Exploring P300-based Biometric for Individual Identification Based on Convolutional Neural Networks

Hongbo Du[1], Ismail Jouny[1], Yih-Choung Yu[1], Sicheng Wang[2]

1. Department of Electrical and Computer Engineering, Lafayette College, Easton, Pennsylvania, USA
2. School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, Georgia, USA
{duh, jounyi, yuy}@lafayette.edu, wangonce@gmail.com

The potential of using the electrical brainwave signals of individual's neural response to stimuli (the event-related potential) as a biometric in subject identification has been investigated. Electroencephalography (EEG) signals from 24 participants actively involving in the P300 Speller task are used to develop biometric systems based on discriminative classifiers. P300 is an event-related potential (ERP) component in human EEG elicited using the oddball stimulus to reflect the individual's reaction in a target detection process [1]. For P300, it is possible to extract unique neural response pattern and information from different subjects to determine the subjects' identity. Biometric recognition based on neural response pattern could be a physiological characteristic. Thus, while P300 inherit the advantages of human physiological features as a mean of individual identification, it is hard to steal, or replicate compared to other physiological features (e.g. fingerprint, iris). This abstract explores the possibility of using P300-based biometric as an individual identification tool. Eight-channel EEG data were recorded, and band-pass filters were applied to remove artifacts and to reduce noise. Topographic plot was used for feature extraction and convolutional neural net (CNN) was applied for classification. SVM and ELM were also used as classifiers.

P300 Speller tasks were performed for each participant. In the matrix formed by numbers and letters, the rows and columns flash successively, randomly and rapidly on a constant rate. The BCI2000 software managed the whole data collecting process and data were sampled at 200Hz [2]. Four participants have 5 sessions of data and the other twenty participants only have 1 sessions of data. A single session of data typically included 13-18 P300 epochs. Participants were required to reduce movement during the experiment. The band-pass filter at 1-35 Hz and notch filter at 59-61 Hz is applied to the raw EEG data by the BCI2000 software to remove artifacts and to reduce noise as well.

The topographic plot visualizes the EEG data matrix by representing the P300 response from all eight channels of the EEG data during one second epoch. The topographic plot can be generated by the offline analysis tool provided by BCI2000 [3]. The horizontal axis of topographic plot represents the time of one epoch and the vertical axis represents the channels. The color represents the average determination coefficient of P300 of the current data, where red color indicates there is a neural response to the expected stimuli [4]. The shape and the location of the neural response can be extracted as features to classify different subjects [3].

A pre-trained CNN model, namely AlexNet is applied as classifier for the topographic plots [5]. Topographic plots are the input of AlexNet and are resized to fit the size of input layer of AlexNet. Linear support vector machine (SVM) and extreme learning machine (ELM) are also used as classifier for EEG data matrix. 20 runs were conducted to compute the accuracy rate for the all three classifiers for both the 4-subject pool and 24-subject pool. 80% of the topographic plots were used for training and rest 20% for testing. Plots were randomized at each run. Results are shown on Table 1 and Table 2.

Table 1. Accuracy Rate for 3 Classifiers in the 4-subject Pool

Classifier	Accuracy Rate (%)
CNN	83.31
SVM	41.52
ELM	32.00

Table 2. Accuracy Rate for 3 Classifiers in the 24-subject Pool

Classifier	Accuracy Rate (%)
CNN	45.45
SVM	29.46
ELM	14.00

Table 1. shows that for the 4 subjects, each of which has relatively larger dataset for training, the approach using AlexNet to classify and topological plots as feature achieves 83.31 % accuracy rate on average. However, the accuracy rates of other two classifiers working on the same dataset are significantly lower. Table 2. shows that for the 24 subjects, 20 of which has relatively smaller dataset for training, the approach using AlexNet to classify and topological plot as feature only achieves 45.45% accuracy rate on average. The accuracy rates of other two classifiers working on the same dataset are also reduced.

Highest average accuracy rate of 83.31% was reached on the datasets of 4 subjects with 5 sessions of data. However, when adding other 20 subjects with only one session of data, the accuracy rate dropped significantly. Thus, a larger amount of data is needed for introducing more subjects into this model. Other learning-based classifiers such as SVM and ELM did not do fare well in comparison, so the convolutional approach may be the appropriate path for individual identification problem.

REFERENCES

[1] M. Fabiani, D. Karis, and E. Donchin, “P300 and Recall in an Incidental Memory Paradigm,” *Psychophysiology*, vol. 23, no. 3, pp. 298–308, 1986.

[2] C. Angeloni, D. Salter, V. Corbit, T. Lorence, Y.-C. Yu, and L. A.Gabel, “P300-based Brain-Computer Interface Memory Game to Improve Motivation and Performance,” *Proc. 38th Northeast Bioeng. Conf*., pp. 35–36, 2012.

[3] Y. C. Yu, S. Wang and L. A. Gabel, "A feasibility study of using event-related potential as a biometrics," *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando, FL, 2016, pp. 4547-4550.

[4] G. Schalk and J. Mellinger, *A Practical Guide to Brain-ComputerInterfacing with BCI2000*, London, the U. K.: Springer, 2010.

[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *International Conference on Neural Information Processing Systems*, pp. 1097–1105, 2012.

Exploring P300-based Biometric for Individual Identification Based on Convolutional Neural Networks

Hongbo Du[1], Ismail Jouny[1], Yih-Choung Yu[1], Sicheng Wang[2]
1. Department of Electrical and Computer Engineering, Lafayette College, Easton, PA
2. School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, Georgia, USA

Abstract

- The potential of using the electrical brainwave signals of individual's neural response to stimuli (the event-related potential) as a biometric in subject identification has been investigated.
- Electroencephalography (EEG) signals from 24 participants actively involving in the P300 Speller task are used to develop biometric systems based on discriminative classifiers.
- Three methods were applied to classify EEG data
- In the first method, topographic plots of P300 are generated and classified using AlexNet, a pre-trained convolutional neural network (CNN).
- In the second and third method, the features of preprocessed EEG data are first extracted. Then support vector machine (SVM) and extreme learning machine (ELM) are applied as classifier.

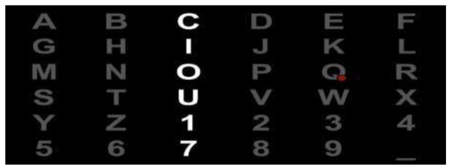
Introduction

- P300 is an event-related potential (EPR) component in human EEG elicited using the oddball stimulus to reflect the individual's reaction in a target detection process [1].
- For P300, it is possible to extract unique neural response pattern and information from different subjects to determine the subjects' identity.
- Biometric recognition based on neural response pattern could be a physiological characteristic.
- While P300 inherit the advantages of human physiological features as a mean of individual identification, it is hard to steal or replicate compared to other physiological features (e.g. fingerprint, iris).

Experiment and Data Acquisition

Experimental set-up

- P300 Speller tasks were performed for each subject.
- In the matrix formed by numbers and letters, the rows and columns flash successively, randomly and rapidly on a constant rate.
- A six by six matrix of letters and numbers flashing successively and randomly by rows and columns was presented on a display screen (19 in. diagonal) as shown in the figure below.
- Each subject sitting approximately 4.5 feet from the computer screen was told to pay attention to the desired letter or number and count the number of times it flashed. A P300 response is elicited by the row or column which the character belongs to [2].

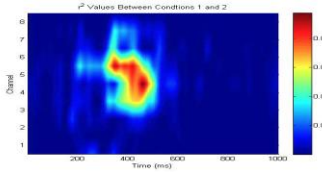


Data Acquisition

- Data were sampled at 200Hz
- Four participants have 5 sessions of data and twenty participants have 1 session
- A single session of data typically included 13-18 P300 epochs.
- A twenty-electrode EEG cap with the international 10-20 standard system (Electro-Cap International Inc., Eaton, OH) and an 8-channel amplification system (EEG 100C, Biopac Systems Inc., Goleta, CA) were used in the EEG data collecting process.
- The 8 channels (C3, Cz, C4, T5, P3, Pz, P4 and T6) were located from to the left earlobe and grounded to right mastoid

Data Processing

- The band-pass filter at 1-35 Hz and notch filter at 59-61 Hz is applied to the raw EEG data by the BCI2000 software to remove artifacts and to reduce noise as well.
- The topographic plot visualizes the EEG data matrix by representing the P300 response from all eight channels of the EEG data during one second epoch.
- The horizontal axis of topographic plot represents the time of one epoch and the vertical axis represents the channels.
- The color represents the average determination coefficient of P300 of the current data, where red color indicates there is a neural response to the expected stimuli [4].
- The shape and the location of the neural response can be extracted as features to classify different subjects [3].
- The shape and the location of the neural response can be extracted as features to classify different subjects [3].



Classifiers

- A pre-trained CNN model, namely AlexNet is applied as classifier for the topographic plots [5].
- Topographic plots are the input of AlexNet and are resized to fit the size of input layer of AlexNet.
- Linear support vector machine (SVM) and extreme learning machine (ELM) are also used as classifier for EEG data matrix.
- 20 runs were conducted to compute the accuracy rate for the all three classifiers for both the 4-subject pool and 24-subject pool.
- 80% of the topographic plots were used for training and rest 20% for testing. Plots were randomized at each run.

Table 1. Accuracy Rate for 3 Classifiers in the 4-subject Pool

Classifier	Accuracy Rate (%)
CNN	83.31
SVM	41.52
ELM	32.00

Table 2. Accuracy Rate for 3 Classifiers in the 24-subject Pool

Classifier	Accuracy Rate (%)
CNN	45.45
SVM	29.46
ELM	14.00

Result and Discussion

- Highest average accuracy rate of 83.31% was reached on the datasets of 4 subjects with 5 sessions of data.
- When adding other 20 subjects with only one session of data, the accuracy rate dropped significantly.
- Thus, a larger amount of data is needed for introducing more subjects into this model.
- In the future, channel-wise study may be needed to determine whether each channel is usable for feature extraction. Bad channels need to be removed and more channels may be also involved in P300 event-related. Also, that different P300 Speller tasks were performed in each trail may also affect the result. Thus, feature experiments might need to be conducted with same P300 Speller task for all subjects

References

[1] M. Fabiani, D. Karis, and E. Donchin, "P300 and Recall in an Incidental Memory Paradigm," Psychophysiology, vol. 23, no. 3, pp. 298–308, 1986.
[2] C. Angeloni, D. Salter, V. Corbit, T. Lorence, Y.-C. Yu, and L. A.Gabel, "P300-based Brain- Computer Interface Memory Game to Improve Motivation and Performance," Proc. 38th Northeast Bioeng. Conf., pp. 35–36, 2012.
[3] Y. C. Yu, S. Wang and L. A. Gabel, "A feasibility study of using event-related potential as a biometrics," 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, 2016, pp. 4547-4550.
[4] G. Schalk and J. Mellinger, A Practical Guide to Brain-ComputerInterfacing with BCI2000, London, the U. K.: Springer, 2010.
[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in International Conference on Neural Information Processing Systems, pp. 1097–1105, 2012.