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

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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>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy Rate (%)</th>
</tr>
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<tbody>
<tr>
<td>CNN</td>
<td>83.31</td>
</tr>
<tr>
<td>SVM</td>
<td>41.52</td>
</tr>
<tr>
<td>ELM</td>
<td>32.00</td>
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</table>

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy Rate (%)</th>
</tr>
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<td>CNN</td>
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<tr>
<td>SVM</td>
<td>29.46</td>
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<td>ELM</td>
<td>14.00</td>
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</table>
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


P300 is an event-related potential (ERP) component in human EEG elicited by 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). Therefore, P300 as a physiological feature is able to be used in biometric recognition system for user identification.[2]

Three methods were applied to classify EEG data: support vector machine (SVM), extreme learning machine (ELM) and convolutional neural networks (CNN). The topographic plot represents the EEG data by visualizing the different reactions. The shape and the location of the neural response can be extracted as features to classify different subjects [3].

The shape and location of the neural response could be a physiological feature to identify different subjects. However, the accuracy rate is dropped when the number of sessions increases. Therefore, more data needs to be collected for the classification process.

### References


