DOI:10.3217/978-3-85125-378-8-86

Proposal on Brain Wave Personal Authentication with Wireless Neuroheadset

K. Tsuru [1], M. Nagaki [2*]

[1] Department of Information Engineering, Oita National College of Technology, Oita, Japan

[2] Department of Computer and Control Engineering, Oita National College of Technology, Oita, Japan

tsuru@oita-ct.ac.jp

Abstract

Brain wave biometric personal authentication is an emerging technology in information security. This form of biometrics is effective in preventing attacks by impostors because of the difficulties of obtaining and impersonating personal brain wave data. Previous studies of this type of biometrics have generally used a wired electrode measurement system, but setting up the system was time-consuming. Hence, we applied brain wave biometrics using a wireless measurement device. Our results showed the authentication rate was over 0.9 on the discrete cosine transform (DCT) feature extraction and application for practical purposes.

1 Introduction

We have studied biometrics on brain waves to develop a diverse and secure authentication system. Brain wave biometrics has two advantages over prevailing biometrics. One is the difficulty of eavesdropping on personal brain wave data. The second advantage is that brain waves can reflect individual mental activities. This property leads to many possibilities for diverse uses of biometrics. Traditional biometric methods used single fixed templates. In contrast, brain wave biometrics could identify people based on templates that reflect different brain activities, such as cognitive processes.

The biometric using the brain wave approach is used to assess α waves. Poulos et al. [1] first tried to identify individuals based on the EEG. They analyzed α waves of four subjects' EEGs, using a neural network classification method. Paranjape [2] also used brain wave data based on α waves during eyes open/closed for biometric analysis. These data based on α waves reported consistent classification results, and this work required only a few electrodes. However, it was necessary for subjects to sit quietly for a relatively long period. A newer method utilized an event-related potential from a cognitive human brain process. Palaniappan [3] investigated the γ wave band of the visual-evoked potential elicited during a mental task for personal identification, and Mercel [4] studied personal authentication based on motor images of left or right hand movement and word generation. In addition we previously studied the approach to the discrete cosine transform (DCT) of motor imageries for features, extracting the best individual features [5]. However, all these studies measured brain signals using the wired electrode system. A major drawback is that preparation for using this system takes time and care, and it is also difficult to realize a brain wave biometric system.

In this paper, we investigate brain wave biometrics using a wireless measurement device on brain signals. This device has not previously been explored for this task. We attempted to classify five healthy subjects based on four situations.

[*] Graduated in March 2014

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2 Methods

Five healthy subjects (4 males and 1 female, age: 20 ± 0.32) provided their informed consent to participate in the experiment on several different days.

2.1 Experimental Paradigm

To show individual features, we prepared four experimental situations as shown below:

Case I:	Close eyes and relax
Case II:	Write consecutive numbers on paper
Case III:	Solve a 40-piece jigsaw puzzle
Case IV:	Read a book

The purpose of Case I is for the subject to measure the authentication rate in a relaxed state of mind. The purpose of Case II is for the subject to measure the authentication rate in a centered state. In Case III, the purpose is for the subject to measure the authentication rate in a centered state with visual information, while in Case IV the purpose is for the subject to measure the authentication rate in a relaxed state with visual information. Four cases were measured in series with a brief resting time after every activity on several different days. The task duration in each case was about 6 minutes. All measurement was carried out on sitting subjects in a room.

2.2 Measurement

We employed an Emotiv EEG neuroheadset [6] to measure brain waves. The Emotiv has 14 saline electrodes with 2 reference electrodes to wirelessly transmit brain wave signals to a computer. The sampling frequency of the brain wave signals was 128 Hz. The brain data was removed as artifacts using digital notch filters (50 Hz and 60 Hz) and a low-pass filter (~43Hz). To avoid the effect of impedance difference, we prepared the low impedance (~ 2 kΩ) of each electrode with an impedance-measuring program. We used C++ program using Emotiv API for storing the brain wave data in a computer. The brain wave data was divided into 8-second lengths, and the average was subtracted. The number of each subject's brain wave data was between 208 and 320 in every case. So we put the data from each case together for all subjects.

2.3 Feature Extraction

We applied feature extraction methods based on DCT feature extraction as follows [5]. First, we employed the spectrum data by fast Fourier transform (FFT) with a rectangular window. With the FFT data, we calculated the sum of every 2 Hz spectrum power band from 0 Hz to 40 Hz. This frequency band included α wave (8–13 Hz), β wave (14–30 Hz), and μ wave (12–18 Hz) activity. The second method was done by adding DCT after the previous method. This method reduced the spectrum data that was converted to DCT data. The DCT is a technique for converting a signal into elementary frequency components. We obtained most of the features from the lower range of the DCT data because the spectrum information concentrated the low portion of these data [5]. These features at 14 electrodes were put into one data set. Thus, we extracted 4 features per each electrode. An authentication rate was required by classifiers on 56 features.

2.4 Classification

We selected three classifiers: linear discriminant analysis (LDA), support vector machine (SVM), and neural network (NN). The probability of personal identification was called an authentication rate. We estimated the rate using a 10-fold cross-validation method.

3 Results

Table 1 shows the results of the average authentication rate that evaluated four features of the DCT data per electrode at 0–40 Hz. Also the authentication rate was calculated by several classification methods. The authentication rates are the average for the five subjects. As NN classification is dependent upon initial values, their authentication rate is calculated based on an average of 10 trials. Taking into account the characteristics of the small subject group, all authentication rates showed consistent results. Those results of the authentication rates were not different among the four cases, as we anticipated.

Case	LDA			SVM				NN
	linear	quadratic	Mahalanobis	rbf	polynomial	quadratic	linear	
I	0.95	0.96	0.96	0.81	0.98	0.99	-	0.92
II	0.99	0.99	0.98	0.80	0.99	0.99	0.99	0.94
III	0.98	0.98	0.96	0.81	0.96	0.99	0.99	0.83
IV	0.98	0.98	0.97	0.81	0.97	0.98	0.97	0.93

-: no convergence

Table 1: Results of average authentication rate of subjects on each classification method. Authentication rate obtained for 4 features per electrode.

Next, we estimated the average authentication rates for each electrode by LDA classifier for finding the area of the head that distinguished our subjects. Table 2 shows average authentication rates. Their rates ranged from 0.47 to 0.76; the average authentication rates of all electrodes in the cases were 0.58, 0.59, 0.60, and 0.60 respectively. The rate of the electrodes used on the occipital region gave consistent results on the whole. Meanwhile, the rate of the electrodes on the temporal cortex regions depends on the activity.

Case	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
I	0.56	0.58	0.50	0.55	0.51	0.56	0.67	0.70	0.61	0.55	0.55	0.58	0.58	0.60
II	0.53	0.58	0.55	0.56	0.52	0.62	0.69	0.71	0.65	0.57	0.56	0.61	0.58	0.50
III	0.53	0.64	0.55	0.55	0.64	0.62	0.65	0.62	0.59	0.60	0.64	0.54	0.59	0.60
IV	0.47	0.58	0.52	0.53	0.57	0.64	0.76	0.68	0.65	0.64	0.69	0.48	0.61	0.59

Table 2: The average authentication rates for each electrode by LDA classifier. The light gray areas are over 0.6 and the dark gray areas are over 0.7

4 Discussion and Conclusion

At first, the experiment preparation time for the wireless neuroheadset took 5 to 10 minutes under low-resistance contact by an impedance check program, but it took subjects one minute to get used to the headset. We think this is within an acceptable range to achieve practical use of personal authentication. In previous brain wave authentication studies, wired electrodes were employed for the measurement. The preparation time for setting electrodes on the skin of the scalp was over 30 minutes.

 DOI:10.3217/978-3-85125-378-8-86

Furthermore, setting them requires help from a few other people. Consequently it is a more challenging process when compared to the existing authentication methods, such as fingerprint, iris, and facial recognition. By contrast, the preparation for using the wireless EEG neuroheadset took little time, and an examinee can prepare for authentication by him/herself. However, we must develop one's positioning method for the location compensation in the next step. Hence, this represents a potential first step towards the practical application of a biometrics system with brain waves.

The authentication rates by DCT feature extraction showed consistent results by all classification methods though five subjects. A previous study showed the authentication rate to be 0.79 for 23 subjects using the wired measurement system [7]. The wireless device indicated the performance of the wired measurement system.

The authentication rate on the occipital electrode was better than that on the temporal electrode. These results were the same for every situation. Under the centered state, such as solving a puzzle or reading a book, the authentication rate on the temporal electrode gave better results. Those results show that brain wave biometrics with several selected electrodes provides a consistent authentication rate.

We investigated the brain wave biometric approach using a wireless brain wave device. The results indicate that the authentication rate of brain wave biometrics was over 0.9. In addition, biometrics using a wireless brain wave device is suitable for a personal authentication system because of its high level of accuracy and short setup time. Moreover, future research should increase the number of subjects in authentication experiments to improve reliability.

Acknowledgements

This study was supported in part by a Grant-in-Aid for Scientific Research (C) 25330163 from the Japan Society for the Promotion of Science (JSPA).

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