed brain activation before causing human error [2], [7]: prefrontal, occipital, and motor areas, as shown in Figure 3 We also used a one-dimensional vector by combining these areas and frequencies (TABLE II) and using them as input.

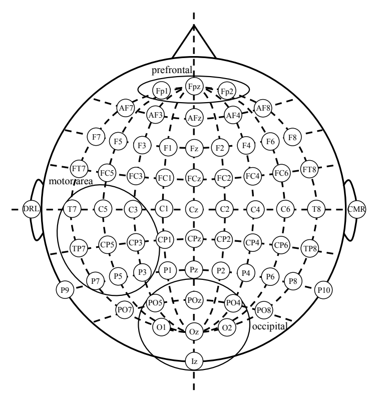

Fig. 3. EEG electrodes.

TABLE II
COMBINATIONS OF BRAIN AREA AND FREQUENCY BAND.

Feature No.	Detail
1	α(8-12 Hz) * occipital(7 Ch.)
2	β(18-24 Hz) * motor area(9 Ch.) θ(3-5[Hz]) * prefrontal(3[Ch.])
3	α(8-12 Hz) * occipital(7 Ch.) β(18-24 Hz) * motor area(9 Ch.) θ(3-5 Hz) * prefrontal(3 Ch.)
4	α * all of brain area(64 Ch.)
5	β+θ * all of brain area(64 Ch.)
6	α+β+θ * all of brain area(64 Ch.)

IV. PREDICTION

Prediction is performed by two types of methods SVM and anomaly detection which was the proposed method.

A. Anomaly detection

For anomaly detection, an AE based on time series data and an AE based on the frequency spectrum were used. The configuration for the time series AE is shown in Figure 4, based on Shallow ConvNet [8] .

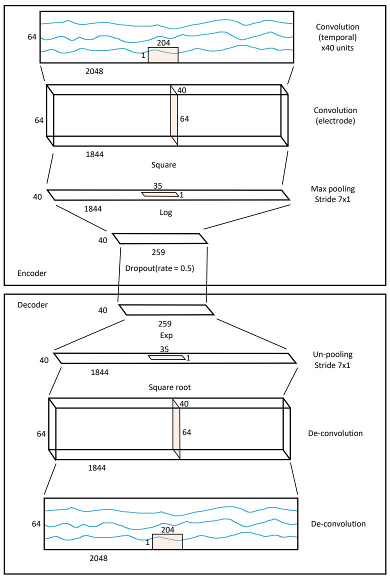

Fig. 4. Time series AE.

The parameters trained using an AE are listed in TABLE III. If there are multiple items or items indicated by a range, the value is searched by “optuna”, which is a Python library.

TABLE III
NETWORK PARAMETERS FOR TIME SERIES

Item	Detail
Epochs	500
Activation function	ReLU
Loss function	MSE
Batch size	16
Optimizer	Adam, MomentumSGD, rmsprop
Weight decay	1e-10˜1e-3
Adam learning rate	1e-5˜1e-1
SGD learning rate	1e-5˜1e-1
SGD momentum	0.9

The configuration of the frequency spectrum AE is shown in Figure 5

“m” in Figure 5 represent the number of input dimensions. The parameters trained with an AE are shown in TABLEIV.

If the correct input data to the trained AE output are correctly reconstructed, the loss will decrease. In contrast, the anomaly data for the input output would not be reconstructed well and thus,the loss will become larger. Using this loss difference, we predicted human error. The error threshold will determined by the validation data. Input validation data to the trained AE and decide the error threshold to maximize the evaluation.

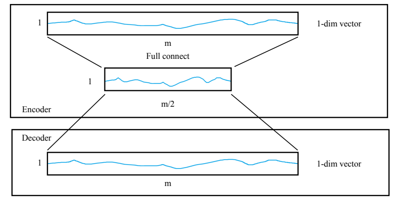

Fig. 5. Frequency spectrum AE.

TABLE IV
NETWORK PARAMETERS FOR FREQUENCY SPECTRUM

Item	Detail
Epochs	3000
Activation function	ReLU
Loss function	MSE
Batch size	16
Optimizer	MomentumSGD
Hidden layer	1
Learning rate	0.1
Momentum	0.9
Weight decay	0.0005

B. SVM

Prediction by SVM performed based on [3].

C. Accuracy

The geometric mean was used for the evaluation of the method, and was expressed using the following formula.

$$Geometric\ mean = (\prod_{i=1}^{n} a_i)^{\frac{1}{n}} = \sqrt[n]{a_1 a_2 \cdots a_n}$$

The advantage of this method is that it provides a lower evaluation for over-fitting. As mentioned earlier, human error is rare, thus the data tend to be biased. We then used geometric mean to suppress the over-fitting to the class with a large amount of data. The actual evaluation used 5-fold cross-validation. When pre-processing was completed, the data were divided into five for each class. In SVM, cross-validation was conducted, one of the divided data was used as test data and the others were used as training data. For anomaly detection by the AE, we prepared five random initialized networks, one of the divided data was used as validation data, another one of the divided data was used as test data, and the others use as training data. Furthermore, in AE, one of the divisions of abnormal data is valid data, and the rest are test data, so there is no abnormal data for training.

V. RESULT

Feature Nos. 1-6 are listed in TABLEII and are the frequency spectrum. Feature No. 7 is the time series data. SVM is only a frequency spectrum prediction, and the AE contains both frequency spectrum and time series data. The geometric mean of each method is shown in TABLEV,VI, and VII, and Figure 6 shows a box plot for each evaluation.

Over-fitting occurs in ”Feature No. 1” prediction by SVM. In addition, the average of the SVM and AE of the frequency

TABLE V
GEOMETRIC MEAN FOR SVM

Sub No.	Feature No.					
	1	2	3	4	5	6
1	0.00	0.40	0.47	0.58	0.51	0.51
2	0.00	0.25	0.49	0.46	0.35	0.50
3	0.57	0.65	0.54	0.57	0.55	0.58
4	0.00	0.51	0.52	0.55	0.45	0.54
5	0.00	0.34	0.45	0.49	0.47	0.42
6	0.15	0.33	0.58	0.58	0.49	0.63
7	0.12	0.40	0.53	0.52	0.44	0.52
Mean	0.12	0.41	0.52	0.54	0.47	0.53

TABLE VI
GEOMETRIC MEAN FOR FREQUENCY SPECTRUM AE

Sub No.	Feature No.					
	1	2	3	4	5	6
1	0.55	0.46	0.50	0.58	0.44	0.51
2	0.55	0.56	0.56	0.56	0.57	0.57
3	0.58	0.50	0.56	0.51	0.51	0.51
4	0.50	0.50	0.52	0.55	0.51	0.58
5	0.53	0.55	0.53	0.50	0.51	0.51
6	0.52	0.50	0.49	0.47	0.50	0.48
7	0.53	0.52	0.55	0.56	0.57	0.60
Mean	0.54	0.51	0.53	0.53	0.52	0.54

TABLE VII
GEOMETRIC MEAN FOR TIME SERIES AE

Subject No.	Feature No.
	7
1	0.67
2	0.54
3	0.69
4	0.67
5	0.47
6	0.67
7	0.68
Mean	0.63

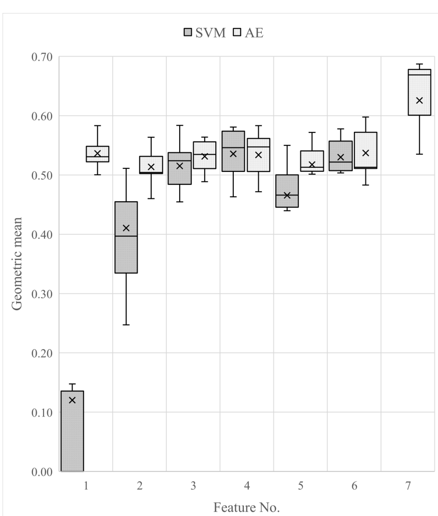

Fig. 6. Box plot of geometric mean.

spectrum is almost the same as the chance level and cannot be classified. In the time series AE, only Participant 5 was below the chance level, and it was above 60 % except for Participant 2 and 5.

VI. DISCUSSION

In SVM using the frequency spectrum, the average was the chance level, which cannot be classified. On the other hand, in the anomaly detection using time series data, the average was 63 % which was possible to classify. Therefore, it is considered that the time series information is lost when calculating the frequency spectrum contains information for detecting errors.

VII. CONCLUSION

In this study, we attempted to predict human error EEG by anomaly detection. By reconstructing the EEG data using an auto-encoder learned from the EEG data that does not include human error, a large reconstruction error occurs when the input contains human error. In this case, the accuracy by the anomaly detection method is about the same as the prediction by the conventional SVM, and the improvement in accuracy by this method in single-trial analysis could not be confirmed.

VIII. ACKNOWLEDGMENT

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