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Classification of alcoholics using gamma band spectral power ratio extracted from single-trial and de-noised VEP signals

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Introduction

In this paper, we classify alcoholics and non-alcoholics using gamma band spectral power ratio extracted from single trials of de-noised Visual Evoked Potential (VEP) signals. Simplified Fuzzy ARTMAP (SFA) neural network is used in the classification. Principal Component Analysis (PCA) is used to reduce the effects of noise. Single trial analysis is possible in our case because gamma band spectrum is above 30 Hz. As such the averaging procedure that is necessary to remove background electroencephalogram (EEG), which is normally below 30 Hz, is circumvented.

Method

VEP data

The VEP signals are extracted during the visual response of two pictures presented with a short interval. The second picture is shown in either matching (S2M) or non-matching condition (S2N) to the first picture (S1). The first picture will evoke object recognition, while the second picture will evoke short-term memory capabilities. 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 are located at standard sites using extension of Standard Electrode Position Nomenclature, American Encephalographic Association. The signals are band-pass filtered between 0.02 and 50 Hz using analogue filters.

The VEP data is recorded from subjects while being exposed to visual stimuli, which are pictures of objects chosen from Snodgrass and Vanderwart picture set [6]. 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. These pictures represent different concrete objects, which are easily named i.e. they have definite verbal labels. One-second measurements after each stimulus onset are stored. Stimulus duration of each picture is 300 ms with an inter-stimulus interval of 1600 ms. The pictures are shown using a computer display unit located 1 meter away from the subject's eyes. Figure 1 shows an illustrative example of the stimulus presentation. For further details of the data collection process, refer to [7, 8].

In the study, 10 alcoholics and 10 non-alcoholics participated. 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 have 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.

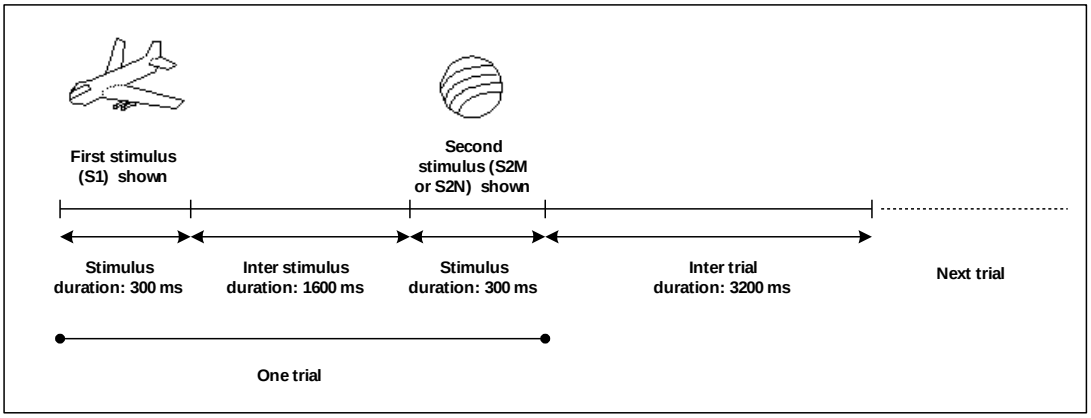

Figure 1: Example of stimulus presentation for the case of S2N

Eye Blink Removal

A common artifact that corrupts the visual stimulus EEG data is eye blinks. Eye blink contamination problem is solved by using a computer program written to detect VEP signals with magnitude under 100 mV. The VEP signals with magnitudes above 100 mV are assumed to be contaminated with eye blinks and are 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 [4, 5]. Mean from the data are removed. This is to set the pre-stimulus baseline to zero.

PCA

PCA [2] is applied to remove noise from the VEP data. The extracted VEP signals consist of two parts: signal and noise. Therefore, using PCA, it is possible to separate noise from signal using the fact that the noise subspace will constitute of principal components (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 noise corrupted VEP signal, the covariance of matrix $\mathbf{x}$ is computed using:

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

Next, matrices $\mathbf{E}$ and $\mathbf{D}$, are computed 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 PCs can now be computed using

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

In this work, Kaiser's rule is used to give the number of required PCs [2]. 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 and PCs corresponding to eigenvalues less than 1.0.

Feature extraction

A total of 20 artifact free trials for each subject (for each stimulus) are used in the experimental study giving a total of 1200 VEP signals. A 10^{th} order forward and 10^{th} order backward Butterworth digital filter (forward and backward operation to give zero phase response) is used to extract the VEP in the 3-dB passband of 30 to 50 Hz. Order 10 is chosen since it gives a 30-dB minimum stopband at 25 and 55 Hz. Parseval's theorem can now be applied to obtain the equivalent spectral power of the signal, $\tilde{x}$ using

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

where N is the total number of data in the filtered signal. This power is normalised with the total power from all 61 channels to give the spectral power ratio. The spectral power ratio values from each of the 61 channels are concatenated into one feature array representing the particular VEP pattern.

Figure 2 shows the process of extracting features from VEP signals for the case of using PCA. The VEP feature extraction without the application of PCA is the same as shown in Figure 2 except that PCA is not used.

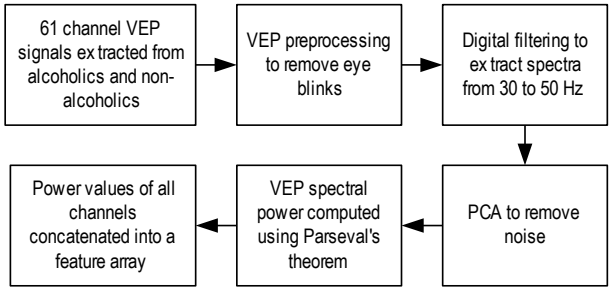

Figure 2: VEP feature extraction

Classification

These VEP feature arrays are classified by SFA into alcoholic and non-alcoholic categories. SFA is chosen as compared to other NN due to its high speed training ability in fast learning mode. FA is a type of neural network that performs incremental supervised learning [1]. In this paper, a simplified version of FA is used [3]. It consists of a Fuzzy ART module linked to the category layer through an Inter ART module. During supervised learning, Fuzzy ART receives a stream of input features representing the pattern and the output classes in the category layer are represented by a binary string with a value of 1 for the particular target class and values of 0 for all the rest of the classes. Inter ART module works by increasing the vigilance parameter, ρ of Fuzzy ART by a minimal amount to correct a predictive error at the category layer. Parameter ρ calibrates the minimum confidence that Fuzzy ART must have in

an input vector in order for Fuzzy ART to accept that category, rather than search for a better one through an automatically controlled process of hypothesis testing. Lower values of ρ enable larger categories to form and lead to a broader generalisation and higher code compression. For further details on FA, refer to [1, 3].

Half of the patterns are used for training while the rest half are used for testing. SFA vigilance parameter (VP) is varied from 0 to 0.9 in steps of 0.1. Figure 3 shows the SFA network architecture as used in the experimental study.

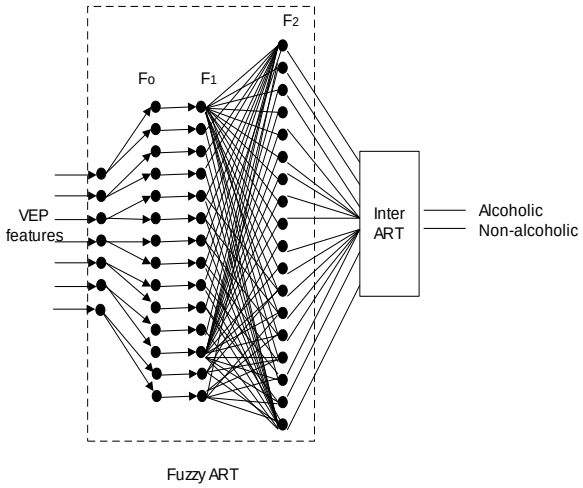

Figure 3: SFA network as used in the study

Results

Table 1 shows the results obtained for SFA classification. The average classification rates of 83.60%, 80.20% and 77.65% are obtained using VEP signals from stimuli S1, S2M and S2N, respectively. De-noising using PCA improves the classification to 95.55%, 89.55% and 89.90%.

Table 1: SFA classification results

FA VP	without PCA			with PCA		
	S1	S2M	S2N	S1	S2M	S2N
0.00	80.50	75.00	72.50	92.50	85.50	84.00
0.10	80.50	75.00	72.50	92.50	85.50	84.00
0.20	80.50	75.00	72.50	92.50	85.50	84.00
0.30	80.50	75.00	73.00	93.00	85.50	84.00
0.40	80.50	80.00	74.50	94.50	83.50	85.00
0.50	81.00	80.00	79.00	96.50	87.50	87.50
0.60	90.50	83.00	78.00	98.00	94.00	96.00
0.70	89.00	87.50	85.00	98.50	94.00	98.00
0.80	87.00	87.50	85.00	97.50	97.00	100.00
0.90	86.00	84.00	84.50	100.00	97.50	96.50
Average	**83.60**	**80.20**	**77.65**	**95.55**	**89.55**	**89.90**

Conclusion

The results indicate that alcoholics could be classified from non-alcoholics using gamma band spectral power ratio. The results also indicate that the best classification is obtained through de-noised VEP signals extracted during the presentation of stimulus S1, rather than S2M and S2N. It can be concluded that long-term use of alcohol results in alterations in the brain that is detectable using gamma band VEP. More studies are necessary to reveal the exact relationship between gamma band and visual response and the effects of alcohol on gamma band VEP.

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