EEG Biometrics for User Recognition using Visually Evoked Potentials

Rig Das[1], Emanuele Maiorana[2], Daria La Rocca[3], Patrizio Campisi[4]

Section of Applied Electronics, Department of Engineering
Roma Tre University
Via Vito Volterra 62, 00146 Roma, Italy,
{rig.das[1], emanuele.maiorana[2], daria.larocca[3], patrizio.campisi[4]}@uniroma3.it

Abstract: Electroencephalographic signals (EEG) have been long supposed to contain features characteristic of each individual, yet a substantial interest for exploiting them as a potential biometrics for people recognition has only recently grown. The biggest advantages of EEG-based biometrics lie in its universality and security, while its major concerns are related to the acquisition protocol that can be inconvenient and time consuming. This paper investigates the use of EEG signals, elicited using visual stimuli, for the purpose of biometric recognition, and evaluates the performance obtained considering various frequency bands, different number of visual stimuli, and various subsets of time intervals after the stimuli presentation. An exhaustive set of experimental tests has been performed by employing EEG data of 50 different healthy subjects acquired in two different sessions, separated by one week time.

1 Introduction

Biometrics-based recognition is an active area of research which has brought to the deployment of automatic recognition systems using mainly fingerprints and face for real life application [JRN11]. In recent years, a growing interest emerged for alternative biometric identifiers like vein patterns, electrocardiographic (ECG) signals, electrodermal response, or electroencephalographic (EEG) signals, to cite a few. Specifically, brain signals, acquired trough electroencephalography, have been investigated mainly in the medical arena. However, despite having large interest in medical applications, EEG signal's use as a biometric identifier is relatively new [CLR14]. The advantage of using EEG biometrics relies mainly in its security being brain signals not acquirable at a distance which makes difficult their synthetic replica [CLR14]. However, one disadvantage of using EEG signals for people recognition is the difficulty for setting up the subject for EEG acquisition and creating an ideal environment for it. The acquisition process in fact requires placing multiple electrodes over the subject's scalp. These electrodes senses the electrical field generated by the brain during resting states or while performing specific tasks, such as receiving audio-visual stimuli, performing imagined or real body movements, speech, etc. The resting state condition or protocol has been for instance considered in [RCS13], where the repeatability of discriminative characteristics of EEG signal over time has been partially addressed, which is essential for biometric recognition. Among the different brain responses that can be acquired as the result of a brain stimulation, in this paper we rely on the visually evoked potentials (VEP), a kind of Event-Related potentials (ERPs) that refer to the electrical potential modification due to brief visual stimuli and recorded from the scalp over the visual cortex [GPP12]. Within this regard, the focus of this paper is the performance evaluation of EEG-based biometric verification based on VEP responses. Specifically, EEG data collected from 50 healthy subjects during two different sessions, acquired at time T_0 and T_0 + 1 week, are employed to test the effectiveness of VEP as a potential biometrics. This large and multiple-sessions database allows us having a significant number of comparisons for a stable and practical result. It is in fact worth remarking that, although several techniques have been recently proposed for EEG-based biometric recognition, most of them have been tested either on small databases with more than a single session, or on datasets comprising recordings from a single session for performance evaluation. In more detail, this paper evaluates the performance achievable when considering various EEG frequency bands. The performed experiments investigate which is the best performing subband among different combinations of different bands in $[0.5; 14\,]Hz$, the most relevant for our analysis [Bas99, CLR14, RCS13]. Moreover, experiments are performed for finding the minimum number of visual stimuli that are required for generating a single ERP, and the best time interval after producing the visual stimuli that can be considered as a EEG signal latency.

2 Related Work on VEP Based Biometric Recognition

In this section some of the earlier works which had evaluated VEP as a potential biometrics are briefly reviewed (Table 1). In [Tou09] Touyama has investigated the possibility of person identification by extracting the P300 evoked potentials from the generated EEG signal, during a target and non-target photo retrieval task. The authors have used Principal Component Analysis (PCA) on the time sequences along with Linear Discriminant Analysis (LDA) for classification, and examined the identification performance. Five male subjects have been considered, with every subject's EEG response acquired for five sessions on a same day upon producing target and non-target stimuli. Each session contained 20 trials with 9 images. For performance evaluation the $0.5-30$ Hz sub-band has been considered, while only the C_z Channel (according to 10-20 international standard) has been used. A leave-one-out approach has been employed by mixing the EEG signals from different sessions for training purposes. Both the target and non-target stimuli are considered together and a performance accuracy of 97.6% achieved. In [GPP12] Gupta et al. have considered EEG signals recorded as responses to three variations of the oddball paradigm: standard oddball, spatially varying oddball and Rapid Serial Visual Paradigm (RSVP), which is nothing but the stimuli on the same spatial position which minimizes the influence of irrelevant stimuli. Eight subjects (4 males and 4 females) have been employed for testing purposes, with acquisitions from a single sessions. Authors achieved a maximum Correct Recognition Rate (CRR) of about 97% when exploiting the RSVP paradigm, with the $1-12$ Hz bandpass frequency. In [YSL13] Yeom et al. have evaluated the differences of the averaged EEG signals generated in response to self-face and non-self-face images. Tests have been performed over 10 different subjects with signals captured in two sessions on different days, where each session included two runs, and each run further composed of 50 trials. For each trial, a total of 20 face images were presented (10 of self-face and

Table 1: Overview of state-of-the-art contributions using VEP from EEG signals as a biometrics.

Paper	DB	Ch.s	Features	Classifier	Performance	Sessions
[DZGE09]	20	20	LDA	KNN	CRR=94%	1
[PM07]	102	61	MUSIC spectrogram	Elman NN	GAR=98.12%	1
[Pal04]	20	61	spectral power ratio	BP NN	CRR=99.15%	1
[GPP12]	8	8	P300	LDA	CRR=97%	1
[Tou09]	5	1 (Cz)	PCA	LDA	CRR=97.6%	5, same day
[YSL13]	10	8	Adapt. discriminative feat.	Non-Linear SVM	CRR=86.1%	2, diff. days

10 of non-self-face images), i.e. 100 trial for each session and 200 trials overall. Cross-validations are performed with random selection of 180 trials for training and remaining 20 trials for test. The proposed method has achieved an overall CRR of about 86.1% with both false acceptance rate (FAR) and false rejection rate (FRR) of 13.9%.

In [DZGE09] Das et al. have used VEP data for person identification. 20 different subject's EEG signal have been collected, using a visual perceptual task in which filtered noise was added with the visual stimuli. Face and car images have been used as a visual stimuli and each of them appeared for $40ms$, after that the subjects had to identify whether a stimuli is car or face. They have also shown that a period of $120 - 200ms$ after the stimulus is the most informative with respect to the individual discrimination. Authors have obtained a classification accuracy around 75% to 94% for the best performing post-stimulus set. This shows that the VEP signals are crucial for person recognition. In [Pal04] R. Palaniappan has investigated VEP data recorded from 20 subjects by producing a single stimuli, which consists of pictures of common objects represented by black and white line. A classification accuracy of 99.6% has been achieved by ANOVA tests on each of the 61 channels. Also in [PM07] Palaniappan et al. used similar protocol for $300ms$ VEP stimuli to collect the EEG signals. A total of 102 subjects were used for collection of EEG data from 61 channels for a total of 3560 VEP and the acquired signals were filtered through a $25 - 56$ Hz bandpass filter to retain the γ waves. The authors have also used CAR filter for reduction of intra-class variance and they have achieved 98.12% of accuracy using all channels. As already remarked in Section 1, most of already proposed works have evaluated recognition performance achievable with EEG signals when using acquisitions from a single session, or from multiple session yet while considering only few subjects. The present paper is the first one properly investigating the discriminative capabilities of VEP responses, by comparing the signals captured from a large number of users during distinct recording sessions, as described in Section 4.

3 Proposed Biometric Recognition System using VEP

3.1 Employed VEP Acquisition Protocol

In this framework we use eight different geometric shapes, as described in Figure 1(c), to generate VEPs. Among these shapes, the circle is considered as target stimulus, with every subject asked to concentrate on it as it appears in the screen. An ERP response is therefore expected to be noted when the target shape appears on the display. All the other

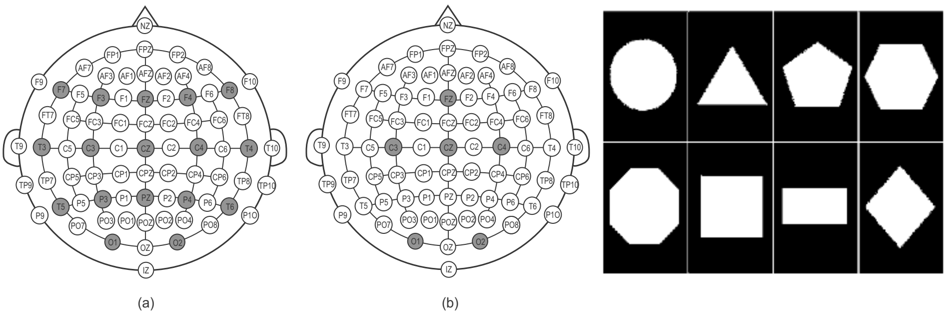

Figure 1: Selected electrode positions. (a) 17 Selected electrodes or Channels, (b) 6 Selected electrodes or Channels $[F_z, C_3, C_z, C_4, O_1, O_2]$, (c) Shapes employed for the Geometric Protocol.

shapes are considered as a non-target stimulus. Each of these shapes is shown for 250 ms, and repeated for 60 times. The EEG data are acquired from 19 different electrodes that are positioned on brain scalp according to the 10-20 international standards. For experimental purposes we consider both kind of responses, generated after the presentation of target and non-target shapes. Specifically, for verification purpose each and every users' acquired EEG signals are compared using the following three schemes, these are: **[Target vs. Target]:** where the recorded EEG signal has been generated due to the target stimulus; **[Non-Target vs. Non-Target]:** EEG signal that has been generated due to the non-target stimuli; **[(Target - Non-Target) vs. (Target - Non-Target)]:** generated by subtracting the EEG signal generated by target and non-target stimuli

3.2 EEG Data Analysis

A preprocessing step is first carried out on the recorded EEG data to increase their signal-to-noise ratio. Specifically, for each subject a Common Average Referencing (CAR) filter is used to calculate the mean of all channels, and subtract this value from all the output channels [CLR14]. The CAR filtered data are then down-sampled up to $128\,$Hz from existing $256\,$Hz using a proper anti-aliasing bandpass filter, and then spectral filtered to $0.5 - 40\,$Hz to retain all the relevant information which are required for feature extraction. The data are then normalized using Z-score transformation to have a zero mean and unitary standard deviation. Finally the data is detrended, by subtracting the mean or a best fit line from the data. After the described preprocessing, performed in all the considered experimental tests, a specific subband is isolated for extracting discriminative information from the available signals. As discussed in Section 4, we in fact perform an analysis of the best performing EEG subband or subband combinations in the range $[0.5; 14\,]$ Hz, conducted when considering the [Target vs. Target] scenario. We also analyze which is the best performing time interval after the stimulus presentation, with a maximum interval of $0 - 700$ms. Specifically, all the possible time intervals $\Delta_T = [t_b; t_e]$, where t_b and t_e values can vary in between $\{0; 100; 200; 300; 400; 500; 600; 700\}\ ms$, can be considered for this aim. As reported in Section 4, also for this analysis a large set of tests are performed for user verification by considering [Target vs. Target] scenario. Once the recorded signals have been filtered, and a specific time interval after the presentation of the stimuli has been determined, the EEG signal corresponding to the target and non-target stimulus

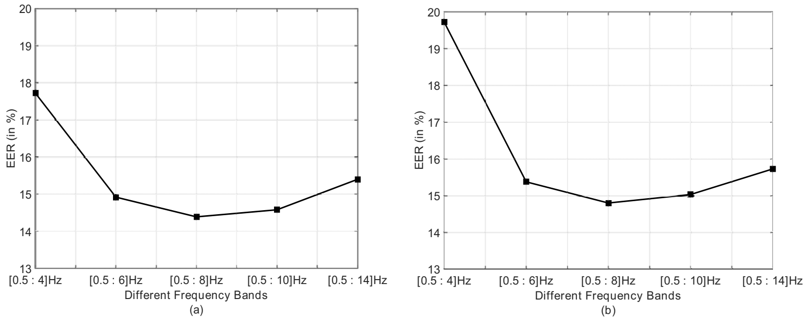

Figure 2: EER *vs* frequency range for (a) 17 and (b) 6 channels fusion

can be processed in order to extract a VEP waveform from them. This task is performed by averaging the responses taken from N events. Since we have 60 events available for each considered shape, as described in Section 4 we select $N = \{20; 30; 40; 45; 50\}$ in the performed tests, to investigate the performance dependence on the number of considered events. The comparison between two VEP waveforms, extracted from two different recording sessions, is performed by resorting to the cosine or to the Euclidean distance. Specifically, the responses extracted from each channel are first compared between them, and the M computed distances are then fused into a single score by taking their average as the output of the matching process. In more detail, in our experiments we consider the responses collected from $M = 17$ channels, selected from the available 19 ones by excluding the two frontal ones, i.e. F_{p1} and F_{p2}, since VEP responses are known to be mostly present in central and occipital regions. In order to minimize the number of employed electrodes, thus reducing the user inconvenience, we also consider a configuration using $M = 6$ channels: $[F_z, C_3, C_z, C_4, O_1, O_2]$. This latter configuration is in fact often employed for BCI applications based on VEP protocols [WW12]. Both the employed montages are shown in Figure 1(a),(b).

4 Experimental Results and Discussion

As already remarked, the experimental validation is performed over a database of EEG signals collected from 50 healthy subjects during 2 different sessions, acquired at one week distance each other. We first focus on the Target vs. Target scenario, where the VEPs generated in correspondence of the selected trigger are employed for biometric recognition. Within this scenario, we evaluate the best performing frequency range, time interval and number of observed events in the following subsection. In more detail, all these evaluations are performed through a cross-validation test by selecting, for 10 different times, a total of N events from the EEG signals during the first recording session of each user, to build the associated enrollment dataset. For each time, intra-class comparisons are performed by randomly selecting, for 10 different times, N events from the second recording session of the tested user as authentication probes. The dimensionality of the number of intra-class comparisons considered for performance evaluation is therefore $[50 \times 10 \times 10]$. Inter-class comparisons are instead obtained by randomly selecting, for each enrolled user, other 20 subject acting as impostors, and selecting N random events from their recordings

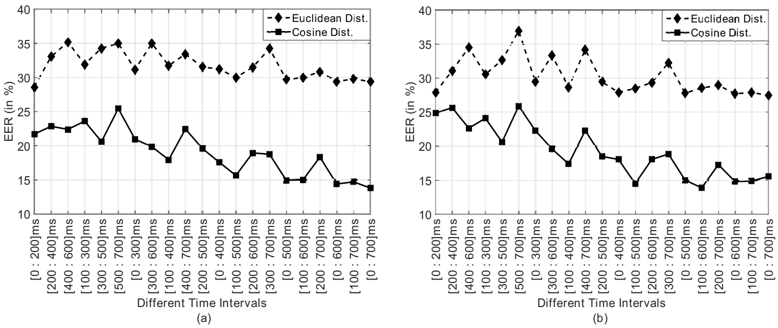

Figure 3: EER *vs* time intervals Δ_T (after visual stimuli) for (a) 17 and (b) 6 channels fusion

from session-2. The dimensionality of the number of inter-class comparisons is therefore $[50 \times 10 \times 20]$. This way, we can evaluate the performance in terms of FRR, FAR and equal error rate (EER) through a very large sets of genuine and impostors comparison scores.

4.1 Results of Frequency Range Selection

For the selection of the best performing frequency range we have set the $\Delta_T = [0; 600]$ms time interval, and evaluated the performance of frequency ranges in between $[0.5; 4\,]Hz$, $[0.5; 6\,]Hz$, $[0.5; 8\,]Hz$, $[0.5; 10\,]Hz$, $[0.5; 14\,]Hz$ when considering the cosine distance for generating matching scores. The performance evaluation tests are done for both the $M = 17$ channels and the $M = 6$ channels configuration, as detailed in Section 3.2. $N = 45$ events are considered for generating ERP responses from the considered target stimuli. Figure 2 shows the performance of all the above mentioned subbands, and it can be clearly seen that $[0.5; 8\,]Hz$ sub-band is the better performing one for both the 17-channel and the 6-channel combinations. Similar experiments are also performed for other frequency ranges such as $[4; 8\,]Hz$, $[4; 14\,]Hz$ and $[8; 14\,]Hz$. Nonetheless, the EER increases substantially for all these latter cases.

4.2 Results of Time Interval Selection

Given the $[0.5; 8\,]Hz$ frequency band, several time intervals Δ_T, starting at the visual stimuli time presentation, are then considered. Figure 3 shows the performance obtained for various Δ_T values, for both the 17-channel and the 6-channel configurations and considering VEP responses obtained with $N = 45$ events. We omit the results obtained for time intervals lasting 100ms from Figure 3, since in these cases the EER is always greater than 25%. To find the best performing distance metric, we also consider the Euclidean (L2) and manhattan (L1) distances along with the cosine one, finding out that the L1 distance performs almost as similar as L2 distance, whose associated performance is reported in Figure 3. It can be clearly seen that matching performed using the cosine distance outperforms the Euclidean distance calculation as cosine distance measures the similarity of vectors by considering the direction of the signal with respect to the origin while Euclidean distance measures the distance between particular points of interest along the vector; e.g. magnitude. So, by considering the entire EEG signal and its direction produces better result than only considering the magnitudes at some particular points; as the magnitude may be same for different EEG signals coming from different sources. Better results are

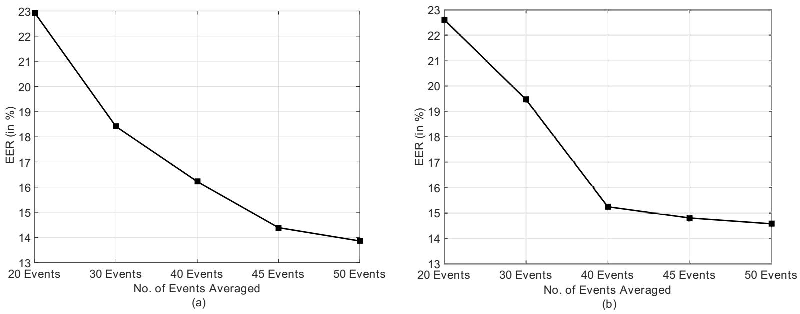

Figure 4: EER *vs* different no of events Δ_N for (a) 17 and (b) 6 channels fusion

typically obtained when considering a large time interval for the considered VEPs, not focusing only on the temporal interval characteristic of ERP responses.

4.3 Results of Required Minimum Number of Events

Having set the $[0.5; 8\,]Hz$ frequency range and the $\Delta_T = [0; 600]ms$ time interval, we also evaluate the performance dependency on the number of events considered for generating VEP responses in Figure 4. The reported results are obtained having set the $[0.5; 8\,]Hz$ frequency range and the $\Delta_T = [0; 600]ms$ time interval, while changing the number of events N as explained in Subsection 3.2. It can be clearly seen that the EER is inversely proportional to the number of events, and VEPs generated by averaging $N = 50$ events produce the lowest EER.

4.4 Performance Evaluation of Proposed Recognition System

By considering $[0.5; 8\,]Hz$ frequency range, $\Delta_T = [0; 600]ms$ time interval and $\Delta_N = 50$ events as selected system parameter, further experiments are carried out to compare the performance achievable when considering the [Target vs. Target], [Non-Target vs. Non-Target] and [Target $-$ Non-Target vs. Target $-$ Non-Target] scenarios. Specifically, in order to present results with a high statistically significance, in this case we carry out a cross-validation process by selecting, for 20 different runs, 40 subjects out of the available 50 for estimating the achievable recognition performance. The rates reported in the following are obtained as the average of the results obtained during each run. Specifically, for each run we evaluate intra- and inter-class scores as described at the beginning of this section, performing several divisions of the data in sessions 1 and 2 to respectively generate the enrollment and testing datasets. Therefore, now the dimensionality of the number of intra-class comparisons is now $[20 \times 40 \times 10 \times 10]$, while the number of inter-class comparisons employed to evaluate the FAR is now $[20 \times 40 \times 10 \times 30]$. Table 2 shows the calculated EER after performing the above mentioned comprehensive testing. It can be seen that by using either using the 17-channel or the 6-channel configuration, EER of around 14.5% can be achieved for the [Target vs. Target] scenario. However, for [Non-Target vs. Non-Target], the considered configurations achieve around 14% and 13% EER respectively. Worse results are obtained when performing comparisons between waveforms obtained as difference between the target and non-target responses. Therefore, it can be concluded from the above results that the [Non-Target vs. Non-Target] scheme is

Table 2: Performance Evaluation of Target and Non-Target stimuli by EER calculation.

Testing Schemes	EER (in %) for 17 Ch. Fusion	EER (in %) for 6 Ch. Fusion
[Target vs Target]	14.82	14.45
[Non-Target vs Non-Target]	13.55	14.01
[(Target − Non-Target) vs (Target − Non-Target)]	23.50	19.66

more stable than the other two, for both the considered channel configurations. This result leads us to consider [Non-Target vs. Non-Target] scheme and the 6-channel scheme for further research on achieving performance stability for EEG-based biometrics recognition.

5 Conclusions

In this paper we have investigated about the use of EEG for the purpose of automatic people recognition. Specifically, visually evoked potentials have been employed in our approach. An extensive dataset of 50 healthy people acquired in two sessions one week time apart has been employed. Different frequency subbands, time intervals and channel configurations have been tested. In summary our analysis can be considered as a preliminary step towards the assumption that, EEG signals generated as a result of VEP, are stable enough for its consideration as a biometric identifier.

References

[Bas99] Erol Basar. *Brain Function and Oscillations: Integrative Brain Function. Neurophysiology and Cognitive Processes*. Springer Series in Synergetics. Berlin: Springer, 1999.

[CLR14] P. Campisi and D. La Rocca. Brain waves for automatic biometric-based user recognition. *IEEE TIFS*, 9(5):782–800, May 2014.

[DZGE09] K. Das, S. Zhang, B. Giesbrecht, and M.P. Eckstein. Using rapid visually evoked EEG activity for person identification. In *IEEE EMBC*, pages 2490–2493, Sept 2009.

[GPP12] C.N. Gupta, R. Palaniappan, and R. Paramesran. Exploiting the P300 paradigm for cognitive biometrics. *Int. Journal of Cognitive Biometrics*, 1(1):26–38, May 2012.

[JRN11] A. Jain, A. Ross, and K. Nandakumar. *Introduction to Biometrics*. Springer US, 2011.

[Pal04] R. Palaniappan. Method of identifying individuals using VEP signals and neural network. *Science, Measurement and Technology, IEE Proceedings*, 151(1):16–20, 2004.

[PM07] R. Palaniappan and D.P. Mandic. Biometrics from Brain Electrical Activity: A Machine Learning Approach. *IEEE TPAMI*, 29(4):738–742, April 2007.

[RCS13] D. La Rocca, P. Campisi, and G. Scarano. On the Repeatability of EEG Features in a Biometric Recognition Framework using a Resting State Protocol. In *IEEE BIOSIGNALS*, '13.

[Tou09] H. Touyama. EEG-Based Personal Identification. *Biomedical Engineering, InTech Journal on*, (22):415–424, October 2009.

[WW12] J.R. Wolpaw and E.W. Wolpaw. *Brain-Computer Interfaces: Principles and Practice*. Oxford University Press, NY, USA, 2012.

[YSL13] S.K. Yeom, H.Il Suk, and S.W. Lee. Person Authentication from Neural Activity of Face-specific Visual Self-representation. *Pattern Recogn.*, 46(4):1159–1169, April '13.