Paper

Multi-Channel Noise Reduced Visual Evoked Potential Analysis

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In this paper, Principal Component Analysis (PCA) is used to reduce noise from multi-channel Visual Evoked Potential (VEP) signals. PCA is applied to reduce noise from multi-channel VEP signals because VEP signals are more correlated from one channel to another as compared to noise during visual perception. Emulated VEP signals contaminated with noise are used to show the noise reduction ability of PCA. These noise reduced VEP signals are analysed in the gamma spectral band to classify alcoholics and non-alcoholics with a Fuzzy ARTMAP (FA) neural network. A zero phase Butterworth digital filter is used to extract gamma band power in spectral range of 30 to 50 Hz from these noise reduced VEP signals. The results using 800 VEP signals give an average FA classification of 92.50% with the application of PCA and 83.33% without the application of PCA.

Keywords: Alcoholics, Fuzzy ARTMAP, Gamma band, Object recognition, Principal component analysis, Visual stimulus

1. Introduction

Evoked potential is typically generated in response to external stimulus. The application of sensory stimulus like visually seeing a set of pictures gives rhythmic Visual Evoked Potential (VEP), which is the coupled and coherent activity of an ensemble of neuronal generators in the brain (2). Over the years, VEP analysis has become very useful for neuropsychological studies and clinical purposes (8). Specifically, the effects of alcohol on the central nervous system of humans and genetic predisposition towards alcoholism have been studied using evoked responses (12) (3).

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

In this paper, a zero phase Butterworth digital filter is used to extract gamma band spectral power of single trial VEP signals buried in the spontaneous EEG activity. Our method assumes that the ratio of VEP to EEG is higher in the gamma band range, thereby circumventing methods like signal averaging to improve the VEP/EEG ratio. This assumption follows research of single trial gamma band VEP signals used to study stimulus specificity of visual responses in humans (11). In addition, it is reported that gamma band spectra centred at 40 Hz is evoked during the application of sensory simulation (2).

Principal Component Analysis (PCA) is a technique commonly employed to reduce the dimension of the feature set (5). In this paper, PCA is applied to reduce noise effects in VEP. VEP signals are more correlated from one channel to another as compared to noise during visual perception. As such, PCA which uses eigen analysis of data covariance matrix can be applied to reduce noise in VEP signals.

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 alcoholics and non-alcoholics using a simplified Fuzzy ARTMAP (FA) neural network (NN) classifier developed by Kasuba (6).

2. Noise Removal Using PCA

PCA (5) 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 x to represent the extracted noise corrupted VEP signal, the covariance of

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matrix x is computed using:

$$R = E(xx^T) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (1)$$

Next, matrices E and D, are computed where E is the orthogonal matrix of eigenvectors of R and D is the diagonal matrix of its eigenvalues, $D = diag(d_1, ..., d_n)$. The PCs can now be computed using

$$y = E^T x^T \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (2)$$

In this work, Kaiser's rule is used to give the number of required PCs [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

$$\tilde{x} = \hat{E}\hat{y} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (3)$$

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

2.1 Simulation Study A simulation study is conducted using emulated VEP signals contaminated with noise. The study is used to show that PCA could considerably reduce noise effects from the emulated VEP signals. VEP signal is emulated using a combination of 5 randomly selected waveforms from 6 basic waveforms, each with different frequency and amplitude. The emulated VEP signals are later normalised to zero mean and unit variance. The basic waveform equation is:

$$G(n) = Asin(\frac{2\pi n f}{f_s}) \cdots\cdots\cdots\cdots\cdots\cdots\cdots (4)$$

where f is the frequency in the gamma band range (randomly selected from 30-50 Hz), f_s is the sampling frequency (256 Hz), and A is the amplitude of the signal. The amplitude is chosen randomly in the range of $20 \sim 30$ units. This variation in the amplitude and frequency are to emulate the real VEP signals. Some of the emulated VEP signals are shown in Figure 1.

The noise is constructed using whitening method, which is as follows. EEG signals are extracted while the subjects are at rest. These signals are first centred to remove the mean and then whitened to remove correlation between its components and to achieve unit variance. Assuming matrix z to represent the extracted signal, whitening seeks to obtain noise matrix $\tilde{z}$, where the covariance of matrix $\tilde{z}$ equals the identity matrix:

$$E(\tilde{z}\tilde{z}^T) = I \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (5)$$

A common whitening method is to use the eigenvalue decomposition of the covariance matrix $E(\tilde{z}\tilde{z}^T) = EDE^T$, where E is the orthogonal matrix of eigenvectors of $E(\tilde{z}\tilde{z}^T)$ and D is the diagonal matrix of its eigenvalues, $D = diag(d_1, ..., d_n)$. Whitening can now be achieved using

$$\tilde{z} = ED^{-\frac{1}{2}}E^T z \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (6)$$

Some of the whitened noise signals are shown in Figure 2.

The VEP signal with noise artifact can now be constructed using

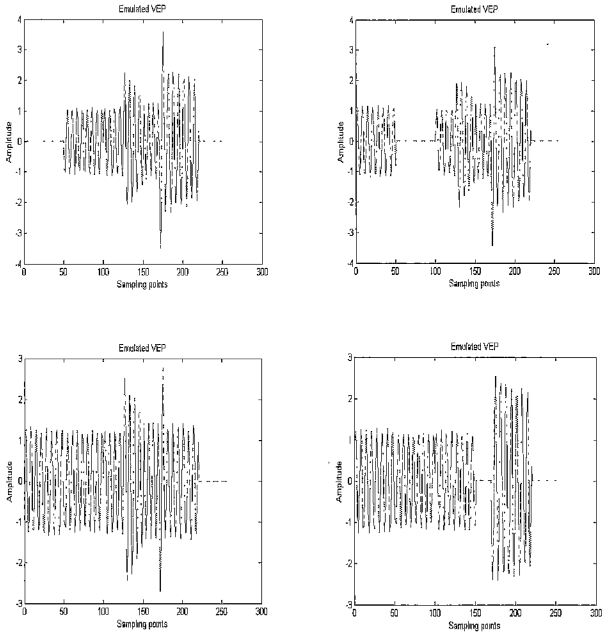


Fig. 1. Emulated VEP signals.

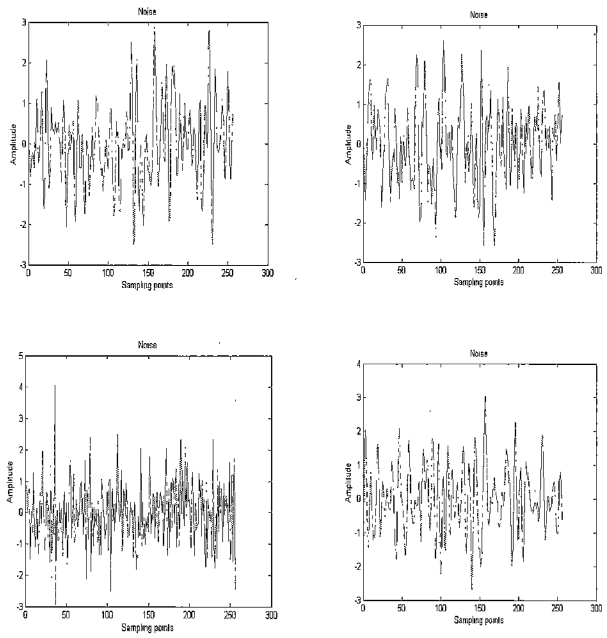
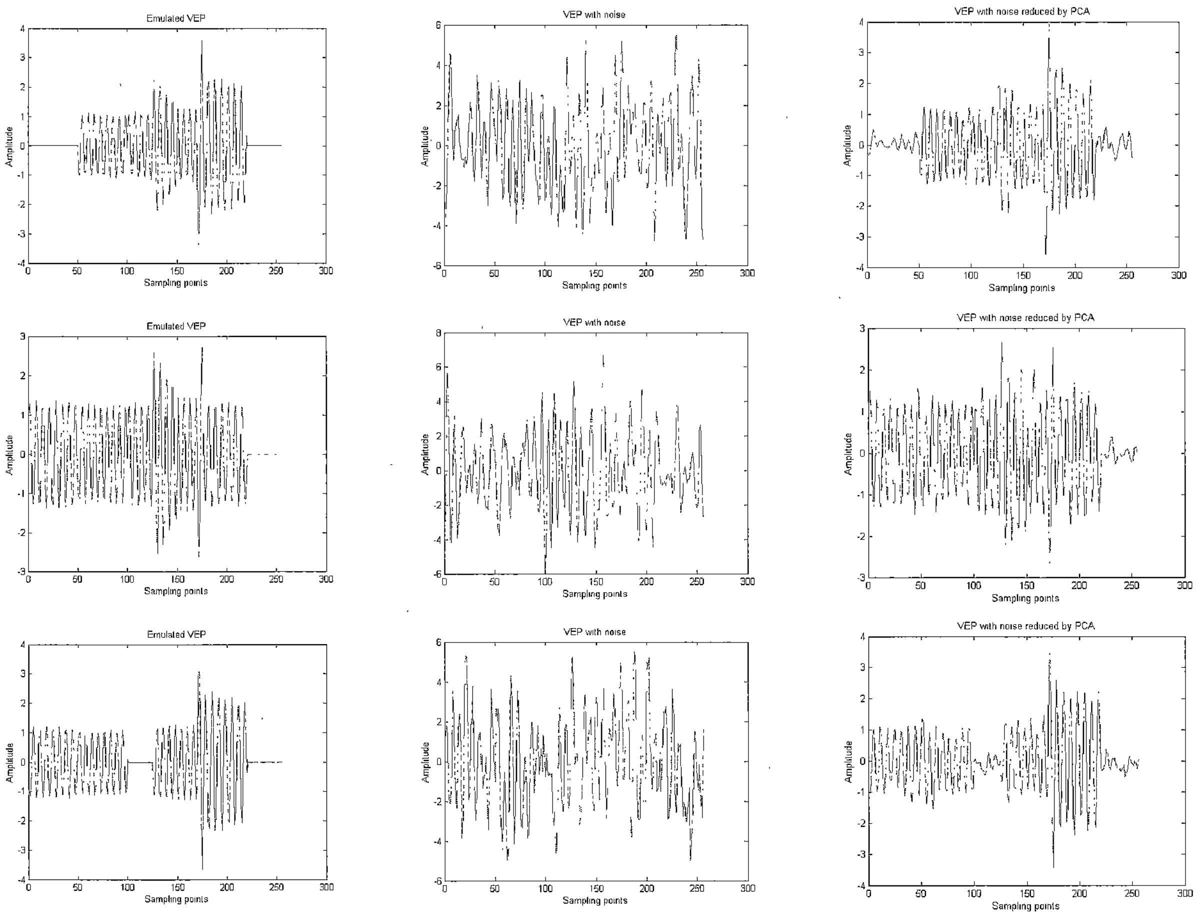


Fig. 2. Whitened noise signals.

$$x(n)_{\text{noise+VEP}} = x(n)_{\text{VEP}} + x(n)_{\text{noise}} \cdots\cdots (7)$$

The signal to noise ratio (SNR) for the real VEP signals vary from case to case. In general, VEP signal levels are comparable to noise levels, i.e. around 0 dB [7, 8]. In this simulation work, the SNR of VEP signals is set approximately to -9 dB i.e. the signal level is approximately 1/3 of the noise level. Sixty-one emulated VEP signals contaminated with noise are created and PCA is applied. Using Kaiser's rule, the number of PCs to reconstruct the data can be determined. Kaiser's rule is chosen because it offers a simple and automated alternative. Other methods like scree graph test could be used but this method requires manual inspection. Using



(a) (b) (c)

Fig. 3. VEP signals (a) emulated (b) with noise (c) with noise reduced by PCA.

Table 1. SNR values of VEP signals in the simulation study.

Signal	SNR		
	Without PCA	**With PCA**	**SNR improvement**
1	-8.64	-4.35	4.29
2	-9.31	-4.27	5.04
3	-8.80	-4.27	4.52
4	-9.31	-4.73	4.58
5	-8.34	-4.17	4.16
6	-9.46	-4.35	5.11
7	-9.04	-4.35	4.69
8	-9.40	-4.64	4.76
9	-8.68	-4.35	4.33
10	-9.31	-4.51	4.80
Average	**-9.03**	**-4.40**	**4.63**

Kaiser's rule, the first 6 PCs are selected for reconstruction.

The first column of Figure 3 shows the emulated VEP signals. The noise contaminated VEP signals are shown in the second column while the third column shows the VEP signals with noise reduced by PCA. From the figure, it be seen that PCA has considerably reduced noise effects from the VEP signals. To further validate the ability of PCA to reduce noise, Table 1 lists the SNR values of noise corrupted VEP and noise reduced VEP signals. The table also shows the SNR improvement after using PCA, which can be seen from the average values of the 10 signals given in the table. Due to space constraints, only values from 10 randomly selected VEP signals are given, but there are improvements in SNR for all the 61 VEP signals.

3. Visual Evoked Potential Data

In this section, the experimental set-up used to record the VEP data is discussed. In addition, pre-processing methods to remove VEP signals with eye blink artifact and setting the pre-stimulus baseline of these signals to zero are described. Twenty subjects participated in the experimental study to record the VEP data that consisted of 10 alcoholics and 10 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 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.

The subjects are seated in a reclining chair located in a sound attenuated RF shielded room. Measurements are taken from 64† channels placed on the subject's scalp, which are sampled at 256 Hz. The electrode positions (as shown in Figure 4) are located at standard sites us-

† In all the experiments in this paper, 3 channels are used as references. Therefore, only 61 channels are used as active channels.

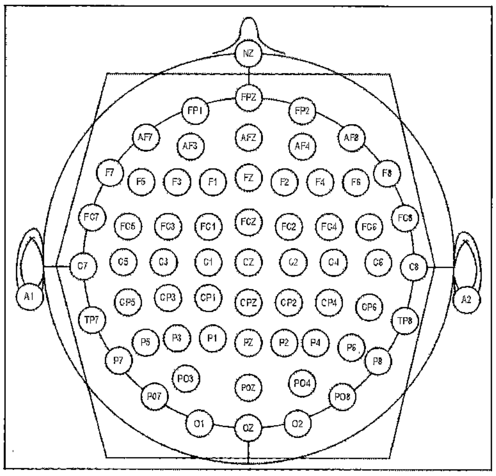


Fig. 4. Electrode positions.

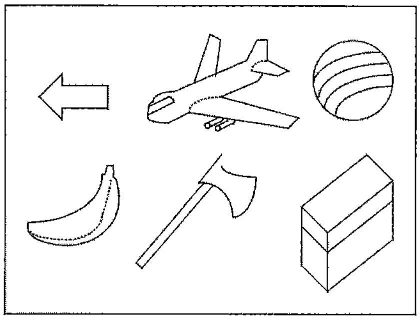


Fig. 5. Some objects from Snodgrass and Vanderwart picture set.

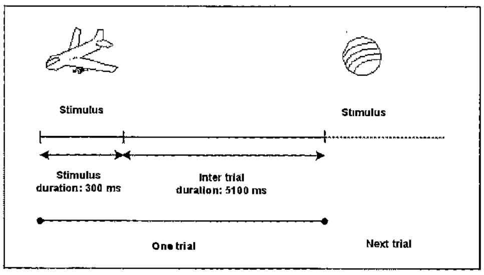


Fig. 6. Example of stimulus presentation.

ing extension of Standard Electrode Position Nomenclature, American Encephalographic Association. The signals are band-pass filtered between 0.02 and 50 Hz using analogue filters.

3.1 Snodgrass and Vanderwart Picture Stimuli 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 [10]. 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. Figure 5 shows some of these pictures. One-second measurements after each stimulus onset are stored. Stimulus duration of each picture is 300 ms with an inter-trial interval of 5100 ms. The pictures are shown using a computer display unit located 1 meter away from the subject's eyes. Figure 6 shows an illustrative example of the stimulus presentation. For further details of the data collection process, refer to [12].

3.2 VEP Pre-Processing 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 mV is used since blinking produces 100-200 mV potential lasting 250 milliseconds [7]. Mean from the data are removed. This is to set the pre-stimulus baseline to zero [9].

4. Classification of VEP Signals

This section discusses the VEP signal classification by Fuzzy ARTMAP (FA) into two categories: alcoholic and non-alcoholic. The VEP feature extraction is described before describing FA classification. The classification experiments are conducted using the extracted VEP with and without the application of PCA.

4.1 VEP Feature Extraction A total of 40 artifact free trials for each subject are used in the experimental study giving a total of 800 VEP signals. A 10th order forward and 10th 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

$$\text{SpectralPower} = \frac{1}{N}\sum_{n=1}^{N}[\tilde{x}(n)]^2 \cdots\cdots\cdots\cdots\cdots (8)$$

where N is the total number of data in the filtered signal. The power values from each of the 61 channels are concatenated into one feature array representing the particular VEP pattern. Figure 7 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 7 except that PCA is not used.

4.2 Classification These VEP feature arrays are classified by FA into alcoholic and non-alcoholic categories. FA 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 [4]. In this paper, a simplified version of FA is used [6]. 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

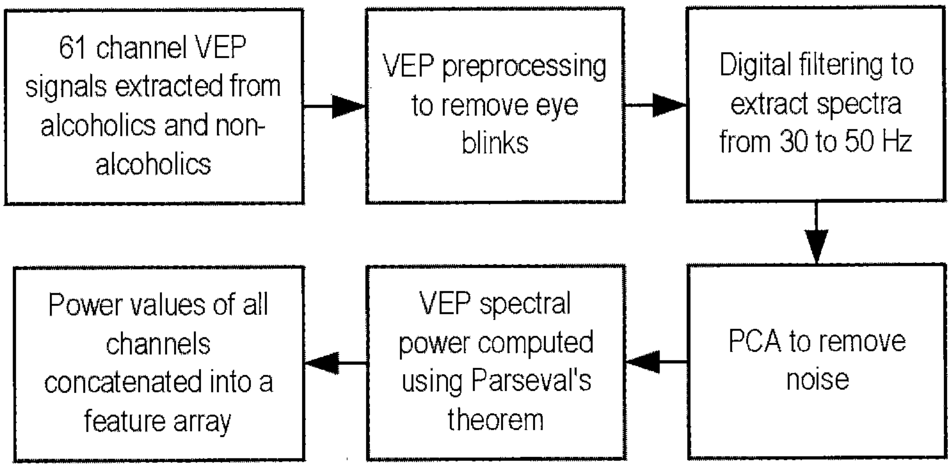


Fig. 7. Example of stimulus presentation.

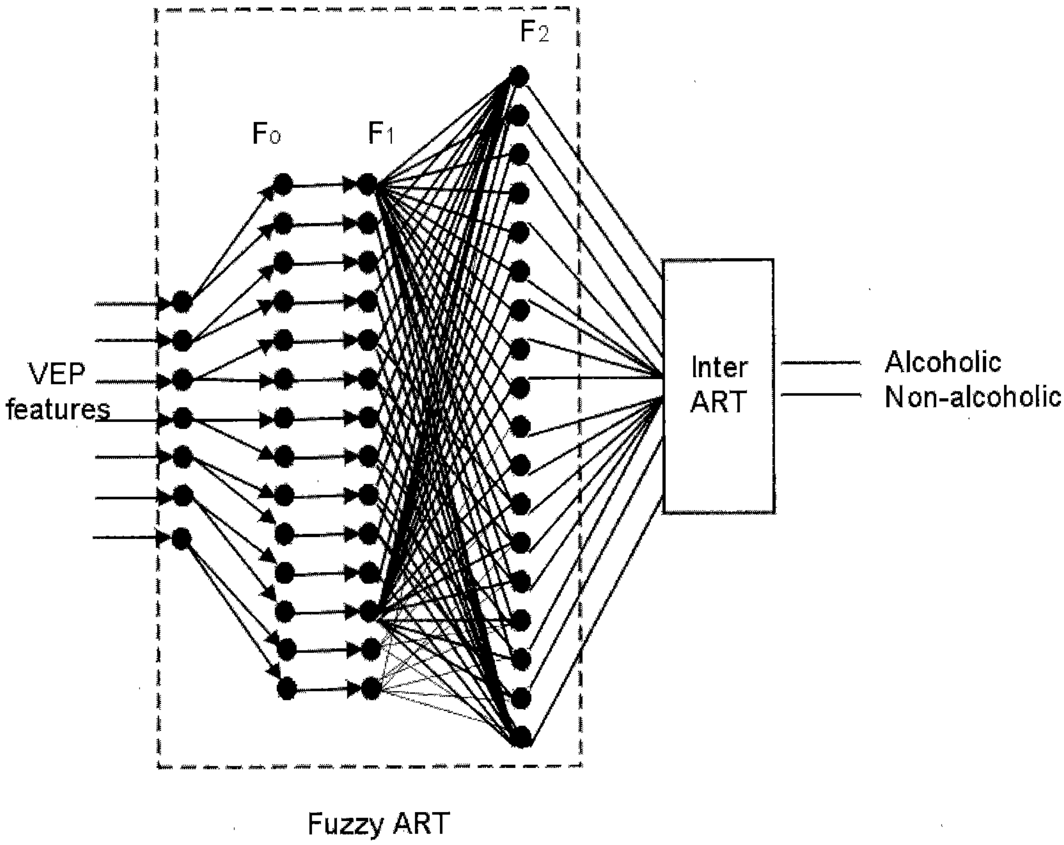


Fig. 8. FA network as used in the study.

classes. Inter ART module works by increasing the vigilance parameter, r of Fuzzy ART by a minimal amount to correct a predictive error at the category layer. Parameter r 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 r enable larger categories to form and lead to a broader generalisation and higher code compression. For further details on FA, refer to [4] [6].

Half of the patterns are used for training while the rest half are used for testing. FA fast learning weight updates vary with different order of input patterns during training. As such, classification performance will vary. This problem is solved using voting strategy [4] with 10 runs. FA vigilance parameter (VP) is varied from 0 to 0.9 in steps of 0.1. Figure 8 shows the FA network architecture as used in the experimental study.

Table 2 shows the results of FA classification with and

Table 2. FA classification results.

VP	With PCA		Without PCA	
	Classification (%)	Training time (s)	Classification (%)	Training time (s)
0	91.25	5.5	80.25	7.5
0.1	92.50	5.5	82.50	7.5
0.2	93.50	5.6	81.50	7.5
0.3	92.00	6.1	81.75	7.0
0.4	90.75	9.1	83.50	10.2
0.5	90.25	9.3	81.00	10.7
0.6	94.50	10.1	83.75	11.1
0.7	91.25	10.6	84.50	11.6
0.8	94.75	10.2	84.25	13.3
0.9	94.25	16.7	90.25	26.8
Average	**92.50**	**8.8**	**83.33**	**11.3**

without the application of PCA for the varying VP values. From the table, it can be seen that FA classification improves considerably with the use of PCA. This is because of PCA's ability to remove noise from the VEP signals. The best classification using PCA is at 94.75% (VP=0.8) while averaged classification of 92.5% is obtained across all the VP values. The case without using PCA gives lower classification values. Best classification is at 90.25% (VP=0.9) while averaged classification is at 83.33%. The use of PCA also reduces the FA training time, which can be seen from the averaged time of 8.8 s using PCA and 11.3 s for without PCA. The computer used for this simulation experiment is Pentium II 266 MMX (with 256 MB RAM), running on Windows 98 platform.

5. Conclusion

In this paper, we have applied PCA to reduce noise from VEP signals. Emulated VEP signals contaminated with noise have been utilised to show the ability of PCA to reduce noise. These noise reduced VEP signals are classified into alcoholics and non-alcoholics category using FA. Gamma band power computed from these VEP signals are used as features by FA. The FA classification results show improvement with the application of PCA to reduce noise in VEP signals as compared to the case without applying PCA. Overall, the good accuracy of FA classification performances indicates that VEP spectral power centred at 40 Hz could be used to classify alcoholics and non-alcoholics.

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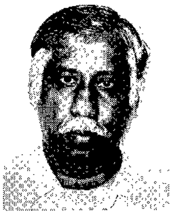

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