CLASSIFICATION OF SINGLE TRIAL GAMMA BAND VEP EXTRACTED DURING OBJECT RECOGNITION

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ABSTRACT

We extract gamma band power (GBP) of single trial Visual Evoked Potential (VEP) signals using a zero phase Butterworth digital filter. The method does not involve the commonly used ensemble averaging and is based on the assumption that SNR of VEP/EEG is higher in the gamma band range. The VEPs are obtained during object recognition of Snodgrass and Vanderwart pictures. PCA is applied to remove noise from the VEP data. We use the extracted GBP to classify alcoholics and non-alcoholics using a Fuzzy ARTMAP (FA) neural network classifier with voting strategy. The average FA classification of 93.8% shows the validity of the proposed method to successfully recognise alcoholics from non-alcoholics using single trial evoked responses.

1. INTRODUCTION

Visual Evoked Potential (VEP) is typically generated by the nervous system in response to visual stimulation [7]. In the recent years, evoked potential analysis has become very useful for neuropsychological studies and clinical purposes [3, 7, 8, 11]. Specifically, the effects of alcohol on central nervous system of humans have been studied using evoked responses [11]. Evoked response has also been used to determine the genetic predisposition towards alcoholism [3].

The VEP signal is embedded in the ongoing EEG with additive noise causing difficulty in detection and analysis of this signal. The traditional technique of solving this problem is to use ensemble averaging [1]. However, this approach requires many trials and the averaged signal might tend to smooth out inter-trial information. In addition it leads to system complexity and higher computational time.

In this paper, we propose a method to extract gamma band power (GBP) of single trial VEPs buried in the spontaneous EEG activity using a zero phase Butterworth digital filter. Our method assumes that SNR of VEP/EEG is higher in the gamma band range, thereby circumventing methods like signal averaging to remove EEG from VEP. Gamma band is particularly chosen since it is reported that gamma band spectra centred at 40 Hz is evoked during the application of sensory simulation [2]. Single trial gamma band VEPs have also been used to study stimulus specificity of visual responses in humans [10].

Parseval's theorem is used to obtain the spectral power of the filtered signal in time domain. Since the entire computation of the features remain in time domain, this method is efficient than methods requiring power spectrum computation like periodogram analysis. The extracted spectral power values are used to classify alcoholic and non-alcoholic subjects based on single evoked responses using a Fuzzy ARTMAP (FA) neural network (NN) classifier.

2. DATA

Ten subjects participated in the experimental study consisting of 5 alcoholics and 5 non-alcoholics. The alcoholics are non-amnesic and have been abstinent for a minimum period of one month (through closed ward hospitalisation) and are also off all medications for the same period of time. Most alcoholics had been drinking heavily for a minimum of 15 years and started drinking at approximately 20 years of age. The non-alcoholic subjects are not alcohol or substance abusers. The subjects are seated in a reclining chair located in a sound attenuated RF shielded room. Measurements are taken from 61 channels placed on the subject's scalp, which are sampled at 256 Hz. The electrode positions (as shown in Figure 1) are located at standard sites using extension of Standard Electrode Position Nomenclature, American Encephalographic Association. The signals are hardware band-pass filtered between 0.02 and 50 Hz. The subjects are grounded with a nose electrode.

The VEP data is recorded from subjects while being exposed to a stimulus, which is a picture of an object chosen from Snodgrass and Vanderwart picture set [9]. These pictures are common black and white line drawings like airplane, banana, ball, etc. executed according to a set of rules that provide consistency of pictorial representation. The pictures have been standardised on variables of central relevance to memory and cognitive processing and they represent different concrete objects, which are easily named i.e. they have definite verbal labels. Figure 2 shows some of these pictures. More information on the data collection process can be obtained from [11].

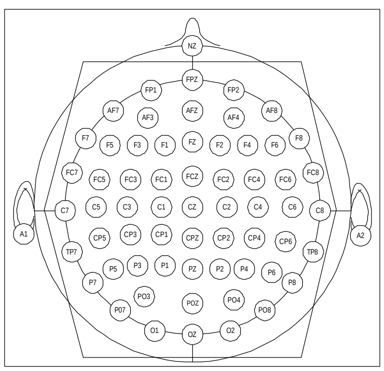

Figure 1: Electrode positions

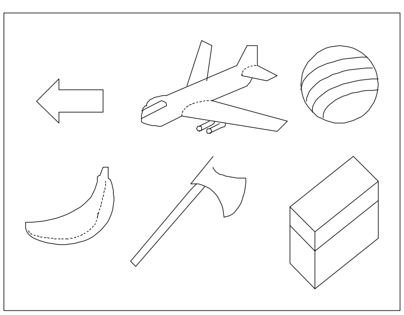

Figure 2: Some objects from Snodgrass and Vanderwart picture set

3. PREPROCESSSING AND GAMMA BAND VEP EXTRACTION

VEP signals with eye blink artifact contamination are removed using a computer program written to detect VEP signals with magnitudes above 100 μV. These VEP signals detected with eye blinks are then discarded from the experimental study and additional trials are conducted as replacements. The threshold value of 100 μV is used since blinking produces 100-200 μV potential lasting 250 milliseconds [6]. A total of 40 artefact free trials are used in the experimental study.

Mean from the data are removed. This is to set the pre-stimulus baseline to zero [8]. A 20^{th} order forward and backward Butterworth digital filter (with zero phase response) is used to extract the VEP in the gamma band range of 30 to 50 Hz. This frequency range also eliminates power line (60 Hz) interference.

Principal component analysis (PCA) [5] is applied to remove noise from the data. The extracted EEG can be thought to consist of both signal and noise [12]. Therefore, using PCA, we can separate noise from signal using the fact that the noise subspace will constitute of PCs with eigenvalues chosen below a certain threshold and eigenvalues with PCs above this threshold represent the signal subspace. Assuming matrix $\mathbf{x}$ to represent the extracted EEG, the covariance of matrix $\mathbf{x}$ is computed using:

$$\mathbf{R} = \mathbf{E}(\mathbf{x}\mathbf{x}^{\mathbf{T}}). \tag{1}$$

Next we compute, $\mathbf{E}$ and $\mathbf{D}$, where $\mathbf{E}$ is the orthogonal matrix of eigenvectors of $\mathbf{R}$ and $\mathbf{D}$ is the diagonal matrix of its eigenvalues, $\mathbf{D} = diag(d_1,....,d_n)$. The principal components (PCs) can now be computed using

$$\mathbf{y} = \mathbf{E}^{\mathbf{T}}\mathbf{x}^{\mathbf{T}}. \tag{2}$$

In our work, Kaiser's rule is used to give the number of required principal components [5]. Using this method, PCs with eigenvalue more than 1.0 are considered to be part of the signal subspace. The signal part of the EEG can now be reconstructed from the selected PCs using

$$\tilde{\mathbf{x}} = \hat{\mathbf{E}}\hat{\mathbf{y}}, \tag{3}$$

where $\hat{\mathbf{E}}$ and $\hat{\mathbf{y}}$ are the eigenvectors with PCs corresponding to eigenvalues more than 1.0.

Parseval's theorem can now be applied to obtain the equivalent spectral power of the signal using

$$Spectral \quad power = \frac{1}{N} \sum_{n=1}^{N} \left[\tilde{x}(n) \right]^2 , \qquad (4)$$

where N is the total number of data in the PCA filtered signal. The power values from each of the 61 channels are concatenated into one feature array representing the particular VEP pattern. Figure 3 shows the process of extracting features from VEP signals.

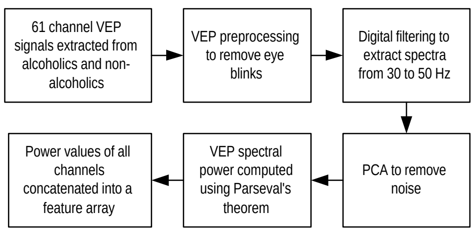

Figure 3: VEP feature extraction

The GBP feature array is used by a Fuzzy ARTMAP (FA) [4] classifier to classify the VEP patterns as belonging to the alcoholic subjects class or non-alcoholic subjects class. Half of the patterns are used for training while the rest half are used for testing. Fast learning method is employed to speed up FA training. Since FA fast learning weight updates vary with different order of input patterns during training, voting strategy is used with 20 simulations. In addition, mean classification values from 20 randomly ordered input patterns are also studied as a comparison. FA vigilance parameter (VP) is varied from 0 to 0.9 in steps of 0.1. Figure 4 shows the used FA network.

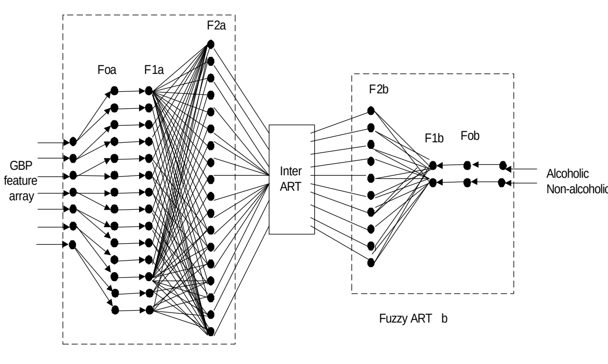

Figure 4: Fuzzy ARTMAP network

4. RESULTS AND DISCUSSION

Table 1 shows the results of the experimental study with PCA and without PCA. Form the table, it can be seen that FA classification improves considerably with the use of PCA. This is due to PCA's ability to remove noise from the VEP data. It can also be seen that FA classification is higher with voting strategy as compared to the mean of random input pattern ordering. For the case with PCA, the best classification is at 96% with a vigilance parameter value of 0.5 (for the case of voting strategy) and 92.68% with a vigilance parameter value of 0.9 (for the case of mean of random input ordering). The former gives an averaged classification of 93.8% across all the vigilance parameter values and the latter gives averaged classification of 89.44%. The case without using PCA gives lower classification values as can be seen from the last two columns of Table 1.

Table 1: FA classification of 20 trials of random input ordering and voting strategy

	PCA		**without PCA**	
FA VP	**Random trial mean**	**Voting strategy**	**Random trial mean**	**Voting strategy**
0	90.35	93.00	78.13	83.00
0.1	87.70	93.00	78.00	81.50
0.2	87.90	93.00	78.38	84.00
0.3	88.75	93.50	77.10	80.00
0.4	87.45	93.50	76.08	77.50
0.5	89.15	96.00	77.08	83.50
0.6	90.50	94.50	75.58	80.50
0.7	90.18	94.00	76.45	80.00
0.8	89.78	94.00	80.23	84.00
0.9	92.68	93.50	87.28	88.50
Average	**89.44**	**93.80**	**78.43**	**82.25**

These results indicate that GBP from single trial VEP can be used to classify alcoholics and non-alcoholics. Single trial analysis eliminates the need for signal averaging to remove background EEG from VEP and therefore offers a computationally attractive alternative.

5. CONCLUSION

This paper has proposed a method of extracting GBP from single trial VEP signals buried in EEG and noise using digital filtering methods and PCA. FA classification using GBP obtained from subjects during the presentation of visuals from Snodgrass and Vanderwart picture set gives good accuracy in differentiating alcoholic from non-alcoholic subjects. This indicates that GBP centred at 40 Hz is closely related to higher brain functions like memory and object recognition, which can be used as a tool to discriminate between alcoholic and non-alcoholic subjects. This would very useful as a preliminary indicative system in cases where a person needs to be tested for alcoholism. The successful classification results obtained in the experimental study also indicate that the alcoholics suffer some form of irreversible alteration in the brain, even after quitting alcohol for some time.

ACKNOWLEDGEMENTS

We thank Prof. Henri Begleiter at the Neurodynamics Laboratory at the State University of New York Health Center at Brooklyn, USA who generated the raw ERP data and Mr. Paul Conlon, of Sasco Hill Research, USA for making the data available to us.

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