Neural Network Classification of Alcohol Abusers Using Power in Gamma Band Frequency of VEP Signals

P. Sharmilakanna and R.Palaniappan
Faculty of Information Science and Technology, Multimedia University, 75450, Melaka, Malaysia

Abstract - **We propose a novel method to classify alcohol abusers. The method efficiently estimates total power in gamma band frequency (GBF) of multi-channel Visual Evoked Potential (VEP) signals in the time domain, circumventing power spectrum computation. These are used as features to classify alcohol abusers from control subjects with Multilayer Perceptron- Backpropagation (MLP-BP) and Fuzzy ARTMAP (FA) neural network classifiers. Perfect classification performance obtained in the experimental study conducted with 20 subjects totaling 800 VEP signals validates the proposed method.**

Keywords - **Alcohol abusers, digital filter, Fuzzy ARTMAP, gamma band frequency, Multilayer Perceptron- Backpropagation, multi-channel Visual Evoked Potential, neural network, single trial analysis**

1. INTRODUCTION

VEP is generated in the brain in response to visual stimulus and can be measured using electrodes placed on the scalp and over the years, it has proved to be very useful for clinical study [2, 5, 6, 9]. In particular, the effects of alcohol on evoked responses have been reported in [2, 9], where it was concluded that alcohol significantly increases the latency of evoked responses in humans. In this paper, we use MLP-BP [11] and FA [4] neural network (NN) classifiers to classify alcohol abusers and control (i.e. non-alcoholic) subjects using multi-channel VEP signals, which are extracted while subjects are seeing pictures from Snodgrass and Vanderwart set [12]. Total power in GBF 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. This method of estimating GBF in time domain circumvents the conventional technique of computing power spectrum.

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 [5, 7, 9]. The common method of reducing this problem is to use signal averaging from a certain number of trials [1, 5, 7, 9]. This approach is useful to study time-domain properties like latency, amplitude, polarity and wave-shape of evoked responses [9]. However signal averaging requires many trials, which leads to system complexity and higher computational time.

Our approach here 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 GBF computed in the time domain is used to classify alcohol abusers based on single evoked responses. GBF in the range of 30 to 64 Hz[1] is specifically chosen since studies in [3, 10, 13, 14, 16] have shown that electric potential in GBF is evoked during the application of sensory simulation. This method uses a high-pass digital filter to extract VEP signals in GBF range. 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. Direct power spectrum computation using techniques like Fourier Transform or autoregressive are not necessary in the method. This results in reduction of computational time and design complexity. These GBF powers are used as features by the NN classifiers to classify alcohol abusers and control i.e. non-alcoholic subjects. The classification performances of this method are compared with the conventional method of computing power spectrum to estimate total power in GBF using periodogram analysis. This is to show that the advantages of lower computational time and design complexity achieved by the proposed method are not compromised with the classification rate of alcohol abusers.

2. EXTRACTING TOTAL POWER IN GAMMA BAND FREQUENCY

The extracted VEP signals are digitally filtered using a difference filter, which acts as a high-pass filter (HPF). The transfer function of the HPF in Z-transform can be written as

$$H(z) = (1 - z^{-1})^{N} . \tag{1}$$

where the gain frequency response is

$$G(f) = (2|\sin pf|)^{N} . \tag{2}$$

[1] Following studies in [3] that proposed gamma band to consist of frequencies around this range.

Eq. 2 could be obtained by replacing $z = e^{j2pf}$ in (1). This filter has N order zeros at z=1 and N order poles at origin. The integer value N can be increased to reduce the bandwidth of the filter. We are interested in VEP signals in the GBF where the frequency of interest is above 30 Hz, therefore a value of 5 for N is sufficient since it gives an attenuation of –17.3 dB at 30 Hz. With N=5, (1) could be expanded to give

$$H(z) = z - 5z^{-1} + 10z^{-2} - 10z^{-3} + 5z^{-4} - z^{-5}, \tag{3}$$

By assuming a sampling frequency of 128 Hz, the highest spectral content in the signal would be 64 Hz (from Nyquist's theorem). At this frequency, the maximum gain amplification is 32, which can be obtained from (2). This value is divided later in the filtered signal so that the maximum gain of the HPF will be unity. The phase calculations are not important since we are interested in the magnitude of the power spectrum only. In the time domain, the filter can be implemented (from (3) by inverse Z-transform) as

$$y(n) = \frac{1}{32} \sum_{r=0}^{5} (-1)^r \, {}^5C_r \, x(n-r), \tag{4}$$

where ${}^QC_r = \frac{Q!}{r!(Q-r)!}$ and $y(n)$ is the output of the filter with $x(n)$ as the sampled input signal. Figure 1 shows how the proposed HPF can be realized using delay, adder and multiplier circuits. Figure 2 shows the magnitude gain of the filter.

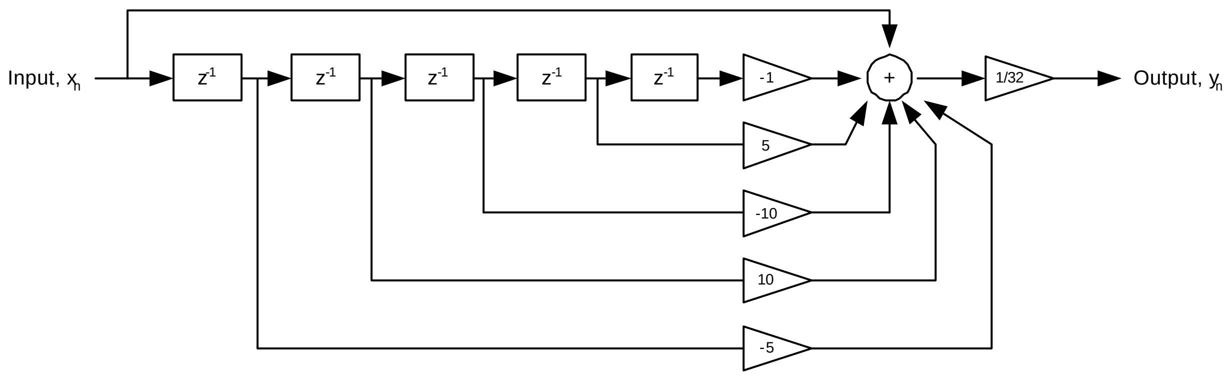

Figure 1: Realization of the proposed high-pass digital filter to extract gamma band VEP

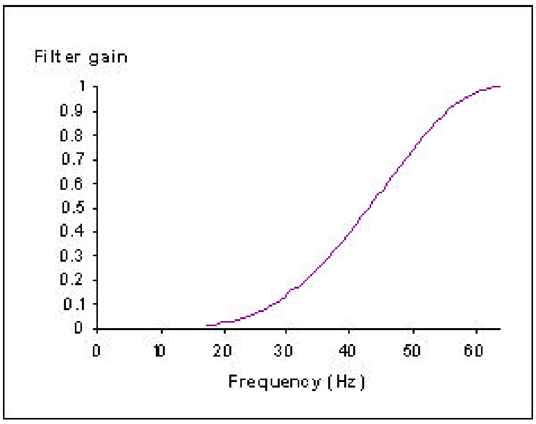

Figure 2: Filter gain

The filtered output, $y(n)$ contains signals mostly in the GBF range of 30-64 Hz and Parseval's theorem can now be applied to obtain the equivalent total power of the signal (in GBF) using

$$Power_{gamma} = \frac{1}{M} \sum_{n=1}^{M} \left[y(n)\right]^2, \tag{5}$$

where M is the total number of data in the filtered signal. Figure 3 shows the procedures involved in this proposed method, which we shall denote as Method A.

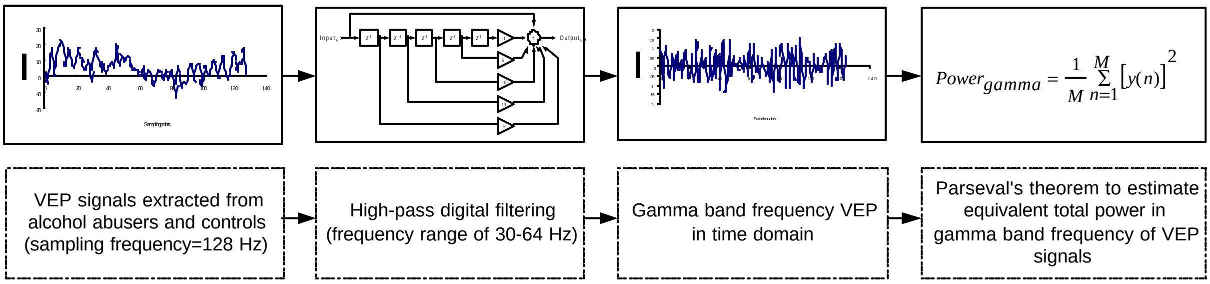

Figure 3: Procedures involved in the proposed method (Method A)

As a comparison to study the classification performances using the proposed method, we use periodogram based method [8] to estimate the total power in GBF of VEP signals. This technique (denoted as Method B) computes power spectrum using Welch periodogram analysis (WPA) with 50% overlap [15]. The total power in GBF, which we have assumed to be from 30-64 Hz are summed. Figure 4 shows the procedures involved in Method B.

Method A requires 40.33 microseconds to compute total power in GBF for data from a single VEP channel whereas Method B requires 34.6 milliseconds. These results are obtained from simulations carried out on a Pentium III 800 MHz PC with 128 MB RAM and software written in C language. The significant reduction in computation time for Method A is since this method requires only a few lines of programming code to implement the filter equation and Parseval's sum operations but Method B requires many lines of programming code to implement Fourier Transform computation in WPA method. It must be noted that although both the methods estimate the total power in GBF of VEP signals, they are nevertheless computationally different and as such, do not give the same outputs.

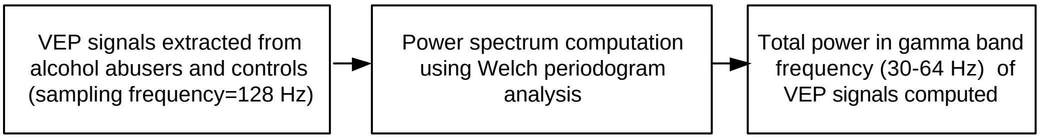

Figure 4: Procedures involved in Welch periodogram analysis (Method B)

3. NEURAL NETWORK CLASSIFIERS

In this paper, 2 NN classifiers: MLP-BP [11] and FA [4] are used to classify alcohol abusers and control subjects using total power in GBF of VEP signals. Figure 5 shows the architecture of the MLP-BP NN used in this study. The output nodes are set at 2 so that the NN can classify into one of the 2 output categories: alcohol and control. The hidden layer nodes are varied from 60 to 100 in steps of 10. The input nodes are set at 64 to accommodate the 64 GBF power values.

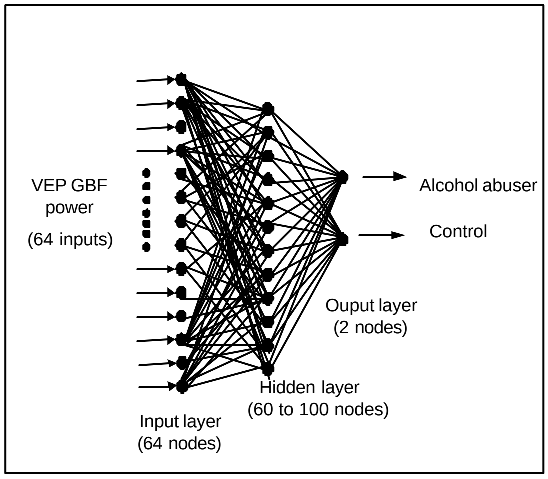

Figure 5: MLP-BP NN architecture

FA is used in addition to MLP-BP due to FA's ability to learn incrementally, i.e. it is both *plastic* and *stable*. Furthermore, it is relatively fast and easier to train as compared to MLP-BP. It consists of two Fuzzy ART modules (Fuzzy ART_a and Fuzzy ART_b) that create stable recognition categories in response to sequence of input patterns. During supervised learning, Fuzzy ART_a receives a stream of input features representing the pattern and Fuzzy ART_b receives a stream of output features representing the target class of the pattern. An Inter ART module links these two modules, which works by increasing the vigilance parameter, p_a of Fuzzy ART_a by a minimal amount to correct a predictive error at Fuzzy ART_b. Vigilance parameter calibrates the minimum confidence that Fuzzy ART_a must have in an input vector in order for Fuzzy ART_a to accept that category, rather than search for a better one through an automatically controlled process of hypothesis testing. Lower values of p_a enable larger categories to form and lead to a broader generalization and higher code compression. Figure 6 shows the structure of FA as used in this study.

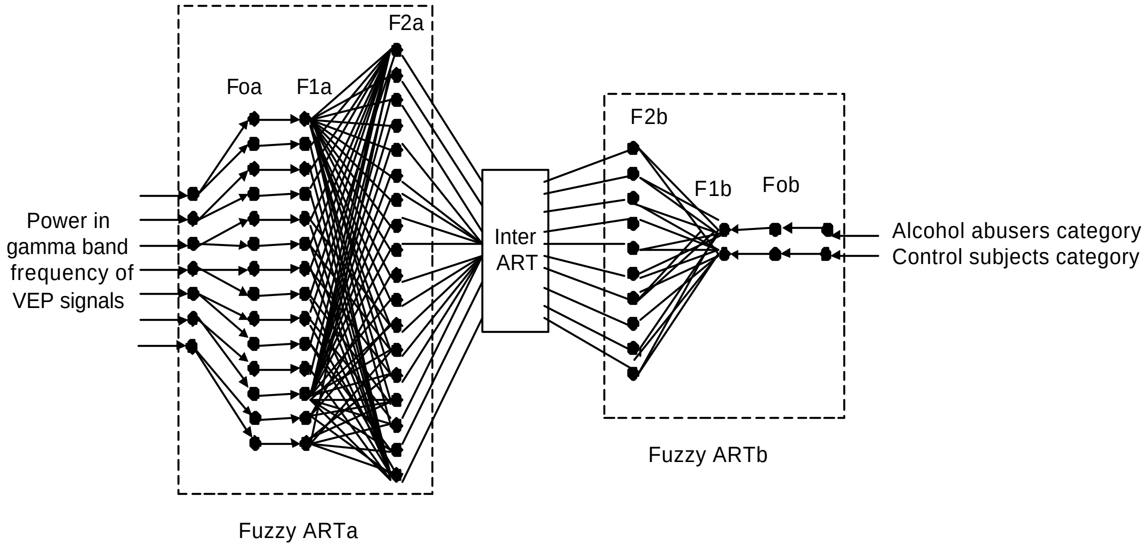

Figure 6: FA NN as used in this study

4. EXPERIMENTAL STUDY

VEP data is recorded from 20 subjects: 10 alcohol abusers and 10 controls where each subject completed 40 trials giving a total of 800 VEP patterns. The alcohol abusers tested have been abstinent for a minimum period of one month and are also off all medications for the same period of time. The controls are carefully matched for age, socioeconomic status and are not alcohol or substance abusers. Measurements are taken for one second from 64 electrodes placed on the subject's scalp, which are sampled at 256 Hz. The electrode positions (as shown in Figure 7) are located at standard sites using extension of Standard Electrode Position Nomenclature, American Encephalographic Association. The VEP data is recorded from subjects while being exposed to a single stimulus, which are pictures of objects chosen from the Snodgrass and Vanderwart picture set [12]. 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. Figure 8 shows some of these pictures and Figure 9 illustrates the presentation of the pictures. The VEP signals are amplified by a gain of 10,000 and band-pass filtered from 0.02 and 50 Hz by Ep-A2 amplifiers (Sensorium, Inc.). Further details of the data collection process can be obtained from [17].

In this study, VEP signals with eye blink artifact contamination are removed in the pre-processing stage using a computer program written to detect VEP signals in any one the frontal or prefrontal channels with magnitudes above 100 μV and these VEP signals detected with eye blinks are then discarded from the experimental study. The threshold value of 100 μV is used since blinking produces 100-200 μV potential lasting 250 milliseconds [7]. Next, the VEP signals are down-sampled by half to obtain an equivalent sampling frequency of 128 Hz. This operation doesn't result in loss of significant information since we are interested in GBF below 64 Hz and this operation allows reduction of computational time in later stages by half. Aliasing effects do not arise because the VEP signals have been filtered to 50 Hz using analog filters as mentioned earlier.

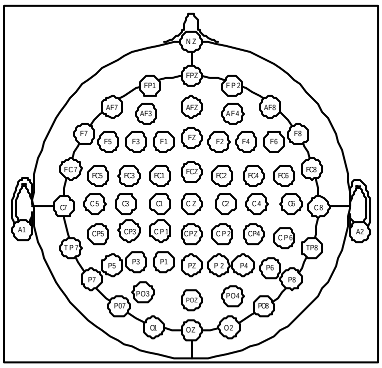

Figure 7: 64 channel electrode system

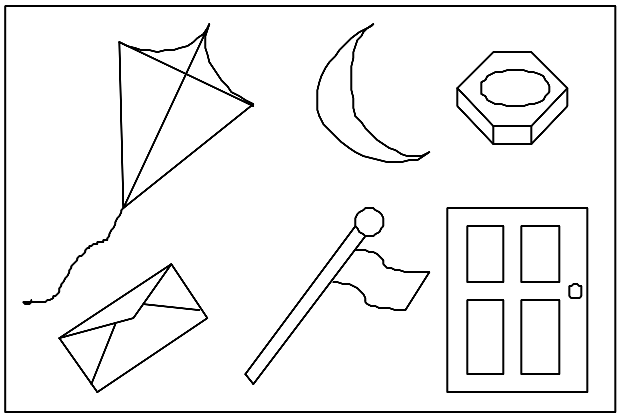

Figure 8: Some pictures from Snodgrass and Vanderwart set

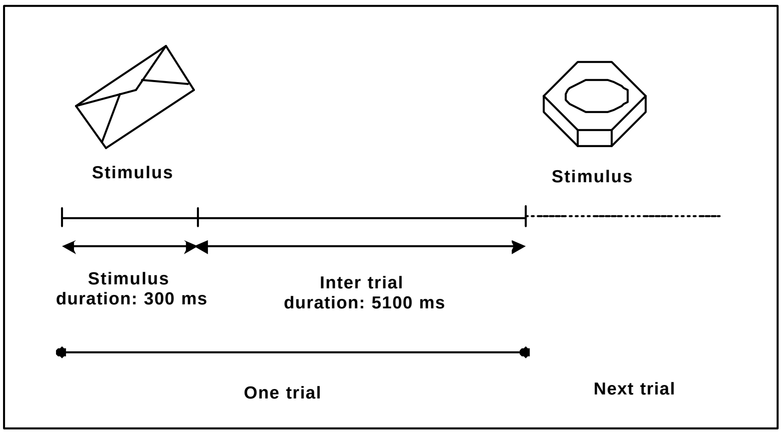

Figure 9: Presentation of Snodgrass and Vanderwart picture stimulus

Total power in GBF from each of the 64 VEP channel obtained from Methods A and B are concanated into a single array of 64 values. MLP-BP and FA use these VEP arrays as inputs to classify alcohol abusers as illustrated in Figure 10. Half of the available data i.e. 400 VEP feature arrays (200 from alcohol abusers and 200 from control subjects) are used to train NNs while the rest half are used in testing. The VEP feature arrays for training and testing data are chosen randomly. 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, it is set to 0.

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 and the learning rate is increased by 5%. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 10000. The average error denotes the error limit to stop neural network (NN) training.

In this study, FA is trained in the fast learning mode with voting strategy of 10 simulations. In addition, 10 FA simulations with random pattern ordering are also conducted. All FA experiments are conducted with p_a varied from 0 to 0.9 in steps of 0.1.

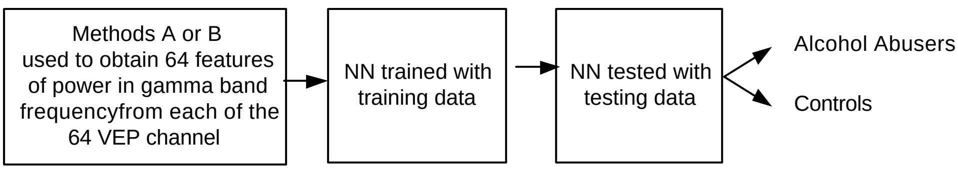

Figure 10: NN training and testing to classify alcohol abusers from control subjects

5. RESULTS

Tables 1-3 gives the results of MLP-BP and FA classification of alcohol abusers using the different methods. Overall, the high classification results shown in the tables show that both methods of extracting total power in GBF of VEP signals can be used to distinguish alcohol abusers from control subjects. This is indicated by the best MLP-BP classification performance: 100% (Method A) and 98.5% (Method B) and FA classification, where p_a value of 0.9 gave the best performance of 96% for the proposed method (Method A) and 94.5% for the WPA method (Method B). From the tables, it can also be seen that Method A gave averaged classification of 99.85% (MLP-BP), 91.13% (FA-voting) and 87.20% (FA-random) as compared to Method B, which gives averaged classification of 99.35% (MLP-BP), 89.58% (FA-voting) and 82.90% (FA-random). Overall, the proposed method results in improved classification performance as compared to the conventional periodogram based method for all the experiments.

MLP-BP performs better than both FA with voting strategy and FA with random pattern ordering. However, MLP-BP training takes longer time as compared to FA training but this is not a serious drawback for offline simulations. MLP-BP classification performances do not vary significantly with the variation in hidden units. However, FA classification performances do vary with p_a values. For all the cases, p_a value of 0.9 gives the best performance. Comparing both the FA classification methods, voting strategy improves the performance for all p_a values as compared to the average of random pattern ordering.

TABLE 1: RESULTS OF FA CLASSIFICATION USING VOTING STRATEGY FOR THE DIFFERENT METHODS

FA p_a	**Voting strategy**	
	Proposed method (Method A)	**WPA (Method B)**
0	92.25	87.75
0.1	90.25	84.75
0.2	87.75	86.50
0.3	86.25	80.50
0.4	89.25	81.25
0.5	91.00	83.25
0.6	91.25	89.25
0.7	92.25	87.00
0.8	95.00	91.00
0.9	96.00	94.50
Average	**91.13**	**89.58**

5. CONCLUSION

We have proposed a method to classify alcohol abusers using total power in GBF of VEP signals with MLP-BP and FA NN classifiers. This novel method employs digital filtering with Parseval's theorem used to compute GBF power of VEP signals in time domain. We compare the classification performance of this method with a conventional method, which uses power spectrum estimation with Welch periodogram analysis. The results from experimental study using 800 VEP signals from 10 alcohol abusers and 10 control subjects show that the proposed method reduces design complexity and computational time. The proposed method also performs better than the conventional method in terms of classification rate. Overall, the results 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 NNs to detect some alterations in the visual perception caused by long-term use of alcohol.

6. ACKNOWLEDGEMENT

We acknowledge the assistance of Prof. Henri Begleiter at Neurodynamics Laboratory at the State University of New York Health Center at Brooklyn, USA who recorded the raw VEP data and Mr. Paul Conlon, of Sasco Hill Research, USA for sending the data to us. We are greatly indebted to Prof. P. Raveendran, Electrical Dept., University Malaya, for his initial guidance on the work that made this publication possible.

TABLE 2: RESULTS OF FA CLASSIFICATION USING RANDOM PATTERN ORDERING FOR THE DIFFERENT METHODS

					Confidence interval (95%)	
	FA p_a	**Average**	**Maximum**	**Minimum**	**Lower**	**Higher**
Proposed method (Method A)	0	87.48	90.50	86.00	86.49	88.46
	0.1	87.05	90.75	82.00	85.26	88.84
	0.2	86.30	91.50	82.50	84.15	88.45
	0.3	85.05	92.75	82.00	82.44	87.66
	0.4	86.13	90.50	82.50	84.54	87.71
	0.5	86.15	90.75	82.50	84.55	87.75
	0.6	85.78	88.50	82.75	84.21	87.34
	0.7	85.98	88.75	82.50	84.38	87.57
	0.8	89.18	92.50	86.25	87.79	90.56
	0.9	92.90	95.00	90.25	91.80	94.00
	Average	**87.20**	**91.15**	**83.93**	**85.56**	**88.83**
WPA (Method B)	0	82.48	86.50	78.00	80.56	84.39
	0.1	80.58	83.00	77.75	79.28	81.87
	0.2	81.33	88.50	73.50	78.07	84.58
	0.3	79.35	86.25	75.25	76.89	81.81
	0.4	79.43	87.50	73.00	76.54	82.31
	0.5	78.00	82.50	75.50	76.53	79.47
	0.6	82.75	87.00	78.75	80.39	85.11
	0.7	84.63	87.25	81.50	83.49	85.76
	0.8	88.10	90.00	84.50	86.71	89.49
	0.9	92.35	93.75	90.25	91.44	93.26
	Average	**82.90**	**87.23**	**78.80**	**80.99**	**84.81**

TABLE 3: RESULTS OF MLP-BP CLASSIFICATION FOR THE DIFFERENT METHODS

Hidden units	**Proposed method (Method A)**	**WPA (Method B)**
60	100.00	98.50
70	99.75	98.50
80	100.00	98.50
90	100.00	98.50
100	99.50	97.75
Average	**99.85**	**99.35**

7. REFERENCES

[1] Aunon, J.I., McGillem, C.D. and Childers, D.G., “Signal Processing in Event Potential Research: Averaging and Modelling,” CRC Crit. Rev. Bioeng., pp. 323-367, vol. 5, 1981.

[2] Begleiter, H. and Platz, A., “The Effects of Alcohol on the Central Nervous System in Humans,” in *The Biology of Alcoholism, Volume 2: Physiology and Behavior,* edited by Kissin, B. and Begleiter, H., Plenum Press, 1972.

[3] Basar, E., Eroglu, C.B., Demiralp, T., and Schurman, M., "Time and Frequency Analysis of the Brain's Distributed Gamma-Band System," *IEEE Engineering in Medicine and Biology Magazine*, pp. 400-410, July/August 1995.

[4] Carpenter, G.A., Grossberg, S., Markuzon, N., Reynolds, J.H., and Rosen, D.B., "Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps," *IEEE Transactions on Neural Networks*, vol. 3, no.5, pp. 698-713, September 1992.

[5] Cooper R., Osselton, J.W., and Shaw, J.C., *EEG Technology*, Butterworths & Company Publishers, 1980.

[6] Hughes, J.R., *EEG in Clinical Practice*, Butterworth-Heinemann, 1994.

[7] Kriss, A., "Recording Technique," *in Evoked Potentials in Clinical Testing*, edited by Halliday, A.M., Churchill Livingstone, 1993.

[8] Liavas, A.P., Moustakides, G.V., Henning, G., Psarakis, E.Z. and Husar, P., "A Periodogram-Based Method for the Detection of Steady-State Visually Evoked Potentials," *IEEE Transactions on Biomedical Engineering*, pp. 242-248, vol. 45, no. 2, 1998.

[9] Misulis K.E., *Spehlmann's Evoked Potential Primer: Visual, Auditory and Somatosensory Evoked Potentials in Clinical Diagnosis*, Butterworth-Heinemann, 1994.

[10] Palaniappan, R. and Raveendran, P. "Single Trial VEP Extraction Using Digital Filter," *Proceedings of IEEE 11th Workshop on Statistical Signal Processing*, pp.249-252, 6-8 August 2001, Singapore.

[11] Rumelhart, D.E., and McCelland, J.L., *Parallel Distributed Processing: Exploration in the Microstructure of Cognition*, MIT Press, Cambridge, MA, vol. 1, 1986.

[12] Snodgrass, J.G. and Vanderwart, M., "A Standardized Set of 260 Pictures: Norms for Name Agreement, Image Agreement, Familiarity, and Visual Complexity," *Journal of Experimental Psychology: Human Learning and Memory*, pp. 174-215, vol. 6, No.2, 1980.

[13] Tallon-Baudry, C., Bertrand, O., Peronnet, F., and Pernier, J., "Induced λ-Band Activity During The Delay of A Visual Short-Term Memory Task in Humans," *Journal of Neuroscience*, vol. 18, no. 11, pp. 4244-4254, 1998.

[14] Varner, J.L. and Rohrbaugh, J.W., "Evoked EEG Gamma Band Response at Slow Rates of Stimulation," *Proceedings of the 14th Annual International Conference of the IEEE EMBS*, pp. 2465-2466, vol. 6, 1992.

[15] Welch, P.D., "The use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms," *IEEE Transactions on Audio and Electroacoustics*, pp.70-73, vol. 15, 1967.

[16] Xiao, D., Yang, H. and Zhou, S., "Extraction of 40 Hz EEG Bursts for Chaos Analysis of Brain Function," *IEEE Engineering in Medicine and Biology Magazine*, pp. 27-32, July/August 1997.

[17] Zhang, X.L., Begleiter, H., Porjesz, B., Wang, W. and Litke, A., "Event related potentials during object recognition tasks," *Brain Research Bulletin*, pp. 531-538, vol. 38, no. 6, 1995.