Classification of Alcohol Abusers: An Intelligent Approach

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Abstract

In this paper we propose a novel method to classify alcohol abusers. The method described efficiently estimated total power in gamma band spectral power (GBSP) of multi-channel visual evoked potential (VEP) signals in the time domain, circumventing power spectrum computation. Then, the total power extracted are used as features to classify alcohol abusers from control subjects using Multilayer Perceptron – Back Propogation (MLP-BP) neural network classifier. As a comparison study the total power using GBSP feature extraction is repeated for four types of Infinite Impluse Response (IIR) filters. Experimental study is conducted with 20 subjects totaling 800 VEP signals, which are extracted while subjects are seeing pictures from Snodgrass and Vanderwart set. Maximum classification of 91% is obtained for Elliptic filter for 20 hidden units. Also Elliptic filter shows the best performance for the averaged values of all the filters and it also has the lower order when compared to other filters

1. Introduction

VEP is generated in the brain in response to visual stimulus and can be measured using electrodes placed on the scalp which was described in the last few chapters and it has been proved by many researchers [3,4,6,8] that the VEP signal is very useful for clinical study. In particular, the effects of alcohol on evoked responses have been reported [3,8] and it was concluded that alcohol can significantly increase the latency of evoked responses in humans. Total power in GBSP from these multi-channel VEP signals are estimated in the time domain and are used as features in the classification process by the NN classifiers. A difficulty encountered in analyzing VEP signals comes from the contamination of spontaneous background electroencephalogram (EEG) brain activity, which is typically many times higher in amplitude as compared to VEP signals which have been proved by many researches [4,7,8]. The common method used by most researches [1,4,7,8] for reducing this problem is to use signal averaging from a certain number of trials. This approach is useful to study time-domain properties like latency, amplitude, polarity and wave-shape of evoked responses. However signal averaging requires many trials, which leads to system complexity and higher computational time.

The method described in this paper is somewhat related to the method used by Palaniappan and Raveendran [9,10], which uses single trial analysis of VEP signals. This is possible because the background EEG is generally limited to frequency below 30 Hz, so spectral range of gamma band will mostly consist of evoked potentials. Total power in GBSP is computed in the time domain and it is used to classify alcohol abusers based on single evoked responses. GBSP in the range of 30 to 50 Hz[1] is specifically chosen since studies in many researches [2,4,9,10,12,14,15] shows that electric potential in gamma band frequency is evoked during the application of sensory simulation. This method uses a high-pass digital filter to extract VEP signals in GBSP range.

Next Parseval's theorem is applied to the output of the filter to estimate the equivalent total power in GBF; therefore the entire computation remains in the time domain as shown by many researches [9,10]. Direct power spectrum computation using techniques like Fourier transform or autoregressive approach is not necessary in this method. This results in reduction of computational time and design complexity. These gamma band spectral power (GBSP) are used as features by the NN classifiers to classify alcohol abusers and control i.e. non-alcoholic subjects. The

[1] Following studies in [2] that proposed gamma band to consist of frequencies around this range.

classification performances of the two neural network classifiers are compared. Figure 1 illustrates various stages in the classification of alcohol abusers, which includes signal preprocessing, feature extraction and classification.

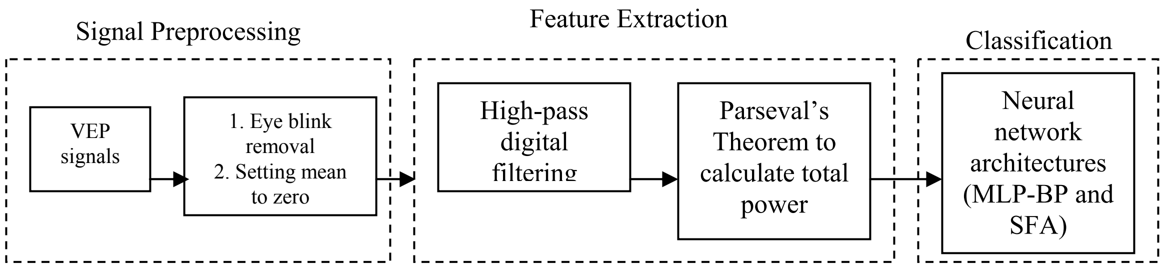

Figure1. Diagram for classification of alcohol abusers from controls

2. Extraction of total power in Gamma Band Spectral Power

The extracted VEP signals are digitally filtered using an Infinite Impulse Response (IIR) digital filter in 3 dB pass band of 30 to 50 Hz. IIR filters are characterized by the following recursive function:

$$y(n)=\sum_{k=0}^{\infty}h(k)x(n-k)=\sum_{k=0}^{N}b_k x(n-k)-\sum_{k=1}^{M}a_k y(n-k) \quad (1)$$

where $h(k)$ is the impulse response of the filter which is theoretically infinite in duration. $x(n)$ and $y(n)$ are the input and output of the filter and b_k and a_k are the coefficients of the filter. The transfer function for the IIR filter is given by

$$H(z)=\frac{b_0+b_1 z^{-1}+...+b_N z^{-N}}{1+a_1 z^{-1}+...+a_M z^{-M}}=\frac{\sum_{k=0}^{N}b_k z^{-k}}{1+\sum_{k=1}^{M}a_k z^{-k}} \quad (2)$$

The filtered output, $y(n)$ contains signals mostly in the GBSP range of 30-50 Hz and Parseval's theorem can now be applied to obtain in equivalent total power of the signal (in GBSP) using

$$Power_{gamma}=\frac{1}{M}\sum_{n=1}^{M}\left[y(n)\right]^2 \quad (3)$$

where M is the total number of data in the filtered signal. Figure 2 shows the procedures involved in the feature extraction of GBSP.

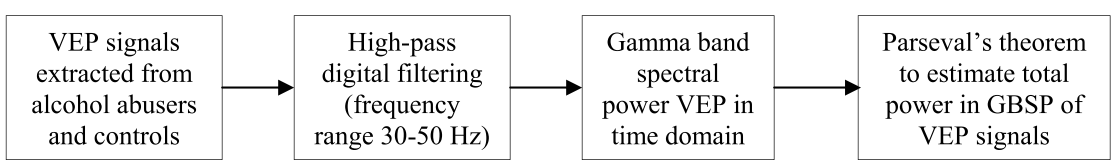

Figure 2. Feature extraction

As a comparison to study the classification performances, the above described total power using GBSP feature extraction is repeated for the four types of Infinite Impulse Response (IIR) filters: Butterworth, Chebyshev – I, Chebyshev – II and Elliptic (Cauer). Even though Finite Impulse Response (FIR) filters are advantages in terms of amplitude changes and no phase distortion, they do not have a sharp roll-off. Therefore IIR filters are used mainly for their sharp roll-off. But the disadvantage is the phase distortion. To solve this problem, the filters are applied twice, first in the forward direction, after which the filtered sequence is then reversed and run back through the filter. The result has precisely zero phase distortion and the magnitude is modified by the square of the filter's magnitude response. The procedure is repeated for the four IIR digital high pass filter with different orders to give 30 dB minimum stop band at 25Hz to

55Hz. The orders for filters are obtained with the help of MATLAB functions which is shown in Table 1.

Table 1. MATLAB function to select filter order

Filters	Order	MATLAB functions used to	
		Filter order selection	Filter Design Command
Butterworth	9^{th} order	BUTTORD	BUTTER
Chebyshev – I	6^{th} order	CHEB1ORD	CHEBY1
Chebyshev – II	6^{th} order	CHEB2ORD	CHEBY2
Elliptic	4^{th} order	ELLIPORD	ELLIP

The VEP signals extracted from the alcohols and control subjects which are sampled at a frequency of 256 Hz, are then applied to the four filters with the different orders as specified in Table 1 and Parseval's theorem as shown in equation (3) is applied to obtain the equivalent spectral power of the signal. This power is normalised with the total power from all the 61 channels to give the GBSP. The spectral power ratio values from each of the 61 channels are concatenated into one feature array representing the particular VEP pattern.

3. Neural Network Classifier

The method uses a high-pass digital filter to extract the VEP signals from 20 subjects (10 alcohols and 10 controls) with 40 trials for each subject. Therefore a total of 800 VEP signals (20 subjects x 40 trials) are stored in an array. The spectral power ratio values from each of the 61 channels are concatenated into one feature array representing the particular VEP patterns which has been already discussed in the first part of this paper. The MLP-BP neural network uses these VEP arrays as input to classify alcohol abusers as illustrated in Figure 3.

The MLP-BP used in this study is shown in Figure 4. The input layer consists of 61 nodes and the input comes from the VEP GBSP feature array. The network consists of one hidden layer. The learning algorithm used to train the network is the Backpropagation. The network is trained by changing the number of nodes in the hidden layer. In this study the number of nodes in the hidden layer is varied from 5 to 50 in steps of 5, but there are no restrictions in the numbering and intervals. Fifty percent of the data i.e. 400 feature arrays (200 from alcohol abusers and 200 from controls) are used to train the network while the remaining fifty percent of the data are used for testing the network. Therefore it is assumed that the training and testing set of data contains equal number of alcohols and control subjects. The VEP feature arrays for training and testing data are chosen randomly. The output layer consists of two nodes. The desired target output is set to 1.0 for the particular category representing the alcohol abuser or control subject, while for the other category i.e. non target, output is set to 0.

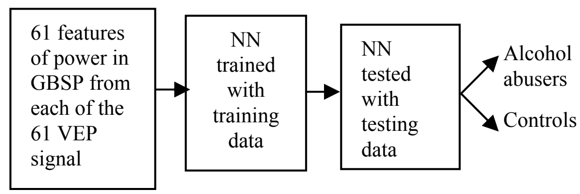

Figure 3. NN training and testing to classify alcohol abusers from controls

The BP training is conducted with momentum parameter. The learning rates are varied according to the change in the average error. The average error is the average of NN target output subtracted by the desired target output from all the training patterns. If the new error exceeds the old error, the new weights and biases are discarded. In addition, the learning rate is decreased. If the new error is less than the old error, the weights and biases are kept unaltered and the learning rate is increased by 5%. Training is conducted until the average error falls below 0.01 or reaches a maximum iteration limit of 10000. The average error denotes the error limit to stop neural network training.

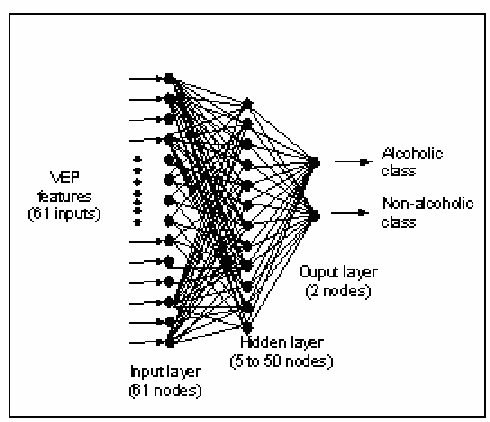

Figure 4. MLP-BP Neural Network

4. Experimental results of MLP-BP classification

The results of MLP-BP classification of alcohol abusers using four types of digital filters are tabulated and shown in Table 2 and Figure 5 shows the graphical representation of the MLP-BP results. The result of MLP-BP classification shows the best performance for elliptic filter.

It is indicated from Table 2 that the best performance of 91% is achieved with 20 hidden units. The averaged values for all the filters are shown in the last row, of the table. The elliptic filter's performance is once again the best when compared to other filters. In addition the elliptic filter uses the lowest order (4th order) while the other filters (Butterworth – 10th order, Chebyshev-I and II – 6th order) uses higher order.

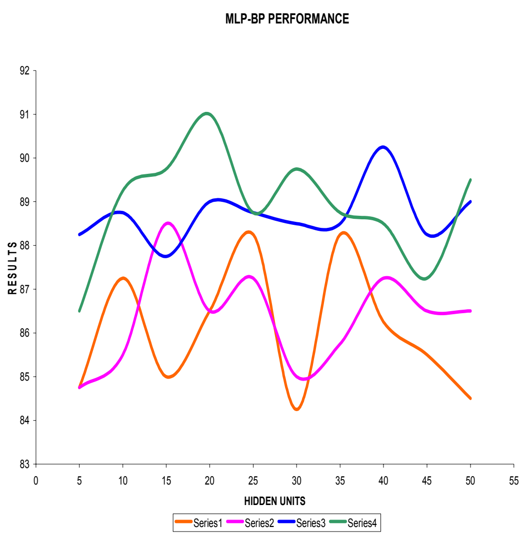

Figure 5: Comparison of MLP-BP classification performance for various filters

The graph in the figure 5 shows that it is not possible to achieve a steady increase or decrease in the output percentage with varying the number of hidden units. So, it is also very difficult to come to a conclusion that either increase or decrease in the number of hidden units may improve the classification performance. Practically, MLP-BP architecture takes more time for training the data set but it takes only a few seconds to test the data set. Also from the Figure 5, it can be seen that the performance of MLP-BP does not vary significantly with the variations in the number of hidden units.

Table 2. Results of MLP-BP classification for various filters

Hid. unit	Butter worth	Chebys hev – I	Chebyshe v – II	Elliptic
5	84.75	84.75	88.25	86.50
10	87.25	85.50	88.75	89.25
15	85.00	88.50	87.75	86.75
20	86.50	86.50	89.00	**91.00**
25	88.25	87.25	88.75	88.75
30	84.25	85.00	88.50	89.75
35	88.25	85.75	88.50	88.75
40	86.25	87.25	90.25	88.50
45	85.25	86.50	88.25	87.25
50	84.50	86.50	89.00	89.50
Avera ge	86.05	86.35	88.70	**88.90**

5. Conclusion

We have proposed a method to classify alcohol abusers using total power in GBSP of VEP signals with MLP-BP neural network classifier. The method employs digital filtering with Parseval's theorem used to compute GBSP of VEP signals in time domain. The results from experimental study using 800 VEP signals from 10 alcohol abusers and 10 control subjects shows the proposed method reduces design complexity and computational time.

MLP-BP classification gives the best classification performance for Elliptic filter for both individual hidden unit (20) and also for averaged hidden units. The reason may be because elliptic filter uses the lower order when compared to other types of filters. The MLP-BP classification performance do not vary significantly with the variation of hidden units. One major drawback in MLP-BP classification is that, it takes more time for training the data.

Overall the results of MLP-BP classification using elliptic filter validate the ability of the proposed method to efficiently classify alcohol abusers using VEP signals. It could be concluded that spectral power in gamma band frequency of VEP signals could be utilized with neural networks to detect some alterations in the visual perception caused by long-term use of alcohol.

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