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Original research article

Classification of color imagination using Emotiv EPOC and event-related potential in electroencephalogram

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ABSTRACT

In this paper, we proposed a method that classifies electroencephalography (EEG) from color imagination data using the Emotiv EPOC headset. For EEG measurement and the event-related potential (ERP) method, brain-computer interface (BCI) systems were used in the experiment. In the experiment, the subjects gaze at a non-flicker visual stimulus of color (i.e., red, green, blue, white, and yellow) and then proceed to imagine the color. To concentrate on the LED light, all experiments were performed in a dimly lit room. The flickered visual stimulus was made using an Arduino microcontroller board and LEDs with the purpose of prompting color imagination. As a result, we obtained significant EEG responses of thoughts related to certain colors. The EEG response is classified using classification algorithms including a support vector machine (SVM) with linear discriminant analysis (LDA), an artificial neural network (ANN) with LDA, and an ANN without LDA. In addition, five-fold cross validation was used to evaluate the performance. From the results, we found robust electrodes (T7 and F4). The technology developed in this paper can be used to assist paralyzed individuals and the elderly.

1. Introduction

Brain-computer interface (BCI) systems are able to transform electroencephalography (EEG) or bio-signals into computer data so that researchers can observe the signal [1]. Currently, BCI systems are an important part of research into controlling devices using EEG. Furthermore, various devices for paralyzed individuals, gaming, and brain development have been developed using BCI systems. In this paper, we propose a method that classifies EEGs using non-flicker visual stimuli and EEGs when imagining a color. This method is intended to assist paralyzed individuals and the elderly.

Non-invasive methods for EEG measurement include the following: event-related potential (ERP), event-related synchronization/desynchronization (ERS/ERD), visual evoked potentials (VEP), steady-state visual evoked potentials (SSVEP), slow cortical potentials (SCP), P300, μ and β rhythms [2]. In this paper, ERP is used for the non-invasive measurement of brain responses.

In 1929, ERP was developed by Hans Berger for EEG. In this method, electrodes are placed on the scalp and output signal is amplified. ERP is the mean of EEG that receives the same repeated stimuli. ERP is the EEG response that is the output of a specific sensory, cognitive, or motor event. The method of ERP provides a non-invasive means of estimating brain function

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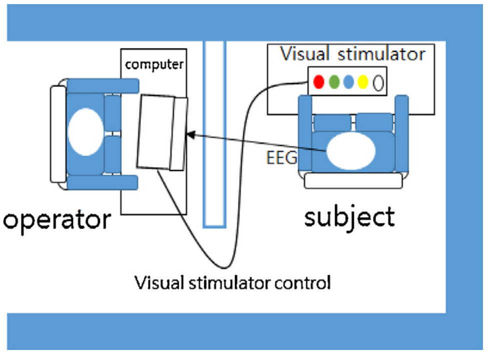

Fig. 1. Layout of shield room.

Fig. 2. Photograph of experimental setup.

in patients with cognitive diseases and dementia [3]. In this paper, P300, N200, and N400 among the ERP data were used. The data is extracted roughly 200 ms, 300 ms, and 400 ms after some stimulus on the ERP [4].

According to a recent study, ERP can be used for research that cannot be analyzed in the frequency domain and the ERP provides a high quality response for brain activity in the time domain. In 2014, ERP was used to evaluate brain activity for adaptation to light of different colors [5] and movements such as sitting and walking [6]. In 2011, ERP was used on children with attention deficit hyperactivity disorder (ADHD) [7]. Currently, many researchers are studying ERP.

Classifying brain waves is important in BCI systems, because the classified data helps to differentiate particular brain signals. In 1995 and 2011, some ERP data was classified using artificial neural networks (ANNs) and linear discriminant analysis (LDA) [8,9]. In 2015, a previous paper by the current author presented the classification of a particular brain wave using LDA and a support vector machine (SVM) [10].

To measure brain waves, this paper used the Emotiv EPOC headset. This headset is more convenient than other devices because of the short preparation time [11]. In addition, the headset has a Bluetooth module for wireless communication. In the experiment, an Arduino microcontroller board and LEDs were used to create visual stimuli. The ANN, LDA, and SVM were used for classifying the P300, N200, and N400 from the ERP data [12].

2. Material and methods

2.1. Experimental setup

The experiments were carried out in a shielded room at the Department of Electrical and Electronics Engineering, Chung-Ang University. The layout of the shielded room is shown in Fig. 1. A window is positioned in the middle of the layout of the shield room, such that the operator can supervise all subjects. In addition, the lights were dimmed (<2 lx) and were kept at the same intensity during all experiments. Subjects were seated in a comfortable environment, approximately 50 cm away from the visual stimulator. Fig. 2 shows a photograph of the experimental setup.

2.2. Visual stimulator

For the experiment, a visual stimulator was made using an Arduino board and LEDs. The colors of the LEDs used were red (≈5 lx), green (≈7 lx), blue (≈45 lx), yellow (≈32 lx), and white (≈100 lx). To control the LEDs, each LED was connected to the Arduino. A serial port connects the Arduino to the laptop to allow control of the Arduino and LEDs. Fig. 3 shows the Arduino, LEDs, and a speaker of the visual stimulator for the experiment.

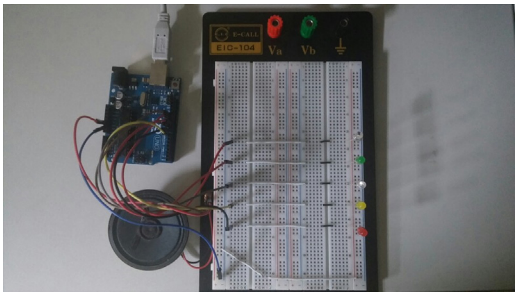

Fig. 3. Visual stimulator.

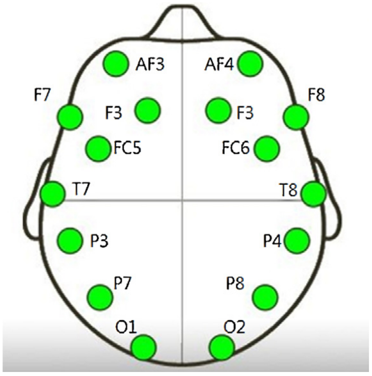

Fig. 4. Locations of electrodes and the conditions of connections.

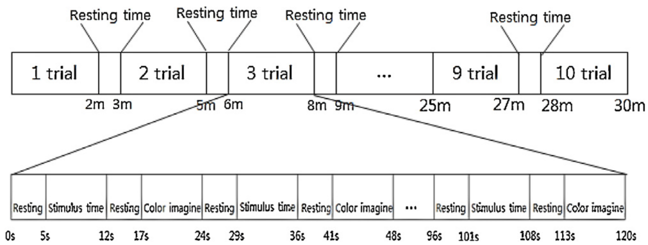

Fig. 5. Progress of the experiment and timing of each trial for obtaining training data.

2.3. EEG recording

The EEG data were recorded using the Emotiv EPOC headset. The headset includes 14 electrodes and 2 reference electrodes. The electrodes are located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. In the experiment, all electrodes were used, excluding FC6 because of a headset malfunction. Fig. 4 shows the location of the electrodes, and the condition of the connections. The experiment started when all of the circle indicators in Fig. 4 were green (indicating ready status). The sampling rate of the headset was 128 Hz. Each electrode impedance was decreased using a saline solution until the circles turned green, indicating that the impedance level required by the software was reached. For the EEG recording in the experiment, the Emotiv EPOC software development kit was used.

2.4. Experimental paradigm

Ten healthy volunteers participated (males: 10, age: 23–27) in this experiment. Only three subjects had previously participated in research involving any type of BCI system. Each subject was instructed to focus his sight on a fixed LED when the LED was on, and to imagine the LED color when hearing a beep from the speaker. Before the LED is turned on, the subjects have a rest period of 5 s. The red LED is then turned on for 5 s, followed by another 5 s rest period, followed by 2 beeps with an interval of 7 s. During this period, the subject is asked to imagine the red color of the LED. The entire cycle, which is repeated 5 times in the following color progression: red, green, blue, white, and yellow. In the case of training data, the same stimulus color was used. This process was a single trial and progressed for ten trials. In the case of the testing data, the stimulus color used was randomly selected. Fig. 5 shows the progress of the experiment and the timing of each trial for the training data.

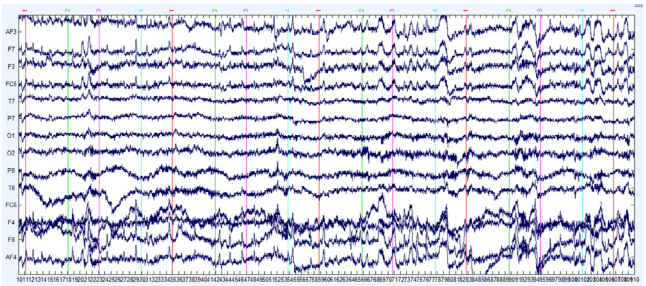

Fig. 6. Raw EEG signals with event value. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.)

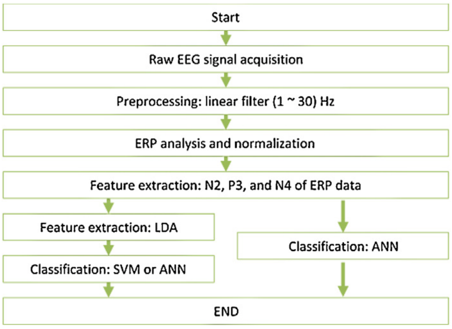

Fig. 7. Process of ERP classification.

2.5. Data analysis

EEGLAB, an open source toolbox for MATLAB, is used for analysis of the recorded EEG data. For event recoding, the Bandicam program is employed to check the state of the serial port and timing of the recorded EEG. For the ERP analysis, events were chosen when the LED was on and off, and when the subjects imagined the color prompted by the beep. Fig. 6 shows the raw EEG data for subject 1's experiment using a white LED; the picture explains the events for ERP. In Fig. 6, red lines labeled 1 refer to the EEG when the LED is on, green lines labeled 2 refer to the EEG when the LED is off, and pink lines labeled 3 and blue lines labeled 4 refer to the EEG when the subject imagines the color of the LED after being prompted by the beep.

2.6. Process of ERP classification

Fig. 7 presents the process of ERP classification. The algorithms used for classification were the support vector machine (SVM) and the artificial neural network (ANN). Before ERP analysis, a band pass filter was applied to the EEG data to avoid noise and distortion. The range of the filter is 1–30 Hz, which includes alpha and beta waves. The waves are more likely to represent an ERP phenomenon. Additionally, linear discriminant analysis (LDA) was used to maximize the variance between the classes. The ratio of variances within a class was not used for dimension reduction.

3. Experimental results

From the results of data analysis, ERP data for each electrode were obtained. Fig. 8 shows the ERP result of subject 1 during the time when the subjects were imagining the colors. Fig. 8 presents the ERP responses at 0, 50, 100, 150, 200, 250, and 300 ms.

Fig. 9 shows the ERP response of color imagination. In Fig. 9, the location of the electrode is 1-AF3. The entire range of the *x* axis is from 0 s to 0.6 s. In the ERP data, the amplitudes of P3, N2, and N4 were chosen and normalized for classification.

Fig. 10 shows subject 1's ERP image from electrode 1-AF3. The image shows 15 smooth periods, and the *x* axis ranges from 0 s to 0.6 s. In Fig. 10, each trial used as training data and testing data for classification is shown.

3.1. Performance of the classifier

SVM with LDA, ANN with LDA, and ANN without LDA were used for classification and to compare the performance of the classifier. In addition, significant and robust electrodes (T7 and F4) were found using the SVM with LDA, ANN with LDA, and ANN without LDA from the results of ERP amplitude at P3, N2, and N4. Fig. 11 shows the average classification results using

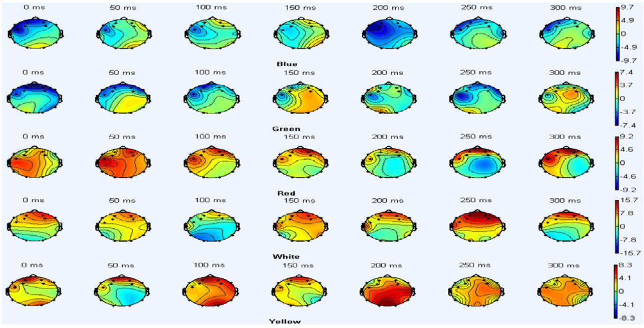

Fig. 8. ERP map series of subject 1 from 100 ms to 500 ms. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

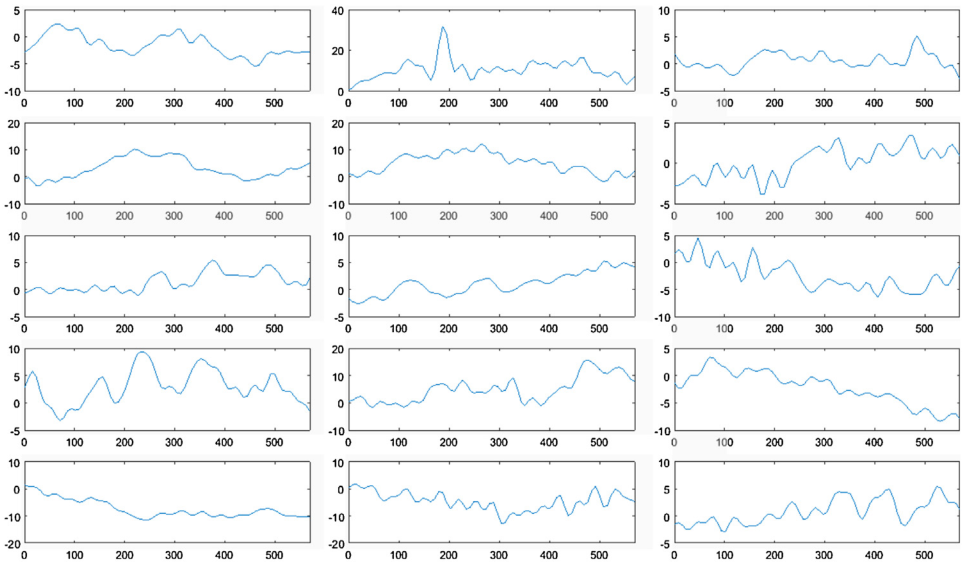

Fig. 9. ERP result of color imagination at AF3. The rows are colors (blue, green, red, white, and yellow). The columns plot subjects 1, 2, and 3.

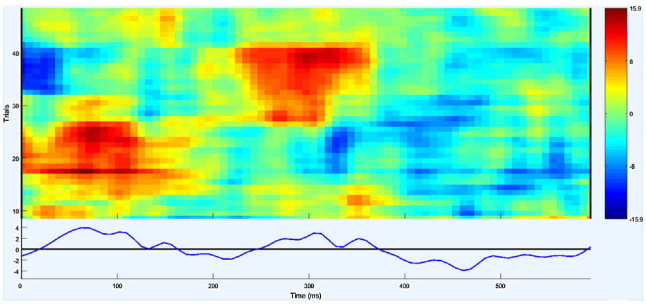

Fig. 10. AF3's ERP image for subject 1. The image has 36 data of the ERP operation results.

the ERP data from all subjects. The results were obtained by SVM with LDA. The quadratic kernel function was used to train the SVM. For the evaluation of the training results, five-fold cross-validation is used. For cross-validation, roughly 186 data points from each subject were used. From the results in Fig. 11, electrodes F3, T7, and F4 have a classification rate of more than 53%.

Figs. 12 and 13 show the results of ANN with LDA and ANN without LDA. For training the ANN, the number of iterations was 3000. The ANN used in the experiment had a node structure of 3 input, 8 hidden, 8 hidden, 3 hidden, and 5 output nodes. Additionally, the ANN consists of a back-propagation algorithm and a multi-layer perceptron algorithm. The activation function of the ANN was a sigmoid function.

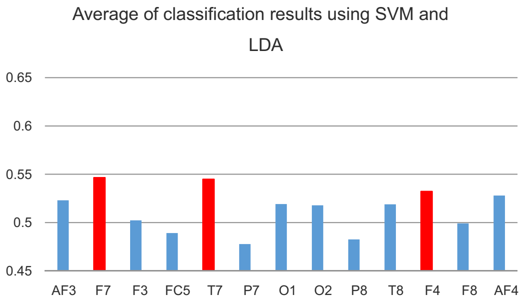

Fig. 11. Average of classification results using LDA and SVM.

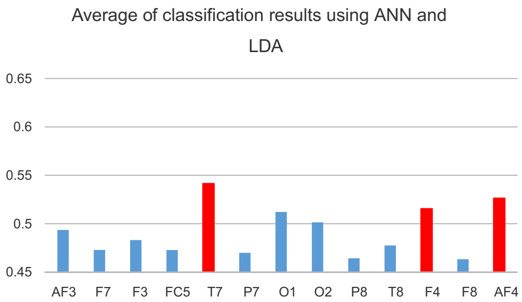

Fig. 12. Average of classification results using LDA and ANN.

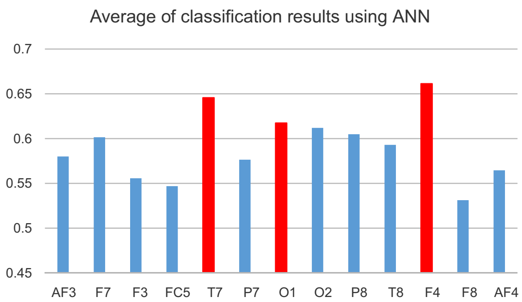

Fig. 13. Average of classification results using ANN.

From the results of Figs. 12 and 13, electrodes T7, F4, and AF4 have better classification rate than the other electrodes. In the case of ANN with LDA, electrodes T7, F4, and AF4 have a classification rate of greater than 51.5%. In the case of ANN without LDA, the classification rate was greater than 61.5%. In addition, electrodes T7 and F4 have high values in the results of all classifiers.

3.2. Classifying the ERP data

According to the average performance of each classifier, ANN is superior to the other methods. To evaluate the performance of the ANN, ERP data for each color is compared using the SVM with LDA. Tables 1 and 2 show the experimental results of color imagination using the ANN at electrodes T7 and F4, respectively. Tables 3 and 4 show the experimental results of color imagination using the SVM with LDA at electrodes T7 and F4, respectively. These results were the averages of five-fold cross-validation results.

4. Conclusion

The classification rates show that the visual stimulus has a significant influence on the BCI System. Using LDA, SVM, and ANN, the significant data were classified. However, using ANN with LDA and SVM with LDA, the classification rates were lower than when using only ANN, although ANN showed a long training delay time. In future research, different features such as O1 or the F7 device of the Emotiv EPOC electrode will be used to collect the data. Other classification algorithms

Table 1
Results of classification rates for each color using ANN at electrode T7.

Subject	Blue	Green	Red	White	Yellow
Subject 1	64.00%	44.44%	75.00%	40.00%	95.79%
Subject 2	40.00%	86.67%	53.33%	73.33%	87.37%
Subject 3	54.00%	65.45%	77.78%	83.64%	77.89%
Subject 4	71.11%	62.22%	92.73%	91.11%	86.67%
Subject 5	66.67%	80.00%	87.27%	97.78%	84.44%
Subject 6	68.00%	57.78%	65.45%	69.09%	54.55%
Subject 7	70.00%	62.22%	54.55%	74.55%	60.00%
Subject 8	40.00%	72.73%	87.27%	69.09%	89.09%
Subject 9	56.00%	76.36%	45.45%	80.00%	87.27%
Subject 10	88.00%	56.36%	54.55%	76.36%	89.09%
Average	61.78%	66.42%	69.34%	75.49%	81.22%

Table 2
Results of classification rates for each color using ANN at electrode F3.

Subject	Blue	Green	Red	White	Yellow
Subject 1	74.00%	58.18%	62.22%	54.55%	84.21%
Subject 2	58.00%	65.45%	82.22%	81.82%	94.74%
Subject 3	70.00%	65.45%	88.89%	49.09%	91.58%
Subject 4	66.00%	67.27%	70.91%	85.45%	67.27%
Subject 5	36.00%	92.73%	87.27%	90.91%	89.09%
Subject 6	48.00%	72.73%	60.00%	52.73%	60.00%
Subject 7	30.00%	92.73%	70.91%	83.84%	78.18%
Subject 8	72.00%	83.64%	83.64%	50.91%	90.91%
Subject 9	62.00%	45.45%	85.45%	70.91%	89.09%
Subject 10	20.00%	83.64%	81.82%	70.91%	80.00%
Average	53.60%	72.73%	77.33%	69.11%	82.51%

Table 3
Results of classification rates for each color using SVM and LDA at electrode T7.

Subject	Blue	Green	Red	White	Yellow
Subject 1	84.00%	84.44%	75.00%	51.11%	40.00%
Subject 2	91.11%	84.44%	73.33%	53.33%	28.89%
Subject 3	88.89%	87.27%	48.89%	38.18%	53.33%
Subject 4	84.44%	86.67%	65.45%	48.89%	62.22%
Subject 5	73.33%	48.89%	82.22%	86.67%	40.00%
Subject 6	92.00%	55.56%	69.09%	52.73%	34.55%
Subject 7	86.67%	35.56%	97.14%	33.33%	22.22%
Subject 8	84.00%	49.09%	86.67%	56.36%	53.33%
Subject 9	91.11%	86.67%	71.11%	71.11%	26.67%
Subject 10	95.56%	57.78%	76.36%	66.67%	22.22%
Average	87.11%	67.64%	74.53%	55.84%	38.34%

Table 4
Results of classification rates for each color using ANN at electrode T7.

Subject	Blue	Green	Red	White	Yellow
Subject 1	96.00%	91.11%	67.50%	57.78%	29.47%
Subject 2	75.56%	86.67%	88.89%	46.67%	37.78%
Subject 3	77.78%	92.73%	66.67%	61.82%	53.33%
Subject 4	95.56%	71.11%	47.27%	53.33%	40.00%
Subject 5	95.56%	64.44%	51.11%	70.00%	33.33%
Subject 6	94.00%	80.00%	74.55%	54.55%	23.64%
Subject 7	82.22%	100.00%	68.57%	44.44%	24.44%
Subject 8	90.00%	56.36%	55.56%	49.09%	42.22%
Subject 9	86.67%	77.78%	55.56%	57.78%	22.22%
Subject 10	73.33%	28.89%	49.09%	88.89%	51.11%
Average	86.67%	74.91%	62.48%	58.43%	35.76%

such as deep learning will be used for color classification. Furthermore, studies on reducing the delay time needed for the training of neural network algorithms will be conducted.

The results of this research showed that, using a person's simple perception of a basic color, a machine can recognize the person's thoughts. With further research and experiments, it will be possible to assist paralyzed individuals and the elderly using this technology. Thus, color imagination has the potential to be adopted in medical institutions and public areas.

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