Electroencephalogram Data for Classifying Answers to Questions with Neural Networks and Support Vector Machine

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***Abstract*—This paper proposes a method for classifying answers to conversational questions from Electroencephalogram (EEG) data. The proposed method includes steps for EEG recording, feature extraction, and answer classification. For EEG measurements, this paper employs a simple electroencephalograph. The EEG signals from the frontal lobe are recorded. The EEG features are calculated by normalizing the EEG signals and using Convolutional Neural Networks (CNN) for extraction. The answers to questions are then classified from the EEG features using a support vector machine. To show the effectiveness of the proposed method, we conducted experiments using real EEG data. The experimental results confirm that the mean recognition accuracy was 99% or more if the CNN features are individual to the subject. These results suggest that the answers to yes/no questions can be classified using EEG signals and that the EEG analysis technique using CNN and the support vector machine is suitable for extracting and classifying EEG features.**

***Index Terms*—electroencephalogram, answers of questions, convolutional neural networks, personal differences, human support system, human communication**

I. Introduction

Patients who have amyotrophic lateral sclerosis or aphasic deficits caused by brain infarcts face considerable difficulty in communicating. If a system could detect, classify, and convey a message for the patient, care and quality of life would be much improved. These patients can form messages in their brain, but the neural mechanisms for communication are not entirely clear. Therefore, we need to find any signal of brain activity that is related to a message, in order to relay that message with an automated system. The electroencephalogram (EEG) measures brain waves and can easily be used daily. EEGs have already been used as a brain machine interface and/or Brain Computer Interface (BCI) for environmental control systems in rehabilitation facilities. Therefore, we have focused on detecting features in EEG signals that are related to messages formed in thought. The device reported in this paper detects and classifies answers to yes/no questions in EEG data.

An electrocap with many electrodes is uncomfortable to wear and is thus unsuitable for the long-term recordings involved in day-to-day use of a BCI [1]. Therefore, we have attempted to construct a BCI that uses data from a simple device that uses only dry electrodes. The target-sensing points are in the frontal cortex. Since the frontal cortex is assumed to be the brain area that is associated with speech [2], [3], the EEG activities in the prefrontal cortex are relevant. The EEG signal from the frontal cortex is also different for different people [4], [5]. Therefore, any algorithms and techniques for feature extraction must also account for personal differences in EEG signals.

Many approaches are used for analyzing EEG signals [6], such as the EEG feature extraction from the power spectrum and spectral centroid, special EEG feature extraction techniques, factor analysis, Principal Component Analysis (PCA) [7]-[9], Independent Component Analysis (ICA) [9], [10], EEG pattern classifiers, artificial neural networks [9], the *k*-nearest neighbor algorithm (*k*NN) [9], [11], Linear Discriminant Analysis (LDA) [12]-[14], Support Vector Machine (SVM) [7], [15], Self-Organizing Map (SOM) [16], and Deep Learning (DL) techniques [17], [18]. Signals of imagined movements have been extracted using those techniques, especially Convolutional Neural Networks (CNN), but thoughts about human communication have not been detected using DL with EEG signals.

This paper proposes a method for detecting yes/no answers to questions in normal communication by analyzing EEG signals. The proposed method employs CNNs and a SVM. The CNNs are used to extract the EEG features. The SVM is then used to classify answers to questions using the EEG features. The feature extraction parameters are learned with data individual to each subject because the EEG signals include personal differences. Real EEG data was used to verify the effectiveness of the method for communication assistance.

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II. Proposed Methods

The proposed method consists of three steps: EEG recording, feature extraction, and answer classification. A simple electroencephalograph is employed to record EEG signals daily. The EEG features are extracted by CNNs after normalizing the EEG signals. In answer detection, the SVM is employed to classify the answers using the extracted EEG features. Fig. 1 outlines the procedure of the proposed method.

A. EEG Recordings

The EPOC+ device developed by EMOTIV was used to record the EEG signals. The EPOC+ uses dry sensors and has 14-channel electrodes. Two reference electrodes are attached over the bone just behind each ear lobe, and the exploring electrodes are placed according to the international 10/10 system at AF3, F7, F3, T7, T8, F4, F8, and AF4. The device offers high resolution, neuro-signal acquisition, and wireless processing in a neuro-headset.

The EEG data are sent to a computer through a serial port. Table I and Fig. 2 show the specification of the EPOC+ device and sample data of the EEG signals.

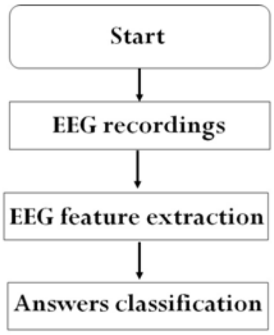

Figure 1. Procedure for the proposed method.

TABLE I. Specifications of the EPOC+ Device

Number of channels	14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) plus CMS/DRL references
Sampling rate	128 SPS
Resolution	14 bit
Bandwidth	0.16–43Hz, digital notch filters at 50 and 60 Hz
Dynamic range	8,400 μV(pp)

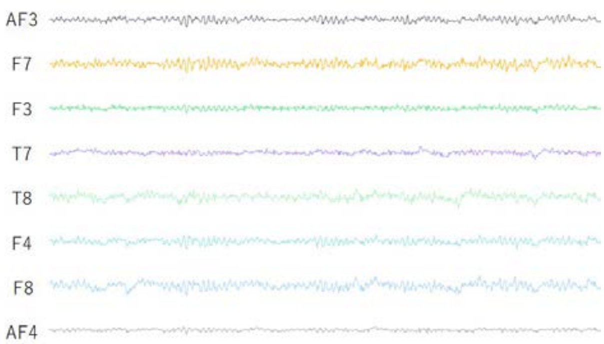

Figure 2. Sample data of the recoded EEG signals.

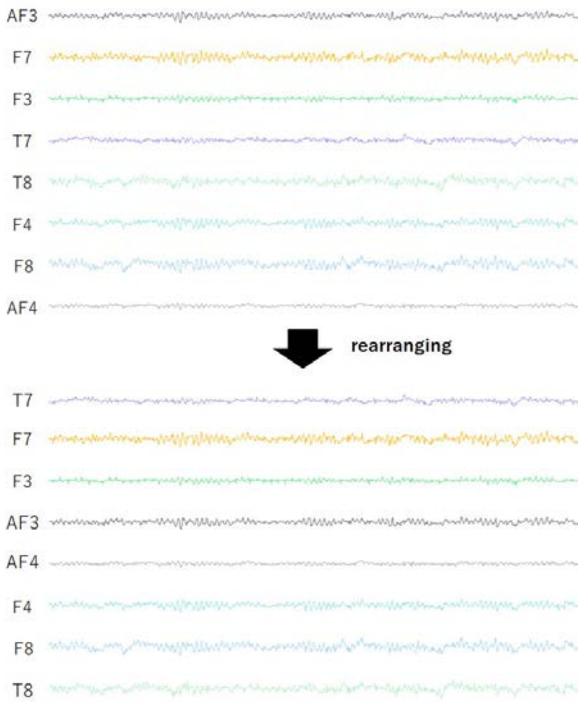

Figure 3. Sample of artificial input data. The black to white gradient in the lower image indicates values from 0 to 1 in the normalized EEG signal values.

B. EEG Feature Extraction

We employ CNNs to extract the EEG features. The feature extraction step consists of two phases: normalization of the EEG signals to prepare input data sets for the CNNs and EEG feature calculation with the CNNs. The EEG signals are normalized as follows:

$$Norm(ch) = (EEG(ch)–Min) / (Max - Min) \quad (1)$$

where *Norm* and *ch* mean the normalized EEG signal and the channel (AF3, F3, F7, T7, T8, F8, F4, AF4). *EEG*, *Min*, and *Max* are the recoded EEG signals on each channel, the minimum value of the EEG signals of all channels, and the maximum value of the EEG signals from all channels, respectively. The proposed method rearranges AF3, F7, F3, T7, T8, F4, F8, and AF4 in T7, F7, F3, AF3, AF4, F4, F8, and T8 to create input data for the CNNs based on the international 10/10 system. Fig. 3 shows the sample we created by fitting input data to the international 10/10 system. The EEG features are then extracted using CNNs. The CNNs are composed of an input layer, three hidden layers, and a full-connection layer. The hidden layer includes convolutional and pooling layers. The features of the EEG signals related to answers are extracted through the convolutional layer. The present proposal uses the n*n filter for the convolutional layer. The noise included in the EEG signals is reduced in the pooling layer by compressing the data. In the full-connection layer, the features of the EEG and noise are extracted and reduced, respectively. The full-connection layer is used to connect the extracted features of the hidden layer and includes the dropout function (the dropout is P%) to protect against overtraining. Fig. 4 shows the structure of the CNNs used with the proposed method. The output of the full-connection layer is regarded as the EEG features.

C. Answer Classification

The SVM is used to classify the answers to questions from the features output by the CNNs. In general, the output layer of the CNNs is a multilayer perceptron (MLP). The MLP is not always a superior discriminator. The pattern recognition accuracy using the MLPs of EEG features showed good results when using the SVM. Fig. 5 shows the structure of the SVM classifier.

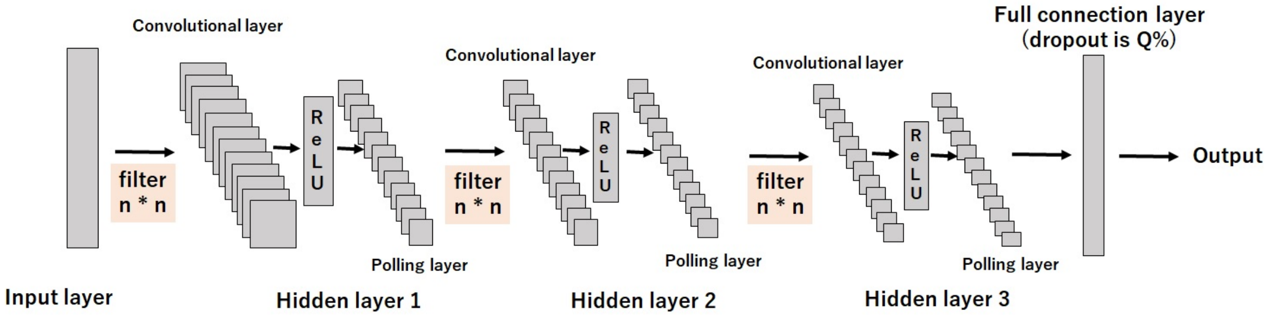

Figure 4. Structure of the CNNs.

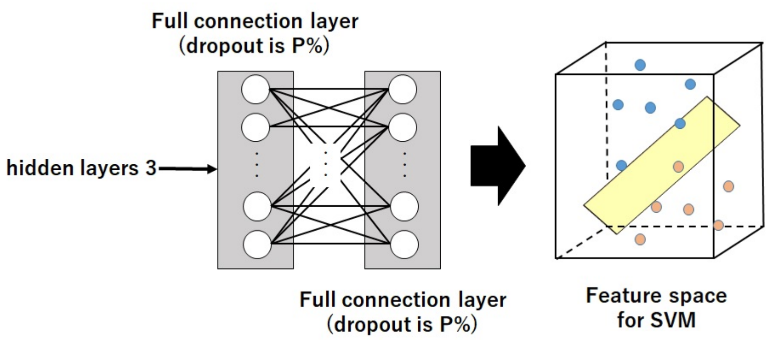

Figure 5. Structure of the SVM.

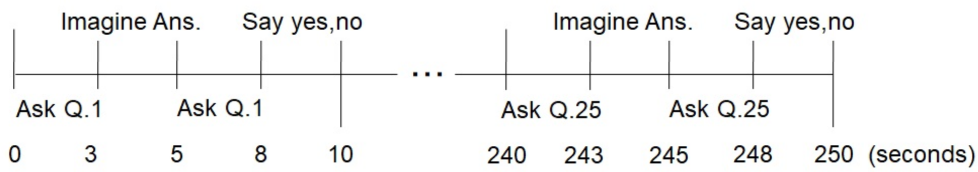

Figure 6. Time course of the experiments. Ask Q. means that the system asks a question to the subject. Imagine Ans. implies that the subject answers the question in his or her brain. Say yes,no implies that the subject says "yes" or "no". The subject answers a set of 25 questions.

TABLE II. NUMBER OF ANSWERS TO QUESTIONS ON EACH SUBJECT; THE ANSWERS ARE PROVIDED AS YES AND NO

	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subjrct7	Subject8	Subject9	Total
Yes	530	560	530	620	530	620	550	420	440	4,800
No	470	440	470	380	470	380	450	580	560	4,180

TABLE III. MEAN AND S.D. OF RECOGNITION ACCURACY FOR ANSWER CLASSIFICATION ON EACH SUBJECT (%)

		Subject1	Subject2	Subject3	Subject4	Subject5	Subject6	Subjrct7	Subject8	Subject9	All
SVM (Pro.)	Mean	99.1	99.1	99.5	99.5	99.3	99.8	99.5	99.9	99.4	76.7
	S. D.	0.9	1.1	0.6	0.5	0.8	0.2	0.5	0.1	0.8	4.0
MLP (Prev.)	Mean	97.9	97.7	97.3	98.7	98.7	98.7	97.9	99.6	97.4	73.6
	S. D.	1.8	3.1	3.9	1.3	1.8	1.0	1.6	0.8	2.0	5.0

III. Experiments

The subjects were all healthy volunteers. The sample size consisted of nine students (mean age = 22.7 years) from Tokushima University, Japan. None had a history of a serious disease. Written informed consent based on the Declaration of Helsinki was obtained from the subjects after a detailed description of the experiment's purpose and procedures. In the experimental sessions, the subjects wore EPOC+ device while sitting on a chair, closing their eyes, and remaining silent. The EEG was recorded in the laboratory with ongoing background noise. Fig. 6 shows the time course of experiments. The recorded EEG signals covered two seconds while the subject imagined a yes/no answer to a question (Imagine Ans. in Fig. 6). Each subject completed ten sets of measurements. These CNN parameters were determined via trial and error. In the parameters of the CNNs, the size of the input layer was 8×128. Three filters were included in the first two hidden layers, and the filter size of the third hidden layer was 2. 50. Convolutional layers were included in hidden layers 1 and 2, and 20 were included in hidden layer 3. The max pooling algorithm was employed in the pooling layer. P of the dropout rate in the full-connection layer was 50. The number of units in the full-connection layer was 2,000. The linear SVM classifier was employed with ten trails to evaluate the proposed method. In the evaluation tests, 80% of the data sets were randomly selected as training data.

IV. Results and Discussions

Table II shows the number of data sets for each subject. We confirmed that the number of answers was different for each subject, because each subject's answers to questions were different. The total numbers of “yes” and “no” were 4,800 and 4,180, respectively.

Table III shows the recognition accuracy for classifying the answers to questions (“yes” and “no”). Pro. And Prev. mark the proposed method and the previous method. In the previous method, MLP was employed as the classifier because the MLP is typically used for such applications. The All column in Table III lists the recognition accuracy when data sets were a mix of data from all subjects. We confirmed that the mean recognition accuracy was 99% or more and that the standard deviation was 1.1% or less when using the proposed methods. The mean and standard deviation was 97% or more and 3.1% or less when using the previous method, respectively. The recognition accuracies of both the previous method and the proposed method were high. These results suggest that signals related to yes/no answers can be detected while the subject forms an answer to the question. The experimental results with proposed method had higher recognition accuracy. Also, the standard deviations of the classifications made by the proposed method were lower. These results suggest that the EEG analysis technique using CNNs and the SVM is suitable for extracting and classifying EEG features related to communication, and the CNN parameters were appropriate.

We confirmed that the mean and standard deviation in the data sets with all subjects; signals (All in Table III) were 76.7% and 4% when using the proposed method and 73.6% and 5% when using the previous method. These results suggest that personal differences in the EEG signals arise when responding to questions, because the recognition accuracy was 97% or more when the parameters for the CNNs were trained individually to each subject.

The target-sensing points were all in the frontal cortex. The experimental results confirm that frontal lobe activity is involved in responding to questions.

V. Conclusions

This paper has proposed a method for detecting yes/no answers using EEG analysis. The proposed method employs CNNs and an SVM and involves three phases: EEG measurement, feature extraction, and answer classification. In the EEG measurements, the simple electroencephalograph was employed to record EEG signals on a daily basis. The EEG features were extracted by normalizing the EEG signals and applying CNNs. The SVM was then employed to classify the answers from the extracted EEG features.

The target-sensing points were in the frontal cortex. To show the effectiveness of the proposed method, we conducted tests using real EEG data. The mean and standard deviation of data sets from all subjects were 76.7% and 4%, respectively, when using the proposed method. These results suggest that there are personal differences in the EEG signals that arise in responses to questions. The recognition accuracy was 99% or more when using the proposed method. These results suggest that it is possible to detect signals related to a yes/no answer by analyzing the EEG signals as the subject forms an answer to the question. We have shown that the EEG analysis technique using CNNs and the SVM is suitable for extracting EEG features and classifying the features. Finally, these results lend further support to the hypothesis that the activities of the frontal lobe are involved in responding to questions.

However, large data sets are required for learning when using CNNs and obtaining such datasets is difficult. Because BCI can be easily constructed, the proposed methods will be improved using additional learning techniques.

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