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Improving visual evoked potential feature classification for person recognition using PCA and normalization

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Abstract

In earlier papers, it was shown that recognizing persons using their brain patterns evoked during visual stimulus is possible. In this paper, several modifications are proposed to improve the recognition accuracy. In the method, gamma band spectral power (GBSP) features were computed from the visual evoked potential (VEP) signals recorded from 61 electrodes while subjects perceived a picture. Two methods were used to improve the classification rate. First, principal component analysis (PCA) was used to reduce the noise and background electroencephalogram (EEG) effects from the VEP signals. Second, the GBSP of each channel was normalized by the total GBSP from all the channels. Three classifiers were used: simplified fuzzy ARTMAP (SFA), linear discriminant (LD) and *k*-nearest neighbor (kNN). The experimental results using 800 VEP signals from 20 subjects with leave-one-out cross-validation strategy showed that PCA improves the classification performance for all the classifiers with normalization giving improved results in certain cases. The best classification performance of 96.50% obtained using the improved method shows that brain signals have suitable biometric properties that could be further exploited.
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1. Introduction

The most common biometric method of recognizing (identifying) or authenticating persons is through fingerprint recognition (Wayman et al., 2004; Pankanti et al., 2000, 2002). However, the individuality of fingerprints has been challenged, i.e. the fingerprints are not proven scientifically to be unique to each individual (Pankanti et al., 2002). Therefore, it becomes important to find alternative biometric methods to replace or augment the fingerprint technology. In this regard, other biometrics like palmprint (Duta et al., 2002), hand geometry (Jain et al., 1999), iris (Daugman, 1999), face (Samal and Iyengar, 1992), electrocardiogram (Biel et al., 2001) and electroencephalogram (EEG) (Poulos et al., 1999; Paranjape et al., 2001; Palaniappan, 2004; Palaniappan and Raveendran, 2002) have been proposed.

However, using EEG as a biometric is relatively new compared to the other biometrics. Poulos et al. (1999) proposed a method using autoregressive (AR) modeling of EEG signals and Learning Vector Quantization neural network to classify an individual as distinct from other individuals with 72–80% success. But the method was not tried to recognize each individual in a group. Paranjape et al. (2001) used AR modeling of EEG with discriminant analysis to identify individuals with classification accuracy ranging from 49% to 85%. Both the methods used EEG

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signals recorded while the subjects were resting with eyes closed (Poulos et al., 1999) and with eyes closed or open (Paranjape et al., 2001).

Visualizing a picture evokes perception and memory and it is our assumption that this level of neural activity between individuals would be different. The study in (Palaniappan et al., 2002a) indicated that the levels of thought process across subjects were different even for similar mental activity. Using this assumption, the previous studies (Palaniappan, 2004; Palaniappan and Raveendran, 2002) have used spectral powers in gamma band range of 30–50 Hz computed from the VEP signals recorded during a visual stimulus for person recognition. Gamma band is specifically chosen instead of alternative frequency bands because another study (Palaniappan et al., 2002b) had successfully used gamma band spectral features to classify alcoholics and non-alcoholics. In addition, Basar (2004) has also discussed the existence of the relationship of gamma band with focused arousal. Because the method used features computed from 61 VEP channels, it is unlikely that different persons will have similar activity in all parts of the brain. Thus, they were found to be suitable for use in biometric applications. These spectral powers were then classified for person recognition using either multilayer perceptron with backpropagation training (MLP-BP) or simplified fuzzy ARTMAP (SFA) neural networks (NNs).

In this paper, we extend the studies from (Palaniappan, 2004; Palaniappan and Raveendran, 2002) by studying the effects of using principal component analysis (PCA) and normalization to improve the person identification method. In addition, we also embark to show that similar classification accuracy to that of SFA NN could be obtained using simpler classifiers like linear discriminant (LD) and *k*-nearest neighbor (kNN). The classification performances given by the classifiers were made reliable through the use of leave-out-one cross-validation (LOO CV) strategy.

2. Methodology

The proposed method could be divided into three stages. The first stage involved recording the VEP signals from the subjects. In the next stage, these VEP signals were processed to remove VEP signals with eye-blink contamination, setting mean to zero, reduce noise effects (through PCA), extract GBSP features and normalization. The third stage involved classification experiments.

2.1. VEP data

Twenty subjects participated in the experimental study. The subjects were seated in a reclining chair located in a sound attenuated RF shielded room. Measurements were taken from 61 channels placed on the subject's scalp, which were sampled at 256 Hz. The electrode positions (as shown in Fig. 1) were located at standard sites using extension of Standard Electrode Position Nomenclature, American Encephalographic Association. The signals were hardware band-pass filtered between 0.02 and 50 Hz.

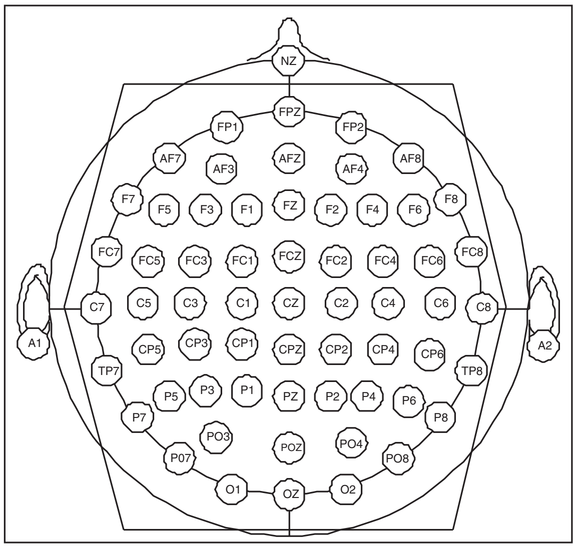

Fig. 1. Locations of electrodes (61 active channels inside hexagon).

The VEP signals were recorded from subjects while being exposed to a stimulus, which consist of pictures of objects chosen from Snodgrass and Vanderwart picture set (Snodgrass and Vanderwart, 1980). These pictures were common black and white line drawings like an airplane, a banana, a ball, etc. that were chosen according to a set of rules that provide consistency of pictorial representation. The pictures have been standardized on variables of central relevance to memory and cognitive processing. These pictures represent different concrete objects, which could be easily named i.e. they have definite verbal labels. Fig. 2 shows some of these pictures.

The subjects were asked to remember or recognize the stimulus. Stimulus duration of each picture was 300 ms with an inter-trial interval of 5.1 s. All the stimuli were shown using a computer display unit located 1 m away from the subject's eyes. The stimuli were not repeated, i.e. all the pictures that were shown were different. One-second measurements after each stimulus onset were stored. Fig. 3 shows an illustrative example of the stimulus presentation. This data set is actually a subset of a larger experiment designed to study the short-term memory differences between alcoholics and non-alcoholics (Zhang et al., 1995, 1997).

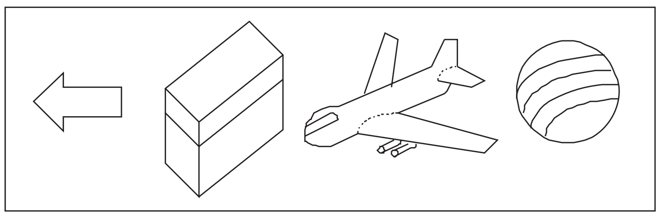

Fig. 2. Some pictures from Snodgrass and Vandervart set.

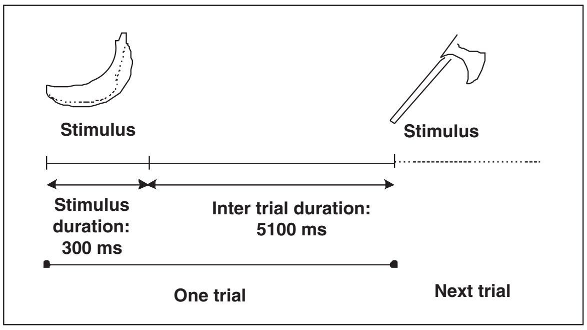

Fig. 3. Example of visual stimulus presentation.

2.2. VEP processing and feature extraction

2.2.1. Eye blink removal

VEP signals with eye blink artifact contamination were removed using a computer program written to detect VEP signals with magnitudes above 100 μV. These VEP signals detected with eye blinks were then discarded from the experimental study. The threshold value of 100 μV was used since blinking produces 100–200 μV potential lasting 250 ms (Kriss, 1993; Misulis, 1994). A total of 40 artifact free trials were stored for each subject. As such, a total of 800 single trial VEP signals were available for analysis. The VEP signals were then set to zero mean. As all the VEP signals were recorded using the same amplifier with same amplification factor, the VEP signals were considered without any scaling.

2.2.2. PCA

PCA and its similar singular value decomposition algorithms have been used to reduce noise effects (like background EEG) from VEP signals (Palaniappan et al., 2002c; Drozd et al., 2005). In this paper, PCA was applied to the 61-channel VEP signals to reduce contamination from noise and background EEG.[1] PCA would also useful to retain the most important components in the signal. In the following discussions, the term noise will be used to denote both noise and background EEG.

The PCA method is as follows. Assuming matrix $\boldsymbol{z}$ to represent the extracted signal, the covariance of matrix $\boldsymbol{z}$ was computed using

$$\boldsymbol{R} = \boldsymbol{E}(\boldsymbol{z}\boldsymbol{z}^{\mathrm{T}}). \tag{1}$$

Next we computed, $\boldsymbol{V}$ and $\boldsymbol{D}$, where $\boldsymbol{V}$ is the orthogonal matrix of eigenvectors of $\boldsymbol{R}$ and $\boldsymbol{D}$ is the diagonal matrix of its eigenvalues, $\boldsymbol{D} = \mathrm{diag}(d_1, \ldots, d_n)$. The principal components (PCs) were computed using

$$\boldsymbol{y} = \boldsymbol{V}^{\mathrm{T}}\boldsymbol{z}^{\mathrm{T}}. \tag{2}$$

The first few PCs account for a large proportion of VEP while the rest represents mostly noise. In our work, Kaiser's rule was used to select the number of principal components (PCs) to be used (Jolliffe, 1986). Using this method, PCs with eigenvalue more than 1.0 were considered to be part of the VEP subspace, while the rest were considered to be part of the noise. The VEP (without noise) was reconstructed from the selected PCs using

$$\tilde{\boldsymbol{z}} = \widehat{\boldsymbol{V}}\hat{\boldsymbol{y}}, \tag{3}$$

where $\widehat{\boldsymbol{V}}$ and $\hat{\boldsymbol{y}}$ are the eigenvectors and PCs corresponding to eigenvalues more than 1.0. Considering all the 800 VEP signals, the number of selected PCs was 26.4 ± 6.7. The total power retained using the selected PCs was 99.58 ± 0.26. Fig. 4 shows an example plot of logarithm of eigenvalue in decreasing values vs. corresponding channels. The use of logarithm is to better illustrate the selection of PCs; the selected PCs would be the PCs with eigenvalue > 1 or log(eigenvalue) > 0.

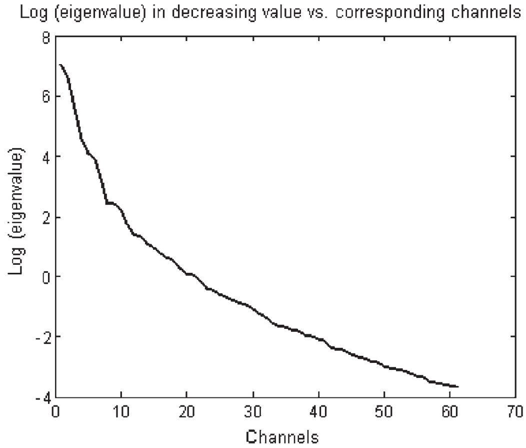

Fig. 4. An example plot of 'log (eigenvalue) in decreasing value' vs. channels in PC selection.

2.2.3. Gamma band spectral power and normalization

A 10th order forward and 10th order reverse Butterworth digital filters were used to extract the VEP in the 3-dB passband of 30–50 Hz, i.e. in the gamma band range. Forward and reverse operation gives zero phase response to remove the non-linear phase distortion caused by Butterworth filtering. MATLABs[2] *filtfilt* function was utilized for this purpose. Order 10 was chosen since it gave a 30-dB minimum stopband at 25 and 55 Hz. Parseval's theorem was now applied to obtain the equivalent spectral power of the filtered signal, $\tilde{x}$ using

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

where $N = 256$, is the total number of data in the filtered signal. These GBSP values from each of the 61 channels were concatenated into one feature vector representing the particular VEP pattern.

[1] Background or ongoing EEG signals are always present in the brain and generally distorts evoked potential signals.

[2] The Mathworks Inc.

This power was then normalized with the GBSP values from all the 61 channels.

2.3. Classifiers

2.3.1. Simplified fuzzy ARTMAP

SFA was used to classify the VEP feature vectors into the respective categories representing the subjects. SFA was chosen due to its high speed training ability in fast learning mode. Fuzzy ARTMAP (FA) is a type of NN that performs incremental supervised learning (Carpenter et al., 1995) and SFA is a simplified version of FA that is specifically used for classification. SFA consists of a Fuzzy ART module linked to the category (i.e. class) layer through an Inter ART module (Kasuba, 1993; Baghmisheh and Pavesic, 2003). Fig. 5 shows the SFA network architecture as used in the experimental study.

During training (supervised learning), Fuzzy ART receives a stream of input features that represent the pattern in F_i nodes and the output class in the category layer, F_o nodes 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.

Vigilance parameter (VP), which could take any value from 0 to 1, calibrates the minimum confidence that Fuzzy ART must have in an input vector in order for Fuzzy ART to accept the selected F_o node, rather than search for another better F_o node through an automatically controlled process of hypothesis testing. Lower values of VP lead to a broader generalization and higher code compression (i.e. less F_o nodes). Higher values of VP will result in over-fitting and the use of more F_o nodes.

Hypothesis testing works by computing the resonance of the input vector and the selected F_2 node is accepted to represent the input vector only if the resonance value exceeds the chosen VP. Here, we varied the VP from $0, 0.1, 0.2, \ldots, 0.9$.

Inter ART module will create mappings between the F_o node to the node in the category layer representing the subject. For all the input patterns presented, it creates a dynamic weight link that consists of a many to one or one to one mapping between the F_o node of Fuzzy ART and the particular category layer node. If a predictive error occurs, i.e. a many to one mapping, then Inter ART match tracking ensues, which will select another F_o node in Fuzzy ART for that pattern. Inter ART module works by increasing the VP of Fuzzy ART by a minimal amount to correct a predictive error at the category layer.

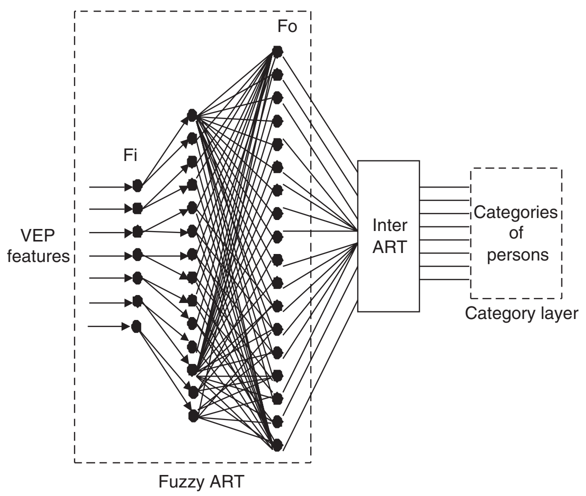

Fig. 5. SFA network as used in the study.

The testing stage works similar to the training stage except that there will be neither match tracking nor hypothesis testing. This is because the input presented to Fuzzy ART F_i nodes will output a specific maximum F_o node, which will be used by the Inter ART module to trigger the corresponding category layer node that refers to the predicted class.

The algorithm for SFA training is given in Appendix A. For further details on SFA, refer to Kasuba (1993) and Baghmisheh and Pavesic (2003).

2.3.2. Linear discriminant

LD classifier is a linear discriminant method that could be used for classification purposes. It is computationally attractive as compared to other computation intensive classifiers like NN. It could be used to classify two or more groups of data. Here, LD was used to classify the VEP feature vectors into one of the categories representing the subjects.

In principle, any mathematical function may be used as a classifier function. In case of the LD as used here, the VEP training feature vectors were used to derive the classification functions as

$$F = \sum_{i=1}^{N} x_i w_i + a, \tag{5}$$

where x_i is the VEP feature vectors, $N = 61$, is the number of features, w_i and a are the coefficients and constant, respectively. The functions would be formed in such a way that the separation (i.e. distance) between the groups was maximized, and the distance within the groups was minimized i.e. the parameters w_i and a were determined in such a way that the discrimination between the groups was best. Using these classification functions, the discriminant scores of each test VEP feature vector occurring in each of the groups were computed. The test VEP feature vector was then assigned to the group with the highest score and then compared with the actual class to determine the classification error.

2.3.3. k-Nearest neighbor

In the k-nearest neighbor (kNN) algorithm, the classification of a new test VEP feature vector was determined by the class of its k-nearest neighbors. Here, the kNN algorithm was implemented using two distance metrics to locate the nearest neighbors: Euclidean, and Manhantan. The decision rule used to derive a classification from the

k-nearest neighbors was the majority rule. The number of neighbors (i.e. k) used to classify the new VEP test vector was varied from $1, 2, \ldots, 10$.

3. Experimental study

Four different feature extraction experiments were carried out in the study. As discussed earlier, the VEP features consisting of GBSP from 61 channels were used to train and test the different classifiers to recognize the subjects. In the first two experiments, these features were obtained without normalization. Normalization here refers to dividing the GBSP features from each channel with the total GBSP from all the channels. This procedure was mentioned in Section 2.2. The second experiment differed from the first where the GBSP features were obtained after applying PCA to reduce noise. The third and fourth experiments involved GBSP features obtained with normalization. The fourth differed from third with application of PCA. Fig. 6 shows the four different procedures of extracting VEP features.

As mentioned earlier, a total of 800 VEP feature vectors (20 subjects × 40 trials) were used in the experimental study. A LOO CV strategy was used to increase the reliability of the classification results. The 800 feature vectors were split into 40 datasets, where each set consisted of a single trial of VEP from all the subjects (i.e. totaling 20 VEP feature vectors). Thirty nine of the datasets were used in training, while the remaining one in testing. Training and testing were repeated for 40 times where for each time, different 39 datasets were used for training and the remaining one for testing. The average results from these 40 classification experiments are reported here.

4. Results and discussion

Table 1 shows the results for experiments using SFA. The results are tabulated for varying VP values from 0 to 0.9 in steps of 0.1. The tables give the Fuzzy ART F_o node size (which represents the size of the SFA), and the SFA classification percentage. Tables 2 and 3 give the classification results using LD and kNN, respectively, where for the latter, k was varied from 1 to 10 in integer increments. The overall averaged values are also shown.

In the following discussion, overall averaged results are used for comparison. From the tables, we could see that the application of PCA improved the classification performance for all the classifiers. However, normalization improved the classification for LD and only when used with PCA for SFA, while it degraded the classification performance for kNN.

From Table 1, it could be seen that PCA and normalization improved the SFA classification performance from 71.14% to 92.84%. In addition, the use of PCA also reduced the Fuzzy ART size (i.e. F_o nodes) from 140.02 to 53.91, which would reduce computational complexity

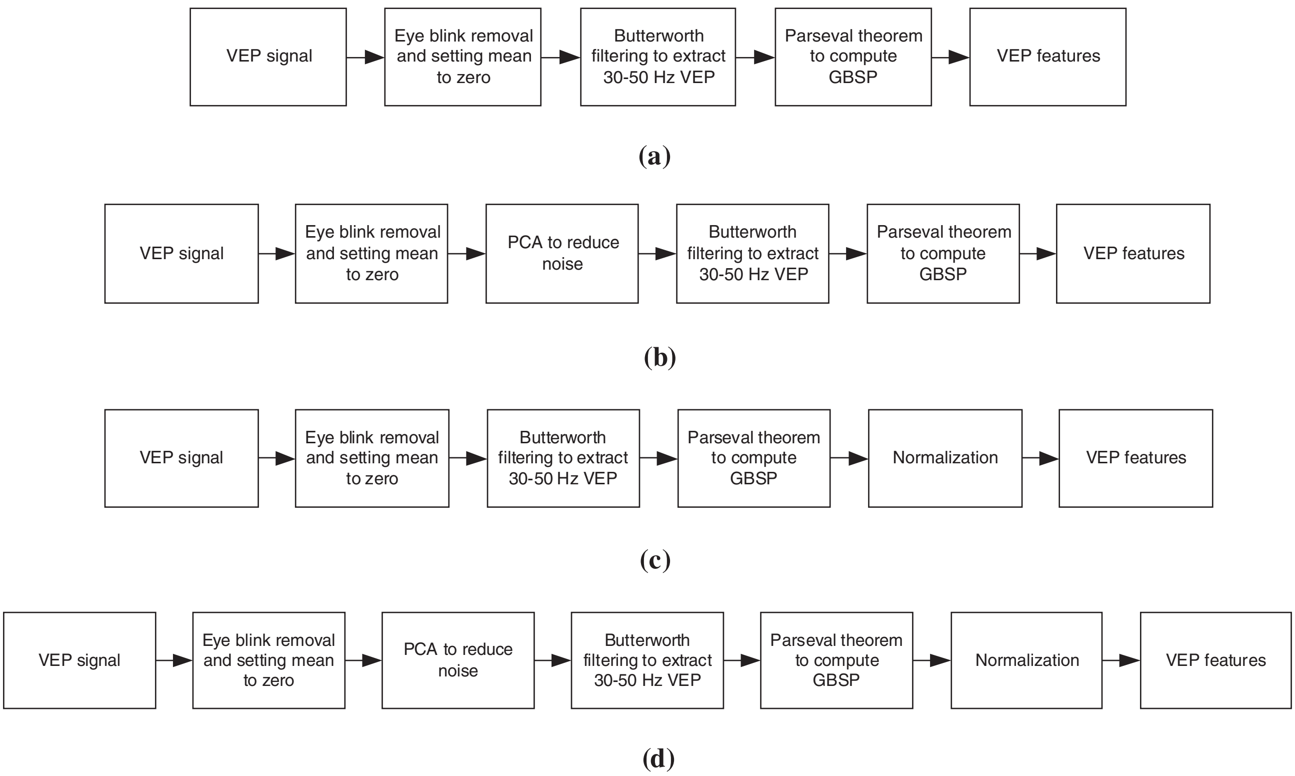

Fig. 6. Four different methods to extract GBSP features from VEP signals. (a) Experiment 1: without PCA and without normalization. (b) Experiment 2: with PCA and without normalization. (c) Experiment 3: without PCA and with normalization. (d) Experiment 4: with PCA and with normalization.

Table 1
Average SFA classification results using LOO CV

VP	Experiment 1		Experiment 2		Experiment 3		Experiment 4	
	Cluster	%	Cluster	%	Cluster	%	Cluster	%
0	126.78	70.88	57.10	91.63	154.83	65.25	41.43	92.25
0.1	126.78	70.88	57.10	91.63	154.83	65.25	41.43	92.25
0.2	126.78	70.88	57.10	91.63	154.83	65.25	41.43	92.25
0.3	126.78	70.88	57.10	91.63	154.83	65.25	41.43	92.25
0.4	126.78	70.88	57.10	91.63	154.83	65.25	41.43	92.25
0.5	127.98	70.63	59.68	91.63	154.88	65.25	41.43	92.25
0.6	129.13	70.50	60.35	91.75	155.13	65.38	41.43	92.25
0.7	133.48	71.00	64.20	92.25	166.68	66.75	51.55	94.25
0.8	151.28	73.00	71.90	92.25	135.78	69.88	70.05	95.25
0.9	224.43	71.88	99.08	93.25	210.25	69.13	127.50	93.13
Average	140.02	71.14	64.07	91.93	159.68	66.26	53.91	92.84

Table 2
Average LD classification results using LOO CV

Experiment 1	Experiment 2	Experiment 3	Experiment 4
84.00	84.25	85.75	96.50

and time. For LD, the improvement in classification performance was from 84.00% to 96.50%, while for kNN, it was from 66.12% to 92.04%.

The results also show that LD classifier gave better results than SFA. This most probably indicates that the VEP data from the subjects were linearly separable. LD is advantageous over SFA due to its lower computational complexity and time. The overall average time required for one experiment of training and testing by each of the classifiers were 2.64 s for SFA, 1.29 s for LD and 0.86 s for kNN.

Applications of PCA resulted in the selection of PCs that were more 'important' and discarded PCs that represented noise, thereby increasing the classification accuracy for all the classifiers. It is however difficult for us to conclude on the effects of normalization as when it was used with PCA, it improved SFA and LD classification performances but degraded kNN classification performance.

Though the raw VEP dataset used in the experimental study here was similar to Palaniappan (2004) and Palaniappan and Raveendran (2002), direct comparison to the results from the previous studies to the results here are not possible as the feature extraction methods differed in addition to the use of LOO CV here to increase the reliability of the classification results.

The experimental setup does require some degree of effort and does consume time (about a few minutes for placement of electrodes and application of electrode paste) but we believe that the recording technique would see improvements in the future, for example the use of special active electrodes that might remove the requirement of the application of electrode paste (conducting jelly). The purpose of the paper is therefore not to propose an industry standard complete system but merely an improved method of using brain signals to identify persons.

5. Conclusion

In this paper, an improved method using classification of VEP features has been proposed as a biometric tool to recognize persons. The VEP features consisted of GBSP values computed from 61 channels extracted while the subjects were seeing a picture. All the different classifiers, SFA,

Table 3
Average kNN classification results using LOO CV

k	Euclidean				Manhanttan			
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 1	Experiment 2	Experiment 3	Experiment 4
1	67.63	92.25	63.63	89.63	70.50	94.50	65.25	91.00
2	63.13	90.75	59.88	87.88	67.38	93.75	63.25	89.50
3	65.38	91.50	60.88	89.00	70.38	94.25	64.50	92.13
4	66.38	91.50	63.00	88.75	70.88	94.63	65.63	92.00
5	65.75	92.25	62.50	90.38	71.00	94.13	66.25	92.88
6	65.50	92.00	63.00	89.50	71.00	94.25	66.50	92.50
7	66.75	91.75	62.50	88.88	71.38	94.00	65.63	92.50
8	67.25	91.25	62.25	89.75	71.50	94.38	66.00	92.38
9	67.25	91.38	63.63	89.75	72.38	94.00	66.38	93.13
10	66.13	90.75	63.50	89.63	72.38	93.88	67.00	92.38
Average	66.12	91.54	62.48	89.32	70.88	94.18	65.64	92.04

LD, kNN gave improved results through the use of PCA and even more improved results for SFA and LD through the use of PCA and normalization. The positive results obtained in this paper show promise for the method to be studied further as a biometric tool to recognize or identify different persons. The method could be used as a unimodal (stand alone) or in part of a multimodal person identification system. The method proposed is advantageous because of the difficulty in establishing another persons exact VEP output (i.e. difficult to forge) but the changes of VEP signals over longer periods of time requires further investigation.

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Appendix A. SFA training algorithm

Step 1. Fuzzy ART initialization:

- Input layer F_i nodes represent a current input vector, $I = (I_1, \dots, I_M)$, with each component I_i in the interval $[0, 1]$, $I = 1, \dots, M$.
- Proliferation of categories is avoided if the inputs are normalized using the method of complement codcomplement coded input I to the field F_i is the $2M$ dimensional vector $I = (a, a^c)$ where $a_i^c = 1 - a_i$.
- For each F_o node $j (j = 1, \dots, N)$, there is a weight vector associated with layer of F_i nodes, $w_j = (w_{j1}, \dots, w_{j,2M})$ of adaptive weights.
- Initially, $w_{j1}(0) = \cdots = w_{j,2M}(0) = 1$, which means that each category is uncommitted.

Step 2. Cluster selection:

- For each input I and F_o node j, the choice function T is defined by $T(I) = |I \wedge w_j|/(\alpha + |w_j|)$, where the fuzzy AND operator $\wedge$ is defined by $(p \wedge q)_i = \min(p_i, q_i)$ and the norm $|\cdot|$ is defined by $|p| = \sum_{i=1}^{M} |p|$ for any M-dimensional vectors p and q.
- F_o node choice is indexed by J, where $T_J = \max\{T_j : j = 1, \dots, N\}$.
- If more than one T_j is maximal, the node with a smaller index is chosen.
- Resonance occurs if the match function, $|I \wedge w_J|/|I|$ of the chosen node meets the vigilance criterion: $|I \wedge w_J|/|I| \geqslant \rho$.
- With resonance and without match tracking (see Step 4), weights are updated (Step 3).
- Mismatch reset occurs if $|I \wedge w_J|/|I| < \rho$, then the value of the choice function T_J is set to 0 and a new index J is chosen. The search process continues until the chosen J satisfies resonance.

Step 3. Weight update:

- Once the search is completed, the weight vector w_J is updated according to the equation $w_J^{(\text{new})} = (I \wedge w_J^{(\text{old})})$, where fast learning is used.

Step 4. Inter ART mapping/match tracking:

- Create mappings between the F_o nodes and category layer nodes to correctly learn to predict the classification patterns.
- For all the input patterns presented, it creates a dynamic weight link that consists of a many to one or one to one mapping between the F_o nodes of Fuzzy ART and category (i.e. class) layer nodes.
- Every time a one to many mapping from a F_o node to category layer is triggered, an error correcting mechanism called match tracking occurs which will increase the vigilance parameter of Fuzzy ART, ρ to a value slightly higher than $\frac{|I \wedge w_J|}{|I|}$ where J is the index of the active F_o node. This is to avoid any confusion in mapping, and hence predictions.
- When match tracking occurs, Fuzzy ART search leads either to another F_o node that correctly predicts the target or to an uncommitted new F_o node and the dynamic weight link between the F_o nodes and category layer nodes is updated.
- After match tacking, ρ is set back to the earlier (baseline) vigilance parameter value.

Steps 1 to 4 are repeated until all the training patterns have been presented.

End of SFA training algorithm.

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