EEG-Based Personal Identification

Hideaki Touyama
Toyama Prefectural University
Japan

1. Introduction

In recent years, there have been many discussions about a new interaction technique which directly connects a human brain and a machine. A brain-computer interface (BCI) is a communication channel which enables us to send commands to external devices only by using brain activities (Wolpaw et al., 2002). As one of the candidates for noninvasive and compact BCI systems, an electroencephalography (EEG) has been investigated. A variety of brain activities have been reported in the context of the BCI based on EEG; for instance, motor imageries (Pfurtscheller & Neuper, 1997; Blankertz et al., 2006), visual evoked potentials (VEP) (Middendorf et al., 2000; Cheng et al., 2002), P300 evoked potentials (Farewell & Donchin, 1988; Bayliss, 2003), etc. With such brain activities, many applications have been developed in laboratories such as a virtual keyboard or computer mouse.

The technique to extract the human brain information provides and has driven a new research paradigm; the EEG-based biometry (or biometrics). The concept of the biometry has lately been more and more emerging (Fig. 1). For example, face, fingerprint, and iris have been considered and the part of those has been in practical use. By using human brain activities as a new modality, we have several advantages (Marcel et al., 2007). It is confidential, very difficult to mimic, and almost impossible to steal, and furthermore easy to change on purpose the 'password' according to the users mental tasks or intentions.

In spite of the expected use, there has been little work on the EEG-based biometry. Paranjape et al. studied on the EEG signals recorded from the subjects with eyes open and closed (Paranjape et al., 2001). They examined EEG trials from 40 subjects, and the classification accuracy of about 80 percent was achieved. Poulos et al. investigated one-channel EEG on occipital site to extract the four major EEG rhythms (alpha, beta, delta and theta) during closed eyes, where the classification performance of 95 percent was obtained involving four subjects and more than 250 EEG patterns (Poulos et al., 1999). Palaniappan et al. reported the VEP-based biometry (Palaniappan et al., 2007). Marcel et al. studied the person authentication based on motor imageries and word generation tasks (Marcel et al., 2007). Thorpe et al. proposed the concept of 'pass-thought' (Thorpe et al., 2006) using P300 evoked potentials based on oddball paradigm with flashing letters on a computer monitor. These works revealed the feasibility of the EEG-based biometry. However, it would be difficult to change the EEG signals (password) on purpose, except for the method using P300 responses.

Biometrics	Behavioral	Voice
		Keystroke
		Signature
	Physiological	Face
		Fingerprint
		Vein
		Iris
		DNA

Fig. 1. A variety of biometrics. There are two main classes. One is behavioral and the other is physiological one. In behavioral class, behavior of a person such as voice, keystroke, signature etc. is used. In physiological class, the shape of the body is used such as face, fingerprint, vein, iris, DNA etc. The EEG is a new modality of the biometry.

In this book chapter, we investigate the possibility of EEG activities during photo retrieval to perform the personal identification extracting the P300 evoked potentials. In particular, the use of non-target photo images is focused in order to improve the identification performances. By using photo retrieval tasks, there is a remarkable advantage mentioned above; it is easy to change the pass-thought based on the scheme of the oddball paradigm. Furthermore, the photo retrieval is very familiar with people and easy to achieve with no training. The identification performances will be examined by using Principal Component Analysis (PCA) with a variety of conditions of EEG averaging.
This chapter is structured as follows: In section 2, the experimental methods will be explained. The analysis protocols and the results of the personal identification will be shown in section 3 and 4, respectively. Finally, the discussions and conclusions will be mentioned including our considerations on future works.

2. Experimental Methods

Five normal volunteers (denoted as s1-s5) with normal vision participated in the experiments as subjects (males, range from 23 and 36 yr). The subjects were naïve for the EEG measurement in this study and comfortably sitting on an arm-chair facing a screen in the electromagnetically shielded room.

2.1 EEG Recordings

To address the performance of the personal identification, a modular EEG cap system was applied for scalp recordings. Only one-channel EEG signals were analyzed from Cz according to the international 10/20 system (Fig. 2). A body-earth and a reference electrode were on a forehead and on a left ear lobe, respectively. The analogue EEG signals were amplified at a multi-channel bio-signal amplifier (MEG-6116, NIHON KOHDEN Inc. Japan). The amplified signals were band-pass filtered between 0.5 and 30 Hz and sampled at 128 Hz by using a standard A/D converter. The digitized EEG data was stored in a personal computer.

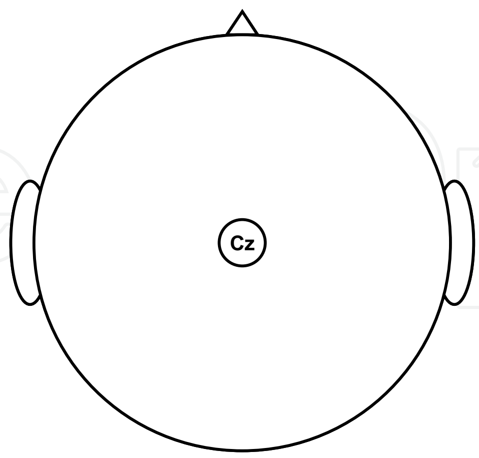

Fig. 2. The electrode montage. Only one-channel EEG was analyzed using a modular EEG cap system according to the international 10/20 system.

2.2 Experimental Tasks

The experimental task sequence was shown in Fig. 3. Nine photo images were randomly projected one by one from backside every 0.5 sec on the screen with about 11.4 degrees of visual angle. Earlier 2 sec was for eye-fixation and the following 4.5 sec included one-time presentation of each photo. The 20-time repetitions were performed to construct 1 session (for 130 sec = 6.5 sec x 20 times). For each subject, the session was repeated at most 5 times to collect the datasets.

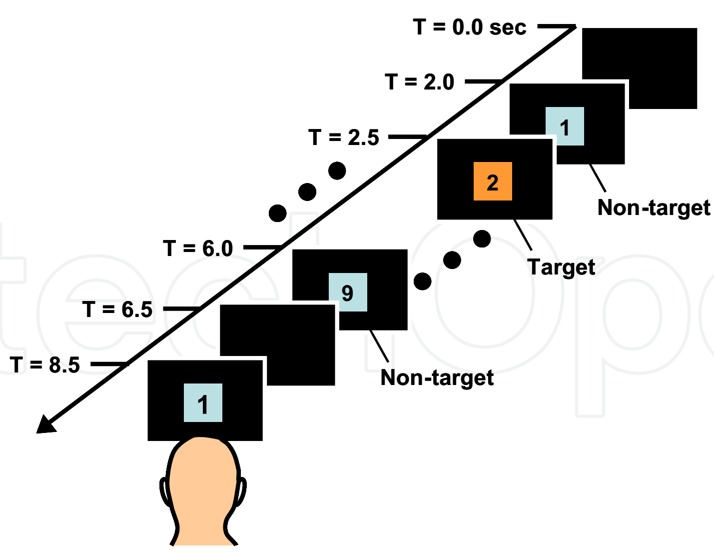

Fig. 3. The experimental task sequence. The subject focused attention on the centre of the interested photo images silently counting the number of times the images were presented.

Photo Number	Photo images
1	Face of a familiar man
2	Female bust with a bikini
3	Face of a baby
4	Face of a puppy
5	Girl's COSPLAY
6	Kiss of men
7	Broken buildings
8	Corpse of a bird (fake)
9	Dolls buried in mud

Table 1. Contents of Photo Images
The contents of photo images used in this study. These photo images were selected in advance by the author.

The task was to focus attention on one or more photo images in which the subject was interested and silently count the number of times that the target photos were presented (oddball tasks). These interested (target) photos were selected just before the experiment by subjects themselves and were keys for the personal identification. For non-interested (non-target) photo images, the subjects were instructed to ignore them. Most of the photo image sets were sampled by the author from a public photo archive Flickr (See the website). The contents of photo images are shown in Table 1, which includes the image of 'Face of a puppy' 'Girl's COSPLAY', and so on.

3. Analysis Protocols

To perform the personal identification focusing on the effect of non-target stimuli, the following analysis protocols were adopted.

3.1 Questionnaire

After the EEG recordings, the subjects received a brief questionnaire. A question was *"Which were your target photos?"* These results were used in the following analyses to assign the tags of 'target' and 'non-target'.

3.2 Averaging

The uniqueness of the recorded EEG activities is one of the important keys to achieve the personal identification. To check this briefly, the average waveforms both for target and for non-target photos were at first investigated for each subject.

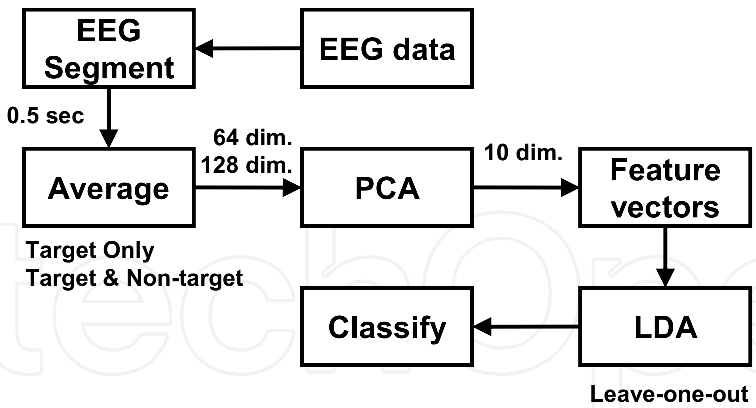

Fig. 4. The identification algorhithm. The Principal Component Analysis (PCA) was used to reduce the dimension of the feature vectors. The classification is done using Linear Discriminant Analysis (LDA).

3.3 The Identification Algorithm

For the personal identification, the EEG data both during target and non-target photo retrieval were extracted for each subject. The datasets were categorized into five according to five subjects. There were totally 1,000 single-trial target EEG datasets for all subjects.

For future applications, only one-channel EEG was investigated in the identification. To examine the use of the non-target photos, the feature vectors were constructed not only from the EEG during target photo retrieval also non-target. From one electrode site Cz, the EEG potential values were considered to have 128-dimensional feature vectors from the 0.5 sec of samples of temporal EEG signals (0.5 sec x 128Hz x 2 (target and non-target)). For target data only, half of the 128 dimensions were considered. The number of the feature dimension was reduced to 10 by applying PCA. Linear Discriminant Analysis (LDA) was used for the classification (Fig. 4). To estimate the identification performance a leave-one-out method was adopted, where only one data was used for the testing and the others were for the trainings. In our study, the number of times of averaging for the non-target photos was twice of that of target photos.

4. Results

In the questionnaire, it was found that the numbers of the selected photos were three, one, two, one and three among nine photo images for the subject s1-s5, respectively.

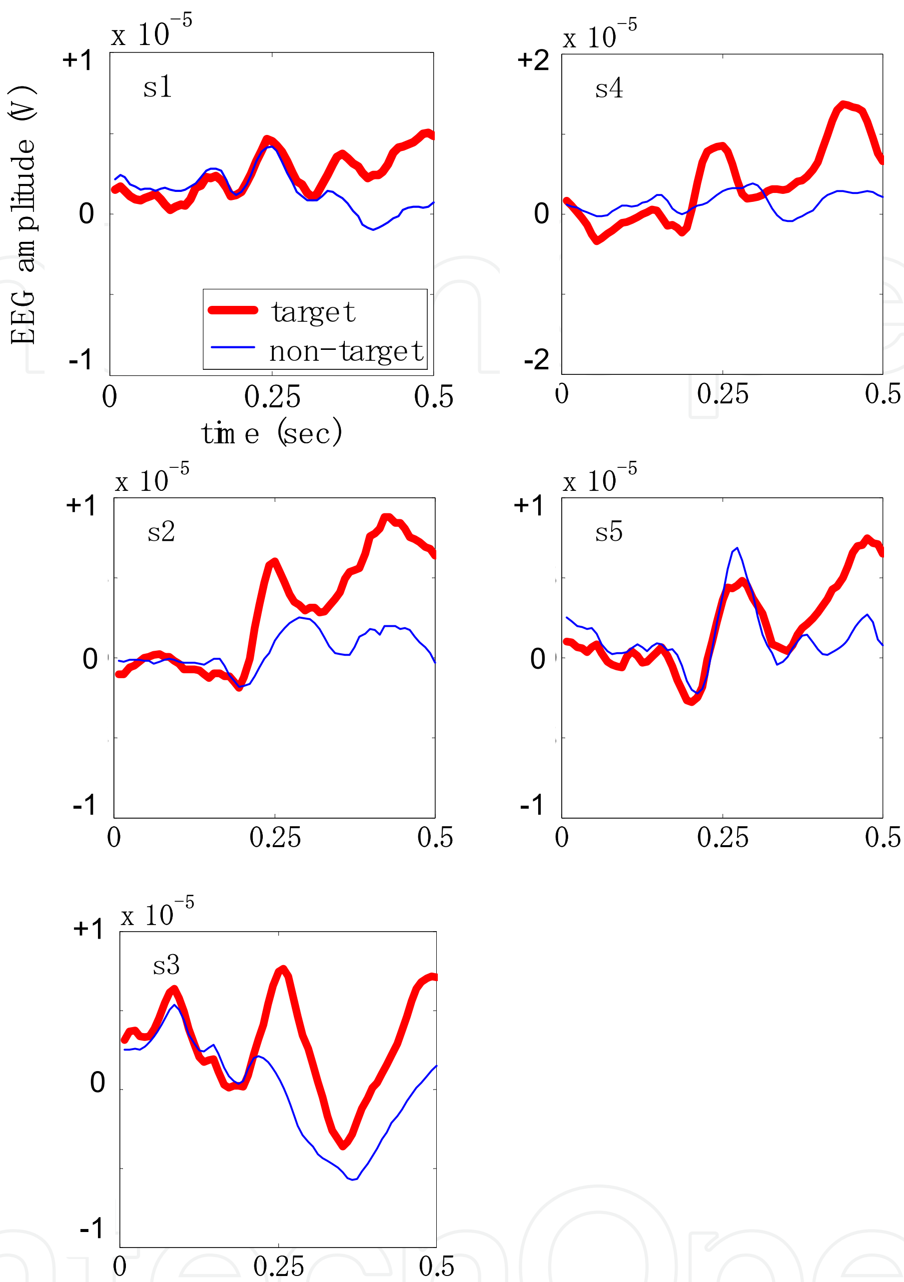

Fig. 5. Average waveforms on one electrode site Cz during target and non-target photo retrieval. The positive potentials were expressed in upper directions (y-axis).

In Fig. 5, it was clearly found that the target and non-target waveforms of each subject were very unique, which would be responsible for the personal identification. The tendency of the enhancements of the EEG amplitudes beyond 0.3sec was observed with target photo images for all subjects. The P300 evoked potentials were clearly observed for some subjects, which would be responsible for the high performance of the oddball-based BCI controls (Krusienski et al., 2007). In our previous works, the identification between target and non-target photo images could be done with 80-90% of the identification performances (Touyama & Hirose, 2008).

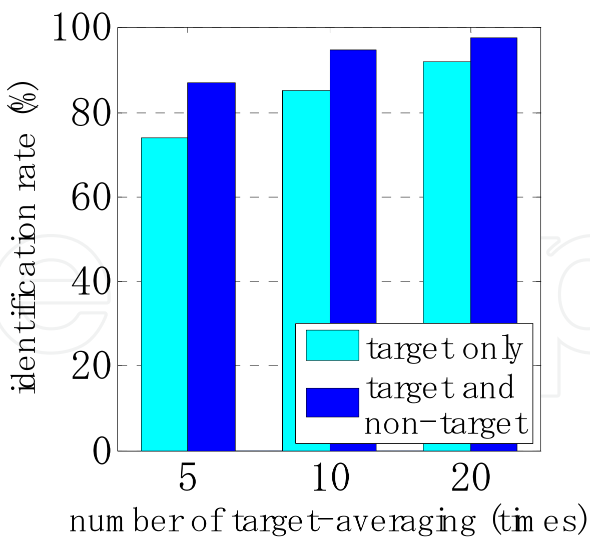

Fig. 6. The dependence of the number of target-averaging times on personal identification rates.

Fig. 6 shows the estimated personal identification rates. It was found that the performances were successfully improved if we consider both target and non-target retrieval. The rates were 87.2, 95.0 and 97.6% for 5, 10 and 20-time target-averaging, respectively. Only with target retrieval, the performances were 74.1, 85.1 and 92.2% for 5, 10 and 20-time target-averaging, respectively.

5. Discussions

In this study, by using human brain activities, the possibility of the personal identification was addressed in offline analyses. It was found that the personal identification was possible with high identification rate using only one-channel EEG signals during photo retrieval. In particular, the performance was enhanced if the system involved the EEG during non-target photo retrieval in addition to that during target photo retrieval. The enhanced performance was 95.0% with 10-time averaging. It was found that the number of averaging time more than 20 had a tendency of saturated performances.

Usually, in the oddball paradigm, the non-target stimuli are more frequently prepared and presented than target ones. Thus, we have lots of non-target stimuli. This means we have a large number of EEG averaging time for non-target stimuli, which would yield to the enhanced performance of EEG based personal identification.

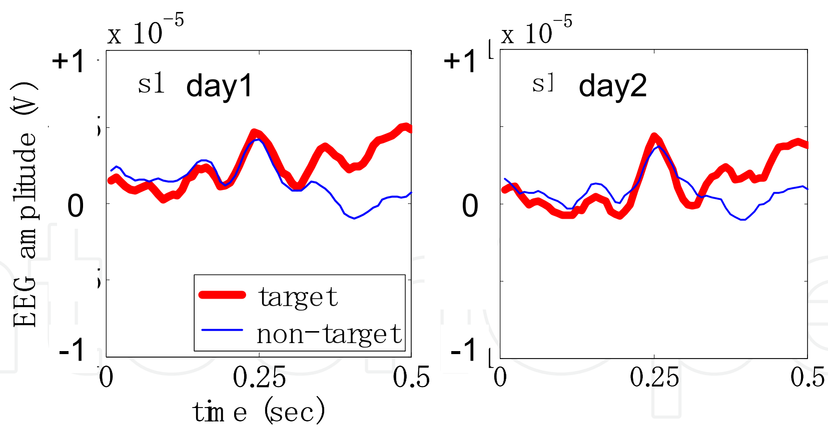

Fig. 7. EEG waveforms during target and non-target photo retrieval for different photo image sets. This result was obtained with the subject s1 over two days (left: day1, right: day2). In both cases, the number of target photos was three. The positive potentials were expressed in upper directions (y-axis).

The subjects in this study selected freely their interested photo images just before the EEG measurement. Our additional experiments revealed the reproducible waveforms if the photo image sets were exchanged to others. One of the examples was shown in Fig. 7. This result suggested the possibility to change target (or non-target) photo images ('password') on purpose, which would be one of the advantages of the EEG-based biometry in oddball paradigm. Furthermore, note that the photo retrieval tasks are easy to achieve for ordinary people.

Here, there were several points to be considered for future developments. The first one is to shorten the time during photo retrieval. According to the experimental protocols in this study, the minimum time to obtain 10-time averaging of target EEG was 15.0 sec (= 4.5 sec x 10 times / 3 photos), if the subject selected three among nine photo images. The increase of the target photo images would be one of the solutions, while the decrease of the P300 amplitudes might be accompanied by more frequent presentations of the target photo images. The second is the authentication. In our study, only the identification was addressed. But, for the practical use, the authentication is very required. In the authentication, the system must confirm and deny the identity claimed by a person (Marcel et al., 2007). The third is the number of the subjects. There is still a possibility to reduce the identification performance with many subjects (for example, more than 100 people). Then, more sophisticated classification algorithm will be investigated in future works.

To achieve higher performance within short time period, there is a possibility to combine other possible brain signals with P300 evoked potentials. For example, in our previous works on the BCI using steady-state VEP, the power spectrum density of such kind of VEP could be different between people. Thus, a variety of experimental tasks should be considered in one experimental session, which will be investigated quantitatively in future works.

The EEG-based personal identification and authentication was motivated and driven by the novel studies on the BCI. The personal identification system would serve rich controls of the BCI systems.

6. Conclusions

In this study, we investigated the feasibility of personal identification using one-channel EEG during photo retrieval in oddball paradigm. The use of non-target photo images was explained to improve the identification performances. The PCA and the LDA were applied to have the identification rates in offline. It was found that the performances were successfully improved if non-target photo retrieval was considered as well as target photo retrieval. The identification rates were 87.2, 95.0 and 97.6% for 5, 10 and 20-time target-averaging, respectively. This study revealed a future possibility of photo retrieval tasks to realize the personal identification using human brain activities, which will yield rich controls of machine for the each user of brain computer-interface.

7. Acknowledgment

This work was partly supported by Tateisi Science and Technology Foundation in Japan.

8. References

Bayliss, J.D. (2003). The use of the evoked potentials P3 component for control in a virtual apartment, *IEEE Transaction on Neural Systems and Rehabilitation Engineering,* 11 (2).

Blankertz, B.; Dornhege, G.; Krauledat, M.; Muller, K.R.; Kunzmann, V.; Losch, F. & Curio, G. (2006). The Berlin Brain-Computer Interface: EEG-based communication without subject training, *IEEE Trans Neural Syst. Rehabil. Eng, 14*(2), Jun, pp. 147-152.

Cheng, M.; Gao, X.; Gao, S. & Xu, D. (2002). Design and Implementation of a Brain-Computer Interface With High Transfer Rates, *IEEE Transactions on Biomedical Engineering, 49*(10), pp. 1181-1186.

Farwell, L.A. & Donchin, E. (1988). Taking off the top of your head: Toward a mental prothesis utilizing event-related brain potentials, *Electroenceph. Clin. Neurophysiol., 70,* pp. 510-523.

Krusienski, D.J.; Sellers, E.W.; McFarland, D.J.; Vaughan, T.M. & Wolpaw, J.R. (2008). Toward enhanced P300 speller performance, *Journal of Neuroscience Methods*, Vol. 167, Issue 1, pp. 15-21.

Marcel, S. & Millan Jose del R. (2007). Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation, *IEEE Transaction on pattern analysis and machine intelligence*, Vol. 29, Issue 4, pp. 743-752.

Middendorf, M.; McMillan, G.; Calhoun, G. & Jones, K.S. (2000). Brain-Computer Interfaces Based on the Steady-State Visual-Evoked Response, *IEEE Transactions on Rehabilitation Engineering, 8*(2), pp. 211-214.

Paranjape, R. B.; Mahovsky, J.; Benedicenti, L. & Koles, Z. (2001). The Electroencephalogram as a Biometrics, *Proc. Canadian Conf. Electrical and Computer Engineering*, Vol. 2, pp. 1363-1366.

Palaniappan, R. & Mandic, D.P. (2007). Biometrics from Brain Electrical Activity: A Machine Learning Approach, *IEEE Transaction on pattern analysis and machine intelligence*, Vol. 29, No. 4, pp. 738-742.

Pfurtscheller, G. & Neuper, C. (1997). Motor imagery activates primary sensorimotor area in man, *Neurosci Lett, 239*, pp. 65-68.

Poulos, M.; Rangoussi, M.; Chrissikopoulos, V. & Evangelou, A. (1999). Parametric Person identification from the EEG Using Computational Geometry, *Proc. IEEE Int'l Conf. Electronics, Circuits, and Systems*, Vol.2, pp. 1005-1008.

See the website, http://www.flickr.com/.

Thorpe, J.; van Oorschot, P. C. & Somayaji, A. (2006). Pass-thoughts: Authenticating with Our Minds, *Proceedings of the 2005 Workshop on New Security, The Association for Computing Machinery*, New York.

Touyama, H. & Hirose, M. (2008). EEG-Based Photo Pickup, *Proceedings of 18th International Conference on Artificial Reality and Telexistence (ICAT 2008)*, pp. 277-280.

Wolpaw, J.R.; Birbaumer, N.; McFarland, D.J.; Pfurtscheller, G. & Vaughan, T.M. (2002). Brain-computer interfaces for communication and control, *Clinical Neurophysiology, 113*, pp. 767-791.

Biomedical Engineering

Edited by Carlos Alexandre Barros de Mello

ISBN 978-953-307-013-1
Hard cover, 658 pages
Publisher InTech
Published online 01, October, 2009
Published in print edition October, 2009

Biomedical Engineering can be seen as a mix of Medicine, Engineering and Science. In fact, this is a natural connection, as the most complicated engineering masterpiece is the human body. And it is exactly to help our “body machine” that Biomedical Engineering has its niche. This book brings the state-of-the-art of some of the most important current research related to Biomedical Engineering. I am very honored to be editing such a valuable book, which has contributions of a selected group of researchers describing the best of their work. Through its 36 chapters, the reader will have access to works related to ECG, image processing, sensors, artificial intelligence, and several other exciting fields.