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Can Visual Evoked Potentials be used in Biometric Identification?

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Abstract—**Due to known differences in the anatomical structure of the visual pathways and generators in different individuals, the use of visual evoked potentials offers the possibility of an alternative to existing biometrics methods. A study based on visual evoked potentials from 13 individuals was carried out to assess the best combination of temporal, spectral and AR modeling features to realize a robust biometric. From the results it can be concluded that visual evoked potentials show considerable biometric qualities, with classification accuracies reaching a high of 86.54% and that a specific temporal and spectral combination was found to be optimal. Based on these results the visual evoked potential may be a useful tool in biometric identification when used in conjunction with more established biometric methods.**

I. Introduction

A biometric is a physical, biological or behavioral characteristic, which can be used to distinguish one individual from another. Biometric-based applications include network and domain access, remote access to resources, transaction security and Web security. Utilized alone or integrated with other technologies such as smart cards, encryption keys and digital signatures, biometrics are increasingly popular in all aspects of our daily lives.

Utilizing biometrics for personal identification or authentication is becoming convenient and considerably more accurate than passwords or PINs. Biometrics link an event to a particular individual, while a password or token may be used by someone other than the authorized user. They are also convenient in that nothing needs to be remembered, offer an audit trail and are becoming socially acceptable and inexpensive. While existing biometrics such as analysis of fingerprint, iris and voice information can provide very good identification accuracies their performance is dependent on willing compliance with strict testing protocol: finger must be placed correctly in the fingerprint scanner/reader, iris must be visible to the scanner, speaker must articulate words which have been trained on the system.

For these reasons, the search for alternatives to the traditional biometrics is becoming increasingly popular. These alternatives may replace, but more likely augment, existing biometrics. Newer biometrics have been suggested such as analysis of the electrocardiogram [1] and the electroencephalogram (EEG) [2]-[4], [7]. The purpose of this study is to establish a standard set of EEG features that is unique to the individual, thus representing a robust biometric. Specifically, the individuality of the evoked potentials of the brain due to a visual stimulus was assessed. Visual evoked potentials (VEPs) are elicited by the sensory stimulation of the visual field and manifest themselves primarily in the occipital region of the brain which is the site of the visual cortex.

There are two main types of standard VEP stimulation: flash stimulus and pattern stimulus. For this study, a pattern reversal stimulus was employed, consisting of a black and white checkerboard, whose checks change colour from black to white and white to black respectively at a rate of 1-3 reversals per second [5]. This results in a VEP of the form shown in fig.1.

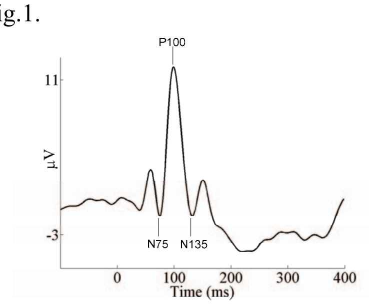

Fig. 1. A normal pattern reversal VEP

There is a very distinguishable peak approximately 100ms after stimulation, known as the P100. There are also two clear troughs called the N75 and N135, around 75ms and 135ms after stimulation. The response is achieved by averaging over a number of responses to single pattern reversals. This is required to reinforce the common features in the potential and to ensure that the response stands out against background brain activity. Unfortunately, this response shows a great deal of inter-subject similarity, especially when compared with the variability found when using a flash stimulus [6], however the pattern reversal is by far the most common method for eliciting VEPs and there is undoubtedly some degree of variability, possibly due to "differences in the anatomical structure of the visual pathways and generators in different individuals" [6]. Thus their use as a biometric may be valid.

Methods to recognize individuals using EEG signals have been proposed: [4] suggests analyzing γ-band activity (30-50Hz) where the abrupt appearance of the outline of an easily recognizable object was used as a visual stimulus and resulted in an average identification accuracy of 95.42%. In [3] Poulos et al. used autoregressive (AR) modelling of α-

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band activity (8-12Hz) from subjects at rest with their eyes closed and reported accuracies of 72-80%. Paranjape *et al.* [7] also used AR modeling from subjects resting with eyes open and eyes closed with accuracies of 49-82% obtained.

II. Aim

In this study combinations of spectral power ratios (SPRs), AR modelling and visually apparent temporal features such as the P100, N75, N135 and others were assessed to investigate the individuality of the pattern reversal VEP for its possible use as a biometric identifier.

III. Methodology

A. Data

13 healthy volunteers took part in this biometric study. Subjects were seated 60 cm from a 19inch computer monitor with a refresh rate of 60 Hz. EEG data was recorded from 64 electrode positions, filtered over the range 0 – 134 Hz and digitised at the rate of 512 Hz using the BioSemi Active Electrode system, which records high-resolution, multi-channel, biopotentials non-invasively from the scalp. Recording began when electrical impedance was reduced to less than 5 kΩ at all scalp sites. After acquisition the EEG signals were filtered with a high-pass filter with passband above 2Hz and a –60dB response at 1Hz and a low-pass filter with 0-35Hz passband and a –50dB response at 45Hz. Thus this study focuses on sub-gamma-band activity.

The stimulus employed was the standard pattern reversal checkerboard as mentioned above. Each subject undertook two sessions of 120 pattern reversals, giving a total of 240 reversals for each subject. A reversal occurred once a second. An equal number of black and white checks were used to ensure a constant mean luminance when a phase reversals occurs. Each check subtended a visual angle of 0.65° both horizontally and vertically, while the checkerboard as a whole subtended visual angles of 5.25° vertically and horizontally.

B. Feature Extraction

Each response was normalized to have zero mean and unit standard deviation. It can be noted that normalizing a zero mean signal to have unit standard deviation is equivalent to normalizing the signal to have almost unit power. Thus all responses also have equal energy after normalization. The responses were averaged over 60 reversals per response giving four responses per subject. This number was chosen so as to give a reasonable VEP, Odom et al. [5] suggest 64 reversals, while also providing adequate number of responses for classification.

i) Temporal Features:

For each response the P100, N75 and N135 are obtained. To extract these the P100 was taken to be the first local maximum between ~78ms and ~117 ms after stimulation. This was done, as it was observed by visual inspection that the P100 of all the responses occurred within this time frame. The N75 was then taken to be the local minimum directly preceding the P100 and the N135 as the local minimum directly succeeding the P100. The amplitudes of the P100 relative to the N75 and N135 are also examined. The latencies of the various amplitudes are not extracted since they are generally very similar from person to person [6].

ii) Spectral Power Ratios:

EEG activity can be divided into five major frequency bands. Two spectral power ratios are extracted based on these bands. The first ratio is that of β-band (15-30 Hz) spectral power to total spectral power: this is extracted because beta-band activity symbolizes an alert but not agitated demeanour, which would be the general manner of most of the subjects during the stimulation process used in this study. This could be considered an indirect consequence of the stimulation process but is worthy of note.

Analysis of the frequency spectrum of a typical VEP showed there to be considerable activity in β-band region. Substantial activity can also be seen in the α-band (8 – 15Hz) and thus the α-band SPRs is also assessed. An elliptical FIR filter was used to extract the desired frequency band signals. The equivalent spectral energies of the pre-filtered and post-filtered signal were then calculated and the ratio computed. The spectral energies are obtained using Parseval's theorem. The spectral power of a given signal x is given by (1):

$$\textit{Spectral Power} = \frac{1}{N}\sum_{n=1}^{N}[x(n)]^2 \qquad (1)$$

where N is the total number of samples in the signal.

iii) AR Model Parameters:

AR modeling is a linear prediction method, where the current sample in a sequence is predicted by way of a weighted sum of the previous p samples (p is the model order and $p<<N$, where N is the total number of samples in the sequence).

$$\hat{s}_n = -\sum_{i=1}^{p} a_{pi} s_{n-i} \qquad (2)$$

Here $\hat{s}_n$ is the current sample being predicted, s_{n-i} the previous p samples of the response and a_{pi} the AR model parameters which are subsequently employed as features. These parameters are calculated using the Burg algorithm, which fits a model, $\hat{s}$, to the input signal, s, by minimizing the mean of the both the forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion [8]. The AR parameters were computed for model orders 3, 4, 5 and 6.

C. Classification

VEPs are required to be classified as belonging to certain individuals. Each individual is termed a class and labeled 1 to K, where K is the total number of classes (13 in this case). A feature vector x is extracted from each VEP and is classified as belonging to one of the K classes.

Linear discriminants were used as the classification model with x classified as belonging to the class that results in the largest discriminant value. The discriminant function is derived from Bayes' rule, which relates the posterior probability to the product of the class conditional probability and the prior probability. Thus there are K different linear discriminant functions for a given x, one for each class. The aim is to find the class for which the posterior probability is largest.

For this study the performance of the LDA classifier is assessed using 4-fold cross-validation i.e. the feature vectors are split into four folds each with one vector from each subject. Four classifiers are then trained using a different fold for testing each time having been trained with the remaining 3 folds. This gives the most accurate assessment of the data as each classifier is trained with the maximum amount of available data, subject to the constraint that the classifiers are trained with an equal amount of data for each person [2]. The classifier also classifies the training data, i.e. classifies the exact same data with which it was trained. This gives another indication of the relevance of the features since useful features should have high training set accuracies.

IV. Results

Biometric classification was calculated for individual features and also channel-feature combinations in order to see which were most appropriate. Initially the most active electrode channels are tested (i.e. Oz, O1, O2) and expanded to include further, more peripheral channels (POz, PO3, PO4, PO7, PO8 and Iz). The electrode locations are given by the international 10-20 system of electrode placement [6].

The tables 1, 2, 3 and 4 show two accuracies for each feature-channel combination: the upper one (in bold) is the test accuracy and the lower the training accuracy. *N/A* also appears in some tables and indicates that the covariance matrix as used in the linear discriminant function was close to being singular. Also “Oz to O2” implies that channels Oz, O1 and O2 were used, “Oz to POz” implies that channels Oz, O1, O2 and POz were used, etc.

i) Temporal Features:

Table 1 shows the classification accuracies for the temporal features. P100 and N75 show most relevance as individual features, and when used together give the highest temporal accuracy result.

TABLE 1: CLASSIFICATION ACCURACIES FOR TEMPORAL FEATURES

	Accuracies for given channels				
Features	Oz to O2	Oz to POz	Oz to PO3 & PO4	Oz to PO7 & PO8	Oz to Iz
P100	**53.6%**	**67.3%**	**61.5%**	**59.6%**	**61.5%**
	69.9%	83.3%	85.9%	89.7%	94.2%
N75	**50.00%**	**61.5%**	**65.4%**	**67.3%**	**63.5%**
	75.00%	88.5%	90.4%	96.2%	96.2%
N135	**36.5%**	**46.2%**	**46.2%**	**55.8%**	**46.2%**
	57.0%	65.3%	74.2%	83.3%	85.3%
P100-N75	**34.5%**	**34.6%**	**50.0%**	**50.0%**	**50.0%**
	63.5%	70.5%	82.6%	85.3%	93.6%
P100-N135	**43.2%**	**46.2%**	**51.9%**	**51.9%**	**46.2%**
	61.5%	73.1%	82.7%	89.1%	91.7%
P100 & N75	**82.7%**	**80.8%**	**69.2%**	**71.9%**	**61.5%**
	98.7%	98.7%	98.7%	100%	100%
P100, N75 & N135	**75.0%**	**69.2%**	**67.3%**	**50.0%**	**N/A**
	100%	100%	100%	100%	N/A

ii) Spectral Power Ratios:

Table 2 shows the accuracies of the SPRs with the β-band SPR considerably outperforming the α-band SPR.

TABLE 2: CLASSIFICATION ACCURACIES FOR SPR FEATURES

	Accuracies for given channels				
Features	Oz to O2	Oz to POz	Oz to PO3 & PO4	Oz to PO7 & PO8	Oz to Iz
α-band	**17.3%**	**17.3%**	**17.3%**	**19.2%**	**17.3%**
	34.6%	43.0%	55.8%	61.5%	66.0%
β-band	**51.9%**	**53.9%**	**55.8%**	**57.7%**	**59.6%**
	75.6%	78.2%	84.0%	89.1%	89.1%

iii) AR parameters:

Table 3 shows the accuracies for AR parameters. A significantly high number of N/A’s when a higher number of channels is used shows that the AR parameters quickly become useless as channel numbers increase. However for lower channel numbers a 3rd or 4th order model works best.

TABLE 3: CLASSIFICATION ACCURACIES FOR AR FEATURES

	Accuracies for given channels				
Model Order	Oz to O2	Oz to POz	Oz to PO3 & PO4	Oz to PO7 & PO8	Oz to Iz
3	**53.9%**	**61.5%**	**55.8%**	**42.3%**	**N/A**
	98.7%	99.4%	100%	100%	N/A
4	**63.5%**	**53.9%**	**42.3%**	N/A	N/A
	100%	100%	100%	N/A	N/A
5	**61.5%**	**53.9%**	N/A	N/A	N/A
	100%	100%	N/A	N/A	N/A
6	**46.2%**	**25.0%**	N/A	N/A	N/A
	100%	100%	N/A	N/A	N/A

Table 4 shows the accuracies for combinations of different features types. Overall using the temporal P100, N75 combination together with the β-band SPR achieved the best identification accuracies.

TABLE 4: CLASSIFICATION ACCURACIES FOR FEATURE COMBINATIONS

	Accuracies for given channels				
Features	Oz to O2	Oz to POz	Oz to PO3 & PO4	Oz to PO7 & PO8	Oz to Iz
P100 & β-band	**71.2%**	**80.8%**	**76.9%**	**73.1%**	**65.5%**
	98.7%	98.7%	100%	100%	100%
P100, N75 & β-band	**86.5%**	**84.6%**	**80.8%**	**65.4%**	**23.1%**
	100%	100%	100%	100%	100%
P100, N75, N135 & β-band	**80.8%**	**78.9%**	**53.9%**	N/A	N/A
	100%	100%	100%	N/A	N/A
P100 & 4th AR	**73.1%**	**71.2%**	N/A	N/A	N/A
	100%	100%	N/A	N/A	N/A
P100, N75 & 4th AR	**78.9%**	**53.9%**	N/A	N/A	N/A
	100%	100%	N/A	N/A	N/A
β-band & 4th AR	**50.0%**	**40.3%**	N/A	N/A	N/A
	100%	100%	N/A	N/A	N/A
P100, β-band & 4th AR	**63.5%**	**34.6%**	N/A	N/A	N/A
	100%	100%	N/A	N/A	N/A

V. Discussion

For the temporal features the P100 and the N75 show most relevance as far as individual features are concerned achieving test accuracies of up to 67.31% and 65.38% respectively. However the P100, N75 combination produces the highest accuracies of temporal features with a test of 82.69% and training accuracy of 98.72%. This is achieved using only channels Oz, O1 and O2. The highest accuracy achieved for the P100, N75, N135 combination is a test accuracy of 75% and a training accuracy of 100%, which is also achieved using Oz, O1 and O2. Generally accuracies increase with the addition of channels. There are, however, two major exceptions to this: results for the P100, N75 combination and the P100, N75, N135 combination decrease with the addition of POz and continue to decrease further with the addition of more channels. Since it is these two combinations that result in the highest temporal accuracies, the use of higher channel numbers does not seem appropriate. The N135, the P100-N75 and the P100-N135 result in poor accuracies compared with other temporal features e.g. the P100-N75 achieved its highest test accuracy of 50% with training accuracy high of 93.59% using channels Oz to Iz.

In the case of the spectral features, the β-band SPR is more successful than the α-band SPRs. The highest β-band accuracy was found for channels Oz to Iz (test: 59.62% and train: 89.10%).

With regard to the AR parameters, as the number of channels increases, the test accuracies begin to suffer especially for the higher model orders. The highest accuracy achieved is 63.46% with a training accuracy of 100% for 4th order parameters using channels Oz, O1 and O2. From the high number of N/A's it can be seen that the classification breaks down for higher orders (i.e. 5th and 6th order) when PO3 & PO4 are included. Thus a model order of 4 seems to be most appropriate for classification if the number of channels used is kept low.

When the temporal features are used with the other feature types the accuracies do increase e.g. for P100 and β-band SPR using Oz to POz test accuracy increases by 67.31% to 80.77% and the training accuracy increases from 83.33% to 98.72%. The highest accuracy achieved was 86.54% with a training accuracy of 100%. This was for the P100, N75 combination and the β-band SPR using channels Oz to O2. When temporal features and AR parameters are used together accuracies increase for fewer channels but N/A's dominate for higher numbers of channels. When beta-band SPR and AR model parameters are employed together the test accuracies decrease on those obtained when using the beta-band alone, suggesting that it is not appropriate to use these feature types together e.g. using Oz to POz test accuracy decreases by 13.55%.

When all the feature types are used together accuracies are quite poor compared with those acquired when the temporal features are used with either the beta-band SPR or AR parameters. The highest achieved was 63.46% with a training accuracy of 100% for channels Oz to O2. Again higher numbers of channels results in a break down of classification.

From the above discussion it can be concluded that VEPs do show considerable biometric qualities with classification accuracies reaching a high of 86.54% with a training accuracy of 100%. The highest area of activity of the responses is localized over the central channels (i.e Oz, O1 and O2). This is backed up by the fact that our best results are obtained when a limited number of channels are used. Also the results show that the simultaneous use of temporal features and the beta-band SPR is most useful. The effect of increasing the number of reversals beyond 60 was not investigated due to the amount of data available.

Conclusion

We have shown that the VEP can be used for biometric identification with classification accuracies of up to 86.54% for a group of 13 subjects. Some individuals in this study showed very clear and distinct VEPs and were consistently classified correctly whereas features extracted for others were somewhat indistinct. This inconsistency casts some shadow over the current use of VEPs as a biometric. However further study of the neurophysiology and the genesis of the VEPs may lead to a more definite clarification of what feature types may be most valuable. That said on the basis of these results it appears that the VEP may, at present, be a useful tool in biometric identification if used in conjunction with biometrics that are currently in use.

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