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Improved Automated Classification of Alcoholics and Non-alcoholics

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***Abstract*—**In this paper, several improvements are proposed to previous work of automated classification of alcoholics and non-alcoholics. In the previous paper, multiplayer-perceptron neural network classifying energy of gamma band Visual Evoked Potential (VEP) signals gave the best classification performance using 800 VEP signals from 10 alcoholics and 10 non-alcoholics. Here, the dataset is extended to include 3560 VEP signals from 102 subjects: 62 alcoholics and 40 non-alcoholics. Three modifications are introduced to improve the classification performance: i) increasing the gamma band spectral range by increasing the pass-band width of the used filter ii) the use of Multiple Signal Classification algorithm to obtain the power of the dominant frequency in gamma band VEP signals as features and iii) the use of the simple but effective k-nearest neighbour classifier. To validate that these two modifications do give improved performance, a 10-fold cross validation classification (CVC) scheme is used. Repeat experiments of the previously used methodology for the extended dataset are performed here and improvement from 94.49% to 98.71% in maximum averaged CVC accuracy is obtained using the modifications. This latest results show that VEP based classification of alcoholics is worth exploring further for system development.

***Keywords*—**Alcoholic, Multilayer-perceptron, Nearest neighbour, Gamma band, MUSIC, Visual evoked potential.

I. Introduction

ALCOHOL abuse results in social and economic losses. In addition, there are hidden damages caused by long-term alcohol abuse like memory, attention and decision-making impairments. These impairments have been shown to persist even after quitting alcohol for a period of time [1]. The impairments could cause accidents especially in certain jobs like driving and machine operation, where it is important to be attentive and to be able to make proper judgements and decisions. Therefore, it becomes important to devise some schemes to screen alcohol abusers (alcoholics) from the rest of the population. An automated scheme would greatly reduce the requirement of psychiatrists to classify the alcoholics.

Visual Evoked Potential (VEP) is one tool that could be used for this purpose. VEP is typically generated in response to external visual stimulus. This electrical signal consists of the activity of an ensemble of neuronal generators producing rhythmic activity in several frequency ranges. These activities are normally random, however with the application of sensory stimulus like visually seeing a set of pictures, these generators are coupled and act in a coherent manner [2]. Synchronisation of this activity gives rise to VEP and its analysis has become very useful for neuropsychological studies and clinical purposes [3].

In a previous pilot study, energies of gamma band VEP signals were used as features to classify 800 VEP feature vectors from 10 alcoholics and 10 non-alcoholics [4]. The method used features from 61 and 8 optimal channels and two neural network (NN) classifiers: Fuzzy ARTMAP (FA) and Multilayer-perceptron (MLP), where the latter gave the best performance of 96.50% using 61 channels.

The method proposed here is based on this previous study [4] but differs in numerous aspects: i) the use of a larger dataset that includes 3560 VEP signals from 62 alcoholics and 40 non-alcoholics; ii) the use of increased filter bandwidth; iii) improved feature extraction technique, specifically the use of Multiple Signal Classification (MUSIC) algorithm to obtain the power of the dominant frequency in gamma band VEP signal; iv) the use of the simple but proven to be effective k-nearest neighbour (kNN) classifier, and v) the use of 10-fold cross validation classification (CVC) scheme. The use of the larger dataset and CVC are to validate the reliability of the results for possible system development. The increased filter bandwidth, the use of MUSIC algorithm for feature extraction and the use of kNN classifier are to improve the classification performance. The kNN classifier would also reduce the design complexity.

II. Methodology

A. Subjects

VEP signals from 62 alcoholics and 40 non-alcoholics totalling 3560 **(**2150 VEP signals from alcoholics and 1410 VEP signals from non-alcoholics**)** were studied here. The alcoholics were significantly older than the non-alcoholics [t(118.9)=12.64, p=0.0001]. The mean age for the non-alcoholics group was 25.81 years old (SD=3.38) ranging from 19.4 to 38.6 years of age. The mean age of alcoholic group was 35.83 (SD=5.33), ranging from 22.3 – 49.8 years. The alcoholics tested had been abstinent for a minimum period of one month (through closed ward detention). Therefore, all alcoholics were fully detoxified and had no alcohol available for that period of hospitalisation. Alcoholic individuals were excluded from the study if they had history of drug dependence, major psychiatric illness, or other diseases related to overt liver, metabolic, vascular and neurological. Most of

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the alcoholics had been drinking heavily for a minimum of 15 years. The diagnosis of alcohol abuse was made by the intake psychiatrist of the Addictive Disease Hospital in Brooklyn according to DSM-III criteria. The alcoholics were non-amnesics. The non-alcoholics were carefully matched for age and were not alcoholics or substance abusers. They were also matched for socioeconomic status.

B. VEP Data

Measurements were taken for one second from 61 active electrodes placed on the subject's scalp, which were sampled at 256 Hz. The electrode positions were located at standard sites (Standard Electrode Position Nomenclature, American Encephalographic Association). The electrode positions are as shown in Fig. 1. These sites were extended by 42 to the 19 sites used in 10-20 electrode positioning system [5].

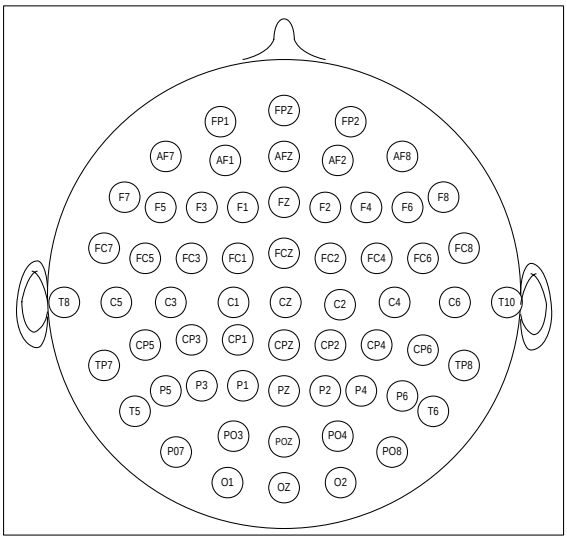

Fig. 1 61 channel electrode system

The VEP signals were extracted from subjects while being exposed to a single stimulus, which were pictures of objects chosen from the Snodgrass and Vanderwart picture set [6]. These shown pictures were common black and white line drawings like aeroplane, hand, banana, bicycle, ball, etc. chosen according to a set of rules that provide consistency of pictorial representation. The pictures had definite verbal labels i.e. they were easily named. Fig. 2 shows some examples of the Snodgrass and Vanderwart pictures. This data set is actually a subset of a larger experiment designed to study the short-term memory differences between alcoholics and non-alcoholics [1].

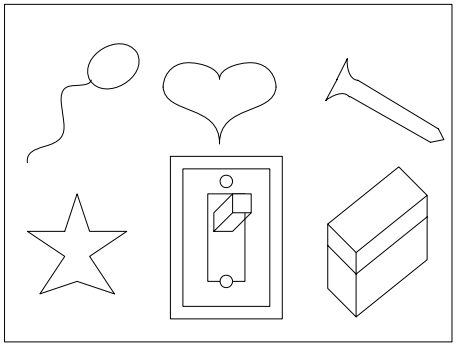

Fig. 2 Some pictures from Snodgrass and Vanderwart set

VEP signals with eye blink artifact contaminations were removed from the dataset. It was assumed that VEP signals with magnitudes above 100μV denotes occurrence of eye blinks [7], so the 61 channel VEP was discarded if any of the channels had amplitudes exceeding this value. The eye-blink free VEP totalled 3150 from 62 alcoholics and 40 non-alcoholics subjects. Actually, the dataset contained more than 3150 VEP signals but only 3150 were eye-blink free. There was a minimum of 10 and a maximum of 50 eye blink free VEP signals from each subject. Fig. 3 shows an example of a recorded VEP signal.

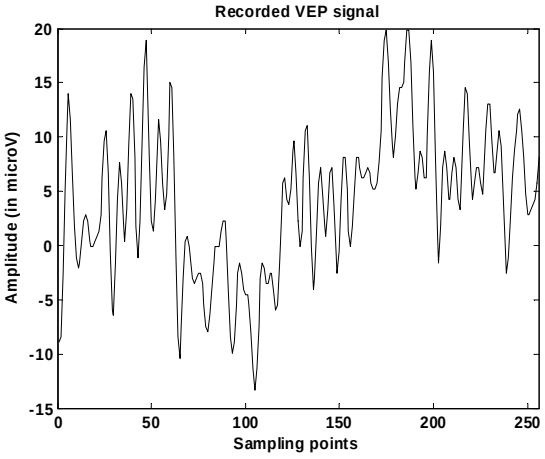

Fig. 3 An example of recorded VEP signal

C. Feature Extraction

There is a major problem encountered in analysing VEP signals, which comes from the contamination of spontaneous background electroencephalogram (EEG) brain activity, which is many times higher in amplitude as compared to VEP signals. The predominant method of extracting VEP signal is to use signal averaging from multi-trial VEP signals [8]. However, there are numerous problems associated with this method like the variation in latency and amplitude for a similar stimulus across different sessions even for the same subject and the difficulty in analyzing single trial VEP cannot be addressed by signal averaging alone.

In the study in this paper, EEG contamination was reduced by using VEP signals in the gamma band range. As such, it was not necessary to increase the signal-to-noise ratio of VEP to background EEG by signal averaging. This relied on the assumption that gamma band spectrum would be evoked during visual stimulus [2]. Since EEG activity is generally limited up to 20 Hz, a high-pass filter that cuts off signals with frequencies below this range will reduce EEG. This is because gamma band (>20 Hz) is beyond the normal EEG spectral range. However, to avoid electromyogram (muscle) signal contamination, a low pass filter that cuts off signals beyond 50 Hz would also be necessary.

Here, these VEP signals were band-pass filtered using a cascade of low pass symmetric (LPS) and high-pass anti-symmetric (HPAS) integer coefficient finite impulse response (ICFIR) filters. In the time domain, these ICFIR filters can be represented as the convolution sum

$$y[n] = \sum_{k=0}^{M} h[k]x[n-k], \tag{1}$$

where *y[n]* is the output at time=*n*, *x[n]* is the input at time=*n*, *M* is the filter order, and *h[k]* are the integer coefficients, which will be symmetric for the low pass filter and anti-symmetric for the high-pass filter. These filters are advantageous as the coefficients are integers, and the symmetry and anti-symmetry properties reduce the requirement of multiplication operation by half [9].

In the time domain, these filters can be implemented by

$$y[n] = \sum_{k=0}^{M} {}^{M}C_k\, x[n-k)], \tag{2}$$
$$\text{and } z[n] = \sum_{k=0}^{N} (-1)^k\, {}^{N}C_k\, y[n-k],$$

where ${}^{P}C_k = \frac{P!}{k!(P-k)!}$, *y[n]* and *z[n]* are the outputs of the LPS and HPAS, respectively.

These filters (sometimes known as sum and difference filters in older textbooks [10]) are similar to the filters used in [4] with the difference being in the filter orders. The study in [4] used orders *M*=28 and *N*=8 to obtain the 3 dB passband range of 32-48 Hz (rounded to the closest integer). However, on closer observation of the VEP dominant frequencies (see Section 2.4), it was noticed that there were dominant frequencies from 23.72 to 51.33 Hz (see Fig. 6 in Section 2.4). As such, the filter orders, *M* and *N* were relaxed to orders 7 and 2, respectively to increase the bandwidth. Fig. 4 shows the magnitude response of the filters with *M*=28, *N*=8 and *M*=7, *N*=2. Note that the centre frequency of the filter (i.e. 40 Hz) does not change with the change in the filter order as the ratio of *M/N* does not change. To obtain zero-phase response, forward and reverse filtering were performed here using the *filtfilt* function in Matlab (Mathworks, Inc.). The magnitude amplification was normalised so that the maximum gain will be unity. Fig. 5 shows an example of the filtered VEP signal.

Next, MUSIC algorithm [11] was used to estimate the dominant frequency and power content where it was assumed there was only one dominant sinusoid in each channel of the filtered VEP signal. This assumption follows another study reported elsewhere [12]. MUSIC algorithm was chosen as in the study by Caspary *et al* [13], it was shown that MUSIC algorithm gives superior resolution to classical Fourier transforms and parametric methods (like autoregressive and prony). The *rootmusic* function in Matlab was utilised for this purpose.

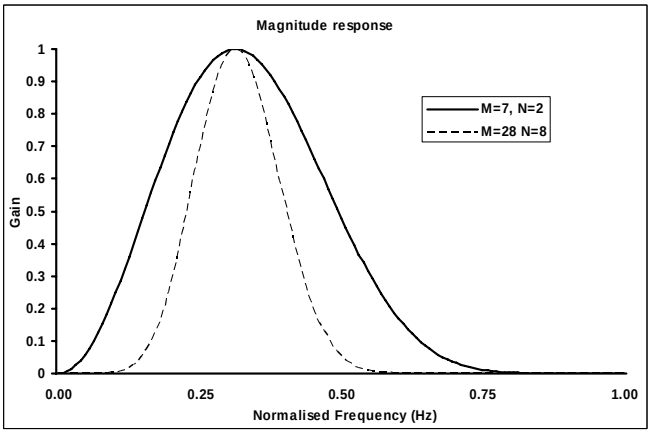

Fig. 4 Magnitude response of the LPS and HPAS filters with different orders

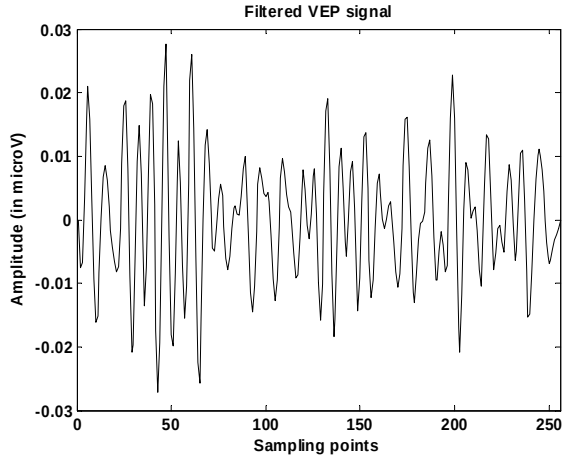

Fig. 5 An example of the filtered gamma band VEP signal

Since the dominant frequencies varied from subject to subject and from channel to channel (as shown in the box-plot Fig. 6 for 61 channels from all the subjects), it was decided that only the power content from the MUSIC algorithm will be used. The power values were normalised using the total power from all the 61 channels. These normalised power values from each of the 61 channels were concatenated into a feature vector.

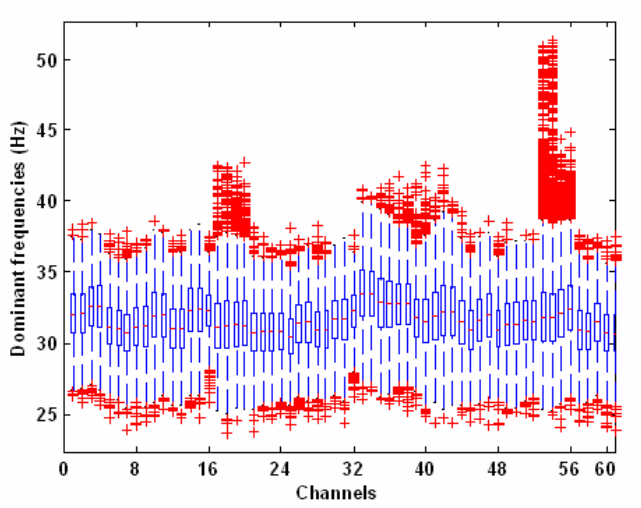

Fig. 6 Box-plot of dominant gamma band frequencies given by the MUSIC algorithm

D. kNN Classifier

In the kNN algorithm [14], the classification of a new test VEP feature vector was determined by the class of its *k* nearest neighbours. Here, the kNN algorithm was implemented using Manhattan distance metric to locate the nearest neighbours. The decision rule used to derive a classification from the k-nearest neighbours was the majority rule. The number of neighbours (i.e. *k*) used to classify the new VEP test vector was varied from 1 to 5 in integer increments.

E. 10-fold CVC Scheme

In the 10-fold CVC scheme, the 3560 VEP feature vectors were divided into 10 sets, with each set containing equal number of feature vectors from alcoholic and non-alcoholic classes. Training was conducted using the nine sets (3204 VEP feature vectors) while testing was conducted with the remaining set (356 VEP feature vectors). This procedure was repeated for 10 times with different sets for training and testing.

III. Results and Discussion

Tables I and II show the classification results using MLP and kNN classifiers, respectively with the 10-fold CVC scheme for features extracted using the original method as used in [4] and the improved method proposed in this paper. The minimum, maximum, and average classification performances from the 10-fold CVC experiments are shown. MLP classification was conducted in addition to kNN to show the improvement in classification performance when kNN was used. The MLP was trained by the resilient-backpropagation algorithm [15] until the mean-square error fell below a threshold of 0.01. Fig. 7 shows the architecture of the MLP as used in this study. The hidden units (HUs) were varied from 10 to 50 in steps of 10 (similar to the study in [4]).

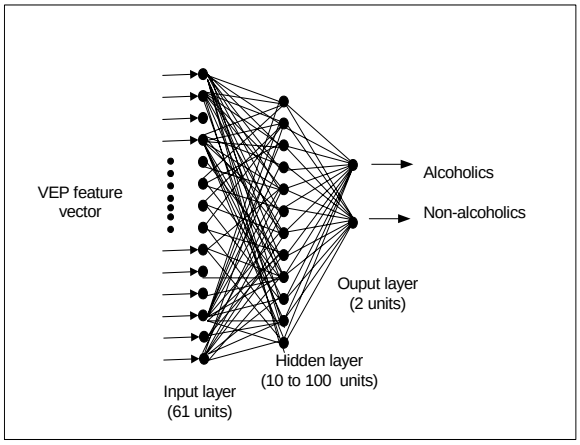

Fig. 7 MLP architecture as used in this study

TABLE I
MLP Classification Results using CVC

HU	Original features (%)			Improved features (%)		
	min	max	mean	min	max	mean
10	91.57	96.07	93.88	94.38	98.88	96.39
20	92.42	95.79	94.24	94.66	97.47	96.35
30	92.13	95.79	94.16	94.94	97.47	96.59
40	92.98	95.51	94.49	94.38	98.03	96.35
50	90.45	96.63	94.30	94.10	98.31	96.27
Average	91.91	95.96	94.21	94.49	98.03	96.39

TABLE II
kNN Classification Results using CVC

k	Original features (%)			Improved features (%)		
	min	max	mean	min	max	mean
1	94.66	97.19	95.73	98.03	99.72	98.71
2	93.26	95.79	94.50	96.91	99.44	97.86
3	93.82	97.47	95.25	98.03	99.72	98.65
4	93.26	95.51	94.36	96.91	99.72	97.84
5	92.70	96.63	94.41	97.19	99.44	98.29
Average	93.54	96.52	94.85	97.41	99.61	98.27

It could be seen that the kNN gave superior classification performance as compared to MLP for both the original and improved feature extraction methods. The performances of the improved method for feature extraction were better than the original method for both the classifiers (in every case of varying *k* and HUs). The maximum averaged classification performance for kNN was 98.71% using the improved method and 95.73% using the original method. Both these classification performances were for the case of k=1. The maximum averaged classification performance for MLP was 96.59% using the improved method and 94.49% using the original method, obtained using 30 and 40 HUs, respectively.

In terms of algorithm, MLP, like other NNs is much more complicated than kNN and requires a lot of effort in the design stage (choosing architecture, learning algorithm, etc). MLP also requires huge training time. The kNN, in contrast, requires no explicit training. A disadvantage of kNN is its higher computation time during testing, since to classify a test VEP feature vector, its distance to all the training VEP feature vectors has to be calculated.

In the previous paper [4], the best classification

performances of 96.50% and 91.50% were obtained using MLP and FA NN with the 61 channel gamma band energy features. The dataset included 800 VEP signals from 10 alcoholics and 10 non-alcoholics, where half of VEP feature vectors were used to train and the rest half to test the NNs without any form of cross validation. It was not possible to make direct comparisons of the classification performances in this study to the previous study because of the difference in the size of the dataset and the use of CVC in this study. As such, the experiments using the feature extraction method proposed as in [4] were repeated for the larger dataset used here and classification performance comparisons were made using CVC scheme. FA NN classifications were omitted here due to the poorer performance given in the previous study. It could be noticed that the classification performances of MLP in this study were lower as compared to the previous study, which were most probably caused by the increase in the size of the dataset.

IV. Conclusion

In this paper, several improvements have been proposed to improve the automated classification performance of alcoholics and non-alcoholics using VEP signals. The experiments in this paper were conducted on a much larger dataset as compared to the previous study and using CVC to validate the reliability of the classification performances. Using the increased band-pass filter width and dominant power features of gamma band VEP proposed in this paper improved the classification performance as compared to the previously used gamma band VEP energy features. On the use of classifiers, the use of the simpler-to-design kNN classifier gave improved classification as compared to the previously used MLP NN. Overall, the results from this study indicate that automated classification of alcoholics is feasible for system deployment.

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References

[1] X. L. Zhang, H. Begleiter, B. Porjesz, and A. Litke, "Electrophysiological evidence of memory impairment in alcoholic patients," *Biological Psychiatry*, vol.42, pp. 1157-1171, 1997.

[2] E. Basar, *Memory and Brain Dynamics: Oscillations Integrating Attention, Perception, Learning, and Memory*, CRC Press, Boca Raton, 2004.

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

[4] R. Palaniappan, P. Raveendran, and S. Omatu, "VEP optimal channel selection using genetic algorithm for neural network classification of alcoholics," *IEEE Transactions on Neural Network*, vol. 13, issue 2, pp.486-491, 2002.

[5] H. Jasper, "The ten twenty electrode system of the international federation," *Electroencephalographic and Clinical Neurophysiology,* vol. 10, pp. 371-375, 1958.

[6] J. G. Snodgrass and M. Vanderwart, "A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity," *Journal of Experimental Psychology: Human Learning and Memory,* vol. 6, no. 2, pp. 174-215, 1980.

[7] A. Kriss, "Recording technique," in *Evoked Potentials in Clinical Testing*, Halliday, A.M.(ed), Churchill Livingstone, 1993.

[8] J. I. Aunon, C. D. McGillem, and D. G. Childers, "Signal processing in event potential research: averaging and modelling," *CRC Crit. Rev. Bioeng.,* vol 5, pp. 323-367, 1981.

[9] S. K. Mitra, *Digital Signal Processing, 3rd ed*., McGraw-Hill International Edition, 2006.

[10] G. E. P. Box, and G. M. Jenkins, *Time Series Analysis: Forecasting and Control,* Holden Day, San Francisco, 1976.

[11] M. Akay, *Detection and Estimation Methods for Biomedical Signals*, Academic Press, 1996.

[12] R. Palaniappan, "Discrimination of alcoholic subjects using second order autoregressive modelling of brain signals evoked during visual stimulus perception," *5th World Enformatika Conference*, Prague, Czech Republic, August 26-28, 2005 (accepted for presentation).

[13] O. Caspary, M. Tomczak, N. Di Renzo, M. Mouze-Amady and D. Henry, "Enhanced high resolution spectral analysis of sleep spindles," *Proceedings of the 16th Annual International Conference of the IEEE EMBS*, vol.2, pp. 1232 – 1233, 1994.

[14] C. M. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, 1995.

[15] M. Riedmiller, and H. Braun, "A direct adaptive method for faster backpropagation learning: the RPROP algorithm," *Proceedings of the IEEE International Conference on Neural Networks*, pp. 586-591, 1993.

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