BIOMETRIC AUTHENTICATION USING BRAIN RESPONSES TO VISUAL STIMULI

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Abstract: This paper studies the suitability of brain activity, namely electroencephalogram signals, as raw material for conducting biometric authentication of individuals. Brain responses were extracted with visual stimulation, leading to biological brain responses known as Visual Evoked Potentials.
We evaluated a novel method, using only 8 occipital electrodes and the energy of differential EEG signals, to extract information about the subjects for further use as their biometric features. To classify the features obtained from each individual, we used a one-class classifier per subject and we tested four types of classifiers: K-Nearest Neighbor, Support Vector Data Description and two other classifiers resulting from the combination of the two ones previously mentioned. After testing these four classifiers with features of 70 subjects, the results showed that visual evoked potentials are suitable for an accurate biometric authentication.

1 INTRODUCTION

This document presents a study on the suitability of induced electroencephalograms (EEGs) for implementing high-quality, practical biometric authentication systems. EEGs are impossible to forge because they reflect the inner self of a person, and they are likely to be different from person to person when performing similar mental activities. However, EEGs are complex and noisy signals, being affected by different brain activities and other body activities as well. Thus, we conducted our study with EEG signals measured in particular scenarios, namely with visual stimulations leading to very focused brain activities known as Visual Evoked Potentials (VEP). To the best of our knowledge, this is the first work on EEG-based authentication using VEPs, though some works exist on EEG-based identification using VEPs and EEG-based authentication using other brain activity stimuli (e.g. specific imagining tasks).

A biometric authentication system has four fundamental requirements (Jain et al., 2000):

- *Universality*: it should be possible to use the system with all persons.
- *Uniqueness*: the system should be able to separate different persons with a reasonably low failure probability.
- *Constancy*: biometric characteristics of the persons should remain fairly constant for a reasonable time (months, years).
- *Collectability*: biometric values should be easy to obtain, easy to quantify and cause no discomfort.

Considering the first requirement (universality), we believe that only a small percentage of people could not use the presented EEG authentication procedure. As we used the perception of simple drawings for triggering EEG signals, people with severe visual impairments or blindness cannot be authenticated.

Considering the second requirement (uniqueness), we did an empirical observation of the separation of individuals among a limited population of 70 people for which we had several EEG samples. Therefore, we have no proof that it will work on other populations, but we cannot as well anticipate any reason for not working.

Considering the third requirement (constancy), our study is still limited. Our authentication system uses images to trigger brain cognitive activities, which are then measured and classified. Cognitive activities may be affected by several factors, such as stress, fatigue, medication, alcohol ingestion, etc., some of them with natural daily variations. However, the raw EEG data used was collected from a set of people at a particular measurement session, thus not reflecting daily variations or even variations along the required time spans (months or years). Neverthe-

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less, in our study we concluded that EEGs collected in a row upon many similar visual stimuli are constant enough for implementing an authentication system based upon them, which is a good starting point.

Considering the fourth requirement (collectability), the current EEG measurement technology raises many problems. As EEG signals are very low-power, EEGs measurement must be done with special care to increase signal-to-noise ratios.

Finally, electrodes must be placed always in the same scalp location, an issue usually solved by using EEG helmets. We anticipate that the actual technological problems for EEG measurement may disappear in a near future, for instance, by using sensors under the scalp, thus we do not see it as a definitive barrier to the use of EEGs for biometric authentication. Nevertheless, in our study we made an effort to facilitate its deployment, both with the current technology or with future solutions. More specifically, we tried to get the best authentication results with the minimum possible set of electrodes (or EEG channels), all of them located in the occipital area of the brain, were the relevant EEG signals are to be measured.

For this study we did not obtain our own EEG samples from people. Instead, we used a public data set[1] containing EEG signals of 70 individuals, acquired with 64 electrodes after their visual stimulation. After an initial period of evaluation, we found that 8 channels, located in the occipital area, where cognitive workload is more relevant, were enough to achieve acceptable authentication results.

For authenticating people using VEP features we used personal one-class classifiers (OCCs). These classifiers get as input the VEP features of the person being classified and produce a TRUE/FALSE output value. We used two different OCCs in order to study which one would produce better authentication results: K-Nearest Neighbor (KNN) and Support Vector Data Description (SVDD) (Tax, 2001). After testing both classifiers, we also tested a two classification architectures combining both KNN and SVDD. These combined classifiers, that we nicknamed OR and AND , produce outputs after computing a logic function of the outputs of each individual classifier.

The results, obtained with personal OCCs of the four types, showed that VEPs can be used as a biometric data for authentication systems, producing results with high correctness, namely low false positive and false negative ratios. The results also showed that correctness is fairly stable for all evaluated subjects, an important requirement of biometric authentication systems.

[1] Hosted in http://kdd.ics.uci.edu

2 ELECTROENCEPHALOGRAMS

EEG signals are electric signals gathered in the scalp of an individual and result from the combination of signals from two different sources: (i) close-by cerebral activity (ii) and non-cerebral origins, such as eye motion, eye blinking and electrocardiac activity, called *artifacts*.

EEG signals are usually decomposed in several frequency bands. Each band contains signals associated with particular brain activities (Basar et al., 1995). The standard EEG frequency bands are: 0.5–3.5 Hz (δ), 4–7 Hz (θ), 8–15 Hz (α), 15–30 Hz (β), 30-70 Hz or around 40 Hz (γ). This last one, γ band, has been related both to gestalt perception (Keil et al., 1999) and to cognitive functions such as attention, learning, visual perception and memory.

For each particular brain activity there is one particular area that produces stronger electrical activity in one of the previously referred frequency bands; similarly, artifact manifestations are more relevant in some parts of the scalp than in others. Consequently, EEG signals are multi-channel signals, where each channel corresponds to a specific scalp electrode location. In this study we will consider only the occipital area of the scalp, which is known to provide stronger electrical signals in the γ band in response to visual stimulation and perception of pictures (W. Lutzenberger and F. Pulvermllera and T. Elbertb and N. Birbaumer, 1995; Tallon-Baudry et al., 1998; Gruber et al., 2002).

2.1 Visual Evoked Potentials (VEPs)

Visual evoked potentials (VEPs) are brain activity responses to visual stimuli, which may comprise different components, such as color, texture, motion, objects, readability (text vs. non-text), etc. Each of these components has impact in the spacial dispersion of the VEP through the scalp, being observed differently in each EEG channel and in different frequency bands. Therefore, for focusing the VEP production and analysis, the set of visual stimuli must be coherent, i.e., it should stimulate always the same brain areas.

Several research works (see Section 3) were previously conducted for achieving individual identification using VEPs produced upon the presentation of images from the Snodgrass and Vanderwart picture set (Snodgrass and Vanderwart, 1980). This standard set of 260 pictures was conceived for experiments investigating differences and similarities in the cognitive processing of pictures. The pictures are black-and-white line drawings executed according to a set of rules that provide consistency of pictorial representation.

Various studies (Başar, 1980; Başar et al., 1987; Galambos, 1992) showed that VEPs recorded from the human scalp contain a train of short latency wavelets in the γ band, precisely time locked to the stimulus and lasting approximately 100 ms. Furthermore, a more recent study showed that perception of pictures from the Snodgrass & Vanderwart picture set induced highly synchronized neural activity, in the γ band, between posterior electrodes (Gruber et al., 2002).

3 RELATED WORK

Poulos *et al.* (Poulos et al., 1998; Poulos et al., 1999) proposed a method to distinguish an individual from the rest using EEG signals. They performed a parametric spectral analysis of α band EEG signals by fitting to them a linear all-pole autoregressive model. The coefficients of the fitted model were then used as features for the identification component. In (Poulos et al., 1998) the identification component was built with computational geometric algorithms; in (Poulos et al., 1999) they changed it to a neural network, namely for a Kohonen's Linear Vector Quantizer (Kohonen, 1989). The cerebral activity was recorded from subjects at rest, with closed eyes, using only one channel and during three minutes.

Although the goal of Poulos *et al.* was person identification using his brain activity, in (Poulos et al., 1999) they experimented classification of a person as one of a finite set of known persons. In the tests they recorded 45 EEG features from each of 4 individuals (the X set) and one EEG feature from each of 75 individuals (the non-X set). The neural network was trained using 20 features from each X member and 30 features from non-X members. Then the system was used to classify the remaining 25 features of each X member and the 45 features from the remaining non-X members. This process was repeated for all the 4 X members, attaining a correct classification score between 72% and 84%.

Using VEPs and signals in the γ band to perform subject identification was proposed by Palaniappan (Palaniappan, 2004) and followed on his posterior studies (Palaniappan and Mandic, 2005; Ravi and Palaniappan, 2005b; Ravi and Palaniappan, 2005a; Ravi and Palaniappan, 2006; Palaniappan and Mandic, 2007). In all these works is used the same dataset of VEPs, recorded from 40 individuals and comprising a 61-channel EEG for 30 VEPs triggered by pictures chosen from the Snodgrass & Vanderwart set.

These six subject identification studies are all similar; they mainly differ in filtering and classification components. First VEP signals are processed to remove artifacts and noise caused by other background brain activities not related with the VEP. Next they are filtered with a pass-band, digital filter in to isolate signals from the γ band. Then, for each of the 61 channels is computed its spectral power and normalized with the energy values from all the 61 channels; the 61 resulting values form a feature array. These features are then used to perform subject identification using a classifier with as many output categories as the number of individuals used to train it; in this case there were 40 individuals, thus the classifier has 40 different outputs. In the experiments, half of the features from each individual were used to train the classifier and the other half for testing the correctness of its output. The tested correctness of all these approaches is somewhat similar, ranging from 85.59% up to 99.62%.

For filtering, in (Palaniappan, 2004; Ravi and Palaniappan, 2005a; Ravi and Palaniappan, 2006) a Butterworth filter was used, while in (Ravi and Palaniappan, 2005b; Palaniappan and Mandic, 2005; Palaniappan and Mandic, 2007) an elliptic FIR filter was used (in the latter the lower pass-band threshold was lower, 20 Hz). For classifying, in (Ravi and Palaniappan, 2005b; Palaniappan and Mandic, 2005; Ravi and Palaniappan, 2006; Palaniappan and Mandic, 2007) was used an Elman back-propagation neural network (Elman, 1990), in (Palaniappan, 2004) a back-propagation multi-layer perceptron, in (Ravi and Palaniappan, 2005a; Ravi and Palaniappan, 2006) a simplified fuzzy ARTMAP (Kasuba, 1993) and in (Ravi and Palaniappan, 2005a) a KNN.

Some attempts were made to reduce the number of channels used in these VEP-based approaches. In (Palaniappan and Mandic, 2007) Davies-Bouldin Indexes (Davies and Bouldin, 1979) were used to order the channels according to their relevance. Correct identification results using the most relevant DBI-oriented channels gave 13.63% with 1 channel, about 50% with 6 channels and 99.0% with 50 channels.

There are already several studies on authentication with EEG signals, but all them use different approaches (Marcel and de R. Milln, 2007; Sun, 2008; Palaniappan, 2008). The table below resumes some of their differences.

	(Marcel and de R. Milln, 2007)	(Sun, 2008)	(Palaniappan, 2008)
EEG channels	α, β	α, β, γ	α, β, γ
Electrodes	8	15	8
Feature array elements	96 (12 freqs./channel)	8 (CSP reduct.)	11 (PCA reduct.)
Tested subjects	9	9	5

In (Marcel and de R. Milln, 2007), authors collected EEGs from subjects performing 3 mental activities: imagination of movements with the right or left hand and imagination of words beginning with the random letter. Features' classification uses Gaussian Mixture Models and Maximum A Posteriori model adaptation. The correctness results were satisfactory but not very conclusive, because the number of evaluated subjects was too small (we used 70). A drawback of the classification approach is that it relies on a generic EEG model, which may not exist or requires training with EEGs from many people.

In (Sun, 2008), authors used 15 signals from the same dataset used in (Marcel and de R. Milln, 2007), raw feature reduction with common spatial patterns (CSP) and using multi-task learning to evaluate the advantage regarding single-task learning.

In (Palaniappan, 2008), authors collected EEGs from subjects performing 5 imagined activities: nothing in particular (baseline activity), mathematical multiplication, geometric figure rotation, letter composition and visual counting. Feature arrays are initially composed by 18 channel spectral powers, 27 inter-hemispheric channel spectral power differences and 18 entropy values (yielding the non-linearity of channel signals). Features are then reduced to 11 elements using Principal Component Analysis (PCA). Features' classification uses a two-stage authentication process using maximum and minimum threshold values stored in personal profiles. Like in the previous article, correctness results were satisfactory but even less conclusive, due to the extremelly small number of evaluated subjects (only 5).

All these three works used imagined activities to focus EEG-signals; we used VEPs instead. The advantages of VEPs is that they do not require any effort from the subjects being authenticated, as VEPs occur without any sort of human control. Furthermore, we did an evaluation with a larger population (roughly an order of magnitude more) than all these works, therefore our results yield a more trustworthy evaluation of the universality and uniqueness requirements. Finally, we did not use more electrodes than any of them, thus we do not require a more complex EEG acquisition setup.

Finally, some studies have been done with multimodal biometrics involving EEG signals (Riera et al., 2008). The main advantage of this approach regarding the simple EEG authentication is that one can reduce the number of electrodes (only 2 were used).

4 AN AUTHENTICATION SYSTEM USING VEP

As previously stated, our goal was to build an authentication system based only in occipital VEP EEG signals gathered by a small number of electrodes. Note that, authentication is different from identification: an identification system gives the identity of the subject being evaluated, while an authentication system gives a yes/no answer whether or not the subject being evaluated is who he claims to be.

The VEP-based identification systems developed by Palaniappan *et al.* are also not directly usable as authentication systems. These systems were designed for identifying members of a set X of N subjects, having N possible output classifications. When these systems are used by other non-X subjects, these will be identified as someone belonging to X. Thus, a non-X person being authenticated only has to guess the erroneous identity the system gives to him, in order to get an authentication match.

Therefore, a new architecture is required to use EEG patterns for authenticating individuals. We propose a new one where we merge part of the contributions of the previously referred systems with some new ideas introduced by us.

4.1 Personal Classifiers

Our key design principle is to analyse EEG patterns in the γ band, namely VEPs in occipital area of the brain, with *one classifier per individual*, and not a classifier for all individuals. Furthermore, we used an OCC for each personal classifier, which is the correct type of classifier for an authentication scenario. Thus, when a subject claims to be X, we use Xs OCC classifier to evaluate the correctness of the claim.

OCCs may have many inputs to handle the features obtained from subjects, but always two possible output responses: TRUE or FALSE. Each personal OCC is trained only with inputs provided by its owner. When the individual being evaluated is the owner of the classifier, the output should be TRUE; otherwise, the output should be FALSE. Other outputs are errors, either false negatives or false positives, respectively.

As previously referred, the goal for this new architecture was to use a reduced number of EEG channels. In the limit we would like to use only one channel, just like in the work of Poulos *et al.*. However, unlike the approach described in (Palaniappan and Mandic, 2007), we have not tried to detect the “best” channels (the ones with less correlation) from a set of measured features. Instead, we chose specific channel locations in the occipital area of the scalp and we ran authentication tests with them to find out the set of channels providing the highest authentication quality.

4.2 Authentication Process

Our authentication process is formed by three main components: (i) EEG signal acquisition, (ii) feature array extraction and (iii) feature array classification. First VEP EEG signals are acquired from electrodes placed in the subject's scalp. Then the feature array extractor processes raw EEG samples from C channels in order to extract a biometric measure of the subject: a feature array with C' energy values. Finally, this feature is processed by the OCC of the subject being authenticated, either to train the OCC or to get a TRUE or FALSE authentication outcome.

4.3 Description of the Data Set

As previously explained, we did not collect EEG signals for this study. Instead, we used a public data set registered for conducting other EEG studies, namely the genetic predisposition of people to alcoholism. Thus, it was not in any way specially gathered for authenticating people.

The data set is composed by EEG signals recorded from 70 individuals, both alcoholic and non-alcoholic, while exposed to short latency (300ms) visual stimuli. Each individual completed a total number of 45 trials corresponding to the visualization of 45 pictures from the Snodgrass & Vanderwart picture set. EEG signals were acquired by 64 electrodes (61 actives + 3 reference), placed in the individuals' scalp, hardware filtered with a 0.1–50Hz passband and measured at a sampling rate of 256 samples per second. For building our authentication system we considered only 8 occipital channels from the 64 available in the dataset — channels PO3, PO4, POZ, PO7, PO8, O1, O2 and OZ.

Individuals were asked to recognise the pictures as soon as they were presented in a CRT screen, located 1 meter away from individuals' eyes. Each picture was presented only for 300 ms, separated by blank screen intervals of 5.1 seconds. After each picture presentation, only 1 second of EEG signal was recorded, corresponding to the VEP occurrence interval.

4.4 Feature Array Extraction

VEP signals, which are raw EEG signals with 1 second measured after the presentation of the stimuli images, are the source data for for the biometric authentication process of each individual. The feature extraction procedure from these signals is detailed below.

Detection of Artifacts. First, VEP signals containing artifacts are discarded. We considered only artifacts produced by eye blinking, which are the most common and intrusive ones. Detection of eye blinking artifacts is achieved with an amplitude threshold method: VEP signals with magnitude above 50 μV are assumed to be contaminated (Sivakumar and Ravindran, 2006) so they are discarded .

EEG γ-band (30-50Hz) Frequency Filtering. The resulting artifact-free VEP signals are filtered with a 30-50 Hz pass-band, using a 10^{th} order Butterworth digital filter. The non-linearity of this filter was cancelled by using forward and reverse filtering. The resulting signal has zero phase distortion and an amplitude multiplied by the square of the amplitude response of the filter. After filtering, the 20 first and 20 last output samples are discarded, because they do not represent a properly filtered signal.

Signal Composition. For computing feature arrays we use C original EEG signals plus differential signals resulting from the subtraction of pairs of the C EEG signals. Thus, features include $C' = C + \binom{C}{2}$ signals, which in our case, for $C = 8$, means that $C' = 36$.

By computing differential signals from the subtraction of pairs of EEG signals we expect to provide to classifiers information about the phase of the EEG signals and not just information about their amplitudes (energies). Phase shifts between subtracted sinusoidal signals with equal frequency and amplitude produce non-null signals with an energy that is a function of the phase shift. Therefore, we included the energy of differential signals in the features because it could denote phase shifts between EEG channels, thus more information about the subjects.

These differential signals are somewhat similar to the ones used in (Palaniappan, 2008) but with two main differences: (i) we compute the energy of differential signals, while they compute differences between powers of different signals and (ii) we produce a differential signal from all pairs of signals, while they only compute differential powers between signal on different hemispheres. Thus, we are able to evaluate phase shifts on differential signals and we produce more information that may help to differentiate subjects.

Energy Calculation and Normalization. The energy of original and differential signals is computed with the Parseval's spectral power ratio theorem:

$$E(s) = \frac{1}{N}\sum_{n=1}^{N} s_n^2$$

where s_n is the n-th sample of signal s and N is the total number of samples in the signal. In our case $N = 216$, because we discard 40 samples of the 256 measured in 1 second of VEP after the γ filtering stage.

Finally, feature values are computed by normalizing the energy feature array. For this normalization we divide all array values by the maximum among them. This way, we get features with elements in the $[0,1]$ interval.

$$F\left[1\cdots C'\right] = \frac{E\left[1\cdots C'\right]}{max\left(E\left[1\cdots C'\right]\right)}$$

4.5 The Feature Classifier

The feature classifier is formed by independent, personal classifiers; so, for authenticating someone claiming to be X, we use the personal classifier of X, or the classifier *owned* by X. Each personal classifier is formed by an OCC, providing two different outputs (or classifications): TRUE and FALSE.

One-Class Classification is a type of classification where we deal with a two-class classification problem (target and outlier) but we only need to provide information to the classifier about the target class. During an OCC train, the boundary between the target class and all other possible outlier classes is estimated from the target class data only. In our authentication goal, the target class is the classifier owner while the outlier class represents all other individuals.

In our study we used two types of OCCs in order to check which one would produce better authentication results: KNN with k=1 and SVDD with a Radial Basis Function kernel (Tax, 2001). We also tested two other OCC architectures, combining the outputs the KNN with SVDD. The goal of the combinations was to evaluate if there was any advantage in combining them in order to complement their individual correctness. The OR combination uses arithmetical averages, and the AND geometrical averages. For simplicity, we will call the first a *OR KNN-SVDD* and the second a *AND KNN-SVDD*.

We also found out that each classifier should be trained with single features from its owner, but should be used for authentication with average tests F features, obtained from the visualization of F images of the subject. A possible explanation of this fact is the following. Perception activities performed by individual's brain are not exactly the same for all visual stimuli, resulting in different VEP features. By training the classifier with as different as possible VEP features from its owner, we improve its ability to recognize them in the future, disregarding possible noise occurrences. On the other hand, by averaging VEP features during authentication processes, we reduce the probability of presenting to the classifier features from its owner too different from the ones it was trained with.

During the training of each classifier, we have to provide a *rejection fraction threshold* that will be used to establish acceptance or rejection ratios. Low rejection fraction values lead classifiers to produce low false negative and high false positive ratios, while high rejection fraction values lead classifiers to produce high false negative and low false positive ratios. The choice of the best rejection fraction threshold implies a balance between security (low false positive ratio) and comfort for the individuals engaged in a correct authentication process (low false negative ratio).

5 EXPERIMENTATION

The number of feature arrays used per subject was variable, both from start (in the data set) and furthermore after eye blink detection. Therefore, we decided to test classifiers with fixed numbers of features and train classifiers with the maximum possible number of features until a given maximum. This is a conservative approach, since some classifiers may not have enough features to be properly trained. Nevertheless, we did not observe abnormal errors in such classifiers.

Thus, to train each personal classifier we used no more than 30 features of its owner. For testing each personal classifier, we used 15 features of its owner and 15 features from each of the other 69 subjects, which makes a total of 1050 test features. Note that each classifier had never "seen" the test feature before. The test features of each individual were used alone or averaged in pairs or trios. The number of features evaluated per classifier is presented in the table below.

Composition of features	Features evaluated per classifier	
	From the owner	Total
Single features	15	$70 \times 15 = 1050$
Pairs of features	$\binom{15}{2} = 105$	$70 \times \binom{15}{2} = 7350$
Trios of features	$\binom{15}{3} = 455$	$70 \times \binom{15}{3} = 31850$

We run authentication tests with all the proposed four classifiers, in order to verify which one of them is more suitable for our authentication system. In the tests we tried also to assess the impact of two configuration parameters for the overall correctness of the authentication system: OCC rejection fraction threshold and classification of multiple, averaged features.

5.1 Overall Evaluation Results

The overall biometric authentication results of the 70 classifiers for three rejection fraction thresholds and different combinations of features are summarized in Table 1. The values presented are the mean and standard deviation obtained from 10 independent tests with the 70 OCCs, each one of them using different features from the owner (to train and test his classifier) and from outliers (to test). The graphics of Fig. 1 show the values of these 10 independent tests per personal classifier, but only for the combined OR KNN-SVDD classifier, using single and trios of features.

Table 1: Mean and standard deviation (inside parenthesis) of correctness results for the four OCC classifiers obtained in 10 independent classification tests. Columns labeled 1, 2 and 3 represent tests using singular features and average combinations of pairs and trios of features, respectively.

	Rejection fraction	Owners Correctness(%)			Outliers acceptance (%)		
		1	2	3	1	2	3
KNN	0.2	78.7 (13.1)	90.6 (7.5)	95.1 (5.3)	5.2 (1.3)	5.6 (1.6)	6.4 (1.9)
	0.5	50.1 (15.9)	65.3 (9.3)	74.1 (8.6)	1.9 (0.7)	2.2 (0.9)	2.3 (1.3)
	0.7	31.3 (18.5)	46.1 (11.3)	66.3 (9.8)	0.9 (0.4)	1.1 (0.5)	1.3 (0.7)
SVDD	0.2	76.1 (12.8)	95.2 (4.9)	98.5 (3.5)	5.7 (1.8)	8.5 (2.1)	10.1 (3.2)
	0.5	58.5 (17.4)	88.3 (8.7)	93.7 (5.7)	2.8 (1.6)	4.4 (1.8)	5.1 (2.7)
	0.7	44.2 (20.5)	77.7 (12.3)	85.3 (9.8)	1.7 (1.6)	2.6 (1.7)	3.6 (1.9)
AND	0.2	83.3 (12.1)	96.4 (6.1)	99.0 (3.0)	4.5 (5.6)	6.0 (7.4)	6.8 (8.2)
	0.5	60.4 (16.8)	85.6 (12.4)	92.8 (11.3)	1.3 (2.2)	1.8 (2.9)	1.9 (3.0)
	0.7	37.8 (18.7)	68.4 (18.1)	79.4 (19.2)	0.4 (0.9)	0.6 (1.1)	0.6 (1.4)
OR	0.2	83.8 (11.0)	96.5 (6.0)	99.1 (3.5)	4.7 (5.7)	6.2 (7.6)	6.8 (8.4)
	0.5	59.7 (17.2)	85.7 (13.1)	92.8 (11.5)	1.2 (1.9)	1.7 (2.8)	2.0 (3.2)
	0.7	38.7 (18.2)	69.8 (18.1)	80.5 (18.1)	0.4 (0.8)	0.6 (1.2)	0.6 (1.3)

The results show that the rejection fraction threshold used while training classifiers had the expected impact on authentication results: for low rejection values the classifier provides a correct classification of its owner (low false negative ratio) but can be mislead by many other individuals (high false positive ratio), while for higher rejection values the correct classification of owners decreases but the same happens to the wrong acceptance of other individuals.

Comparing KNN and SVDD, we can conclude that both have advantages and disadvantages: KNN gives lower outliers acceptance ratios (false positives), while SVDD gives higher owners' correctness ratios (true positives).

The combined OR and AND KNN-SVDD classifiers also have advantages and disadvantages when compared with the isolated OCCs. In general, they decrease the false positive ratio and most times (67%) they increase the owners' correctness ratio. However, they have a noticeable tendency to increase the standard deviation of the results, being thus less assertive than the isolated OCCs. Comparing the two combined KNN-SVDD classifiers, the results show that they are quite similar, but the OR combination is slightly better.

Finally, these results clearly show that the quality of the authentication increases when we use combinations of features instead of singular features. In absolute value, the owners' correctness gain is much higher that the loss in the false positive ratio.

5.2 Evaluation of Individual Classifiers

From the graphics of Fig. 1 we can conclude that average classification results are fairly stable for all the considered subjects. Therefore, with these tests we have reasons to believe that a biometric authentication system using EEGs may be suitable for a large majority of the population. Note that the evaluated subjects already include a group of people (alcoholics) that may have visual cognition problems and that was not noticeable in the authentication results.

A good indicator about an OCC performance is the plot of its receiver operating characteristic (ROC) curve. A ROC curve is calculated with several tests of the classifier with different rejection fraction thresholds applied to target objects and shows the percentage of true positives in order to the percentage of the false positives during each test. Thus, ROC curves are useful to assert the effect of the rejection fraction threshold in tuning the correctness of the OCC.

The OCC with the best performance is the one that simultaneously maximizes true positive ratios and minimizes false negative ratios. This performance can be measure by calculating the area under curve (AUC). This way, the OCC with the higher AUC is assumed to be the OCC with best performance.

Figure 2 shows the ROCs of the 70 individual classifiers and their average AUC values for each of the four OCC types considered; these ROC curves where obtained with feature trios. These results clearly show that for evaluating trios of features the best OCC is the combined OR KNN-SVDD, while the worse is KNN.

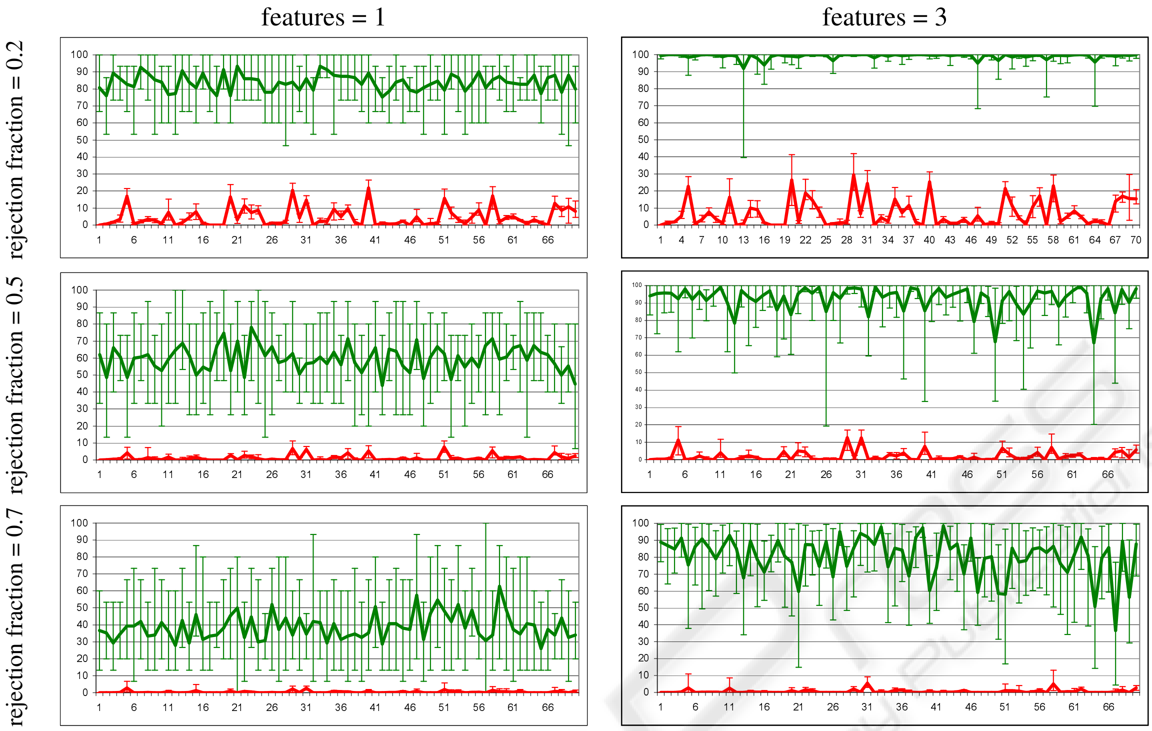

Figure 1: Average individual classification results of the combined OR KNN-SVDD classifier, obtained after 10 independent tests. The upper (green) curve in each graphic shows the average correct owner classifications per classifier, while the lower (red) curve shows the average false positives per classifier. The vertical line under each average value shows the maximum and minimum values observed in the 10 tests.

6 CONCLUSIONS

We presented in this paper a novel method for authenticating individuals using their brain activity. The EEG signals used were VEPs, i.e., brain responses associated to visual stimuli. In the described system we used EEG signals acquired with only 8 electrodes placed on occipital area of the brain, which is associated to visual and cognitive perception.

The authentication system presents several improvements over other previous works in the area of subject identification using VEPs. First, We used a reduced number of electrodes (8) and we placed them in the scalp area where EEG signals have more correlation with the stimuli. Second, we used the differences between pairs of the 8 EEG signals to create other signals (differential signals) that provide extra information to classifiers.

Third, feature arrays with the energy of original and differential EEG signals are classified using personal classifiers.

Forth, we used OCC personal classifiers instead of other types of classifiers (e.g. neural networks) or generic classifiers.

Fifth, OCCs are trained with single owner features but provide better results when tested with average of features instead of single ones.

Regarding other related systems, we used VEPs, which are effortless for subjects, while others used more complex and annoying brain stimuli, such as activity imagining, we obtained satisfactory results with a population one order of magnitude larger then the other proposals (70 vs. 5 or 9 subjects), and we did not use more electrodes (only 8). Therefore, our system has clear advantages regarding the collectability requirements.

Average results obtained with authentication tests with 70 individuals, using a public VEP data set, showed that authentication with EEGs is possible and may be used in future applications. The ratios of owner's correctness and false positives are fairly stable for the tested population, which is a positive indication for the universality and uniqueness of the process.

A fundamental requirement of biometric authentication was not evaluated in this document: constancy. In fact, we assumed that the public data set, per subject, was collected in a very short time, thus it is not possible to take any conclusions about the constancy of VEPs in other scenarios. Since several factors may

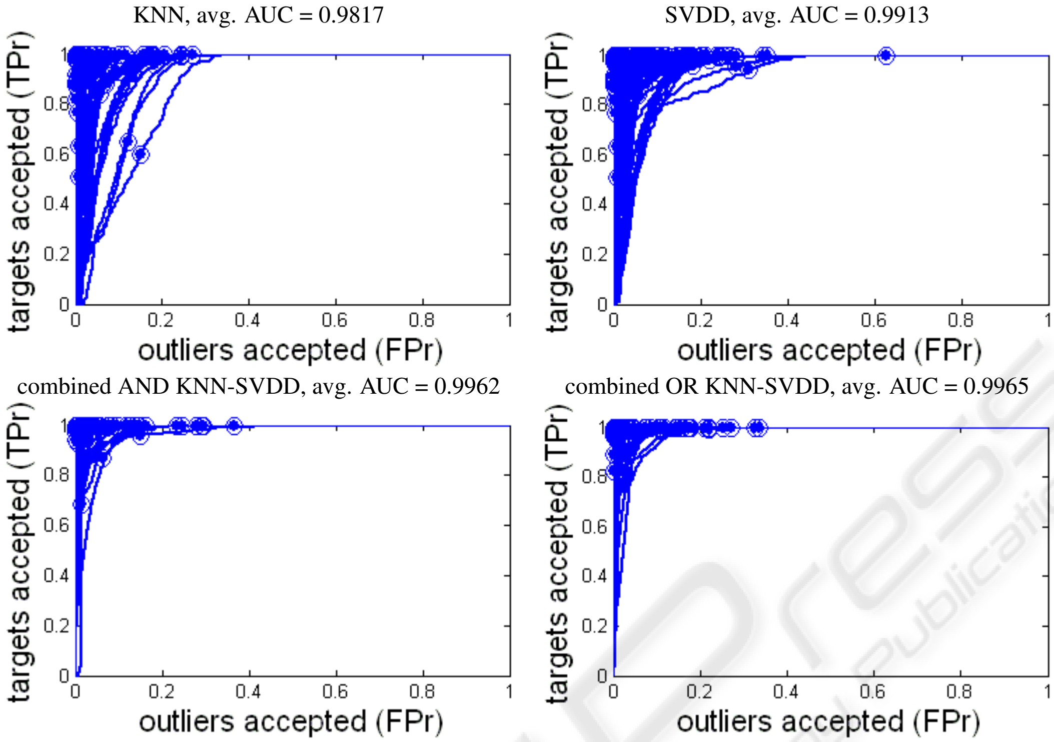

Figure 2: ROC of the 70 individual classifiers and their average AUC for each type of OCC considered and using feature trios.

affect VEPs significantly, such as stress and fatigue, the constancy of VEP-based biometric authentication must be addressed by future research.

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