Leave-one-out Authentication of Persons Using 40 Hz EEG Oscillations

KVR. Ravi and Ramaswamy Palaniappan

Abstract — **It has been shown previously that recognizing persons using 40 Hz electroencephalogram (EEG) oscillations is possible. In the method, features were computed from the Visual Evoked Potential (VEP) signals recorded from 61 electrodes while subjects perceived a picture. Here, two modifications have been proposed to improve the classification performance: Principal Component Analysis (PCA) to reduce the noise and background EEG effects from the VEP signals and normalization. Two classifiers were used: Simplified Fuzzy ARTMAP (SFA), 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 and normalization improved the classification performance for both the classifiers. The best classification performance of 95.25% obtained using the improved method shows that 40 Hz EEG oscillations are suitable for use as biometrics.**

Keywords — **Biometrics, Electroencephalogram, Nearest Neighbor, Person Authentication, Principal Component Analysis, Simplified Fuzzy ARTMAP, Visual Evoked Potential.**

I. Introduction

THE most common biometric method of authenticating persons is through fingerprint recognition [1]. In recent years, alternative biometric methods to replace or augment the fingerprint technology have been proposed. These biometrics are iris, face, speech [1], palmprint [2], hand geometry [3], electrocardiogram [4], electroencephalogram (EEG) [5, 6] and Visual Evoked Potential (VEP) [7] have been proposed.

However, using VEP as a biometric is relatively new compared to the other biometrics. Visualizing a picture evokes perception and memory and it is on the assumption that this level of neural activity between individuals would be different that the previous study [7] used energy of 40 Hz oscillations computed from the VEP signals recorded during a visual stimulus for authenticating the identity of persons. The 40 Hz oscillations were specifically chosen as Basar [8] has indicated the existence of the relationship of these oscillations to perception. As 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 as biometrics. These energy features were then classified for person authentication using either Multilayer Perceptron with Backpropagation training or Simplified Fuzzy ARTMAP (SFA) neural networks (NNs).

In this paper, we extend the studies from [7] by studying the effects of using principal component analysis (PCA) and normalization to improve the person authentication method. In addition, we also embark to show that similar classification accuracy to that of SFA NN could be obtained by using a simpler classifier i.e. 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.

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II. Methodology

A. 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 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.

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 [9]. 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.

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 meter 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. Figure 1 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 [10].

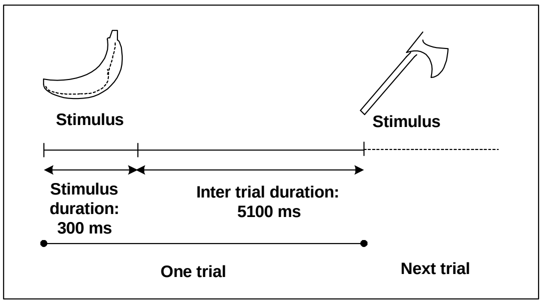

Fig. 1. Stimulus presentation example.

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 milliseconds [11]. 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.

B. PCA

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 $\mathbf{z}$ to represent the extracted signal, the covariance of matrix $\mathbf{z}$ was computed using:

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

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

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

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 [12]. 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

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

where $\hat{\mathbf{V}}$ and $\hat{\mathbf{y}}$ are the eigenvectors and PCs corresponding to eigenvalues more than 1.0.

C. Filtering and Normalization

A 10^{th} order forward and 10^{th} order reverse Butterworth digital filters were used to extract the VEP in the 3-dB passband of 30 to 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. Order 10 was chosen since it gave a 30-dB minimum stopband at 25 and 55 Hz. The energy of the filtered signal was computed. These energy values from each of the 61 channels were concatenated into one feature vector representing the particular VEP pattern.

This energy value was then normalized with the energy values from all the 61 channels.

D. Classifiers

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. SFA consists of a Fuzzy ART module linked to the category (i.e. class) layer through an Inter ART module [13]. Figure 2 shows the SFA network architecture as used in the experimental study.

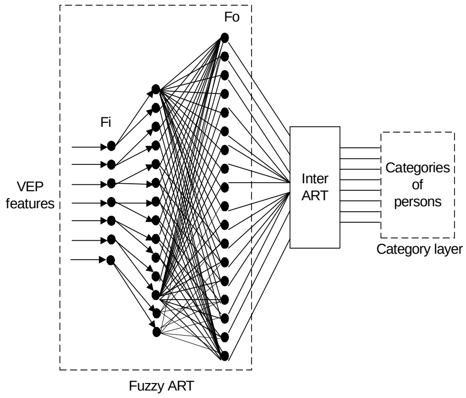

Fig. 2. SFA network as used in the study.

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, ….,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

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

increasing the VP of Fuzzy ART by a minimal amount to correct a predictive error at the category layer.

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.

2) *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 Manhantan distance metric to locate the nearest neighbors. 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,…,10.

III. EXPERIMENTAL STUDY

The VEP features vectors were used to train and test the different classifiers to authenticate the identity of the subjects. In the first experiment, these features were obtained without PCA and normalization. In the second experiment, PCA and normalization were applied.

As mentioned earlier, a total of 800 VEP feature vectors (20 subjects x 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.

IV. 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. Table 2 give the classification results using kNN where *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 and normalization has improved the classification performance for both the classifiers.

From Table 1, it could be seen that PCA and normalization improved the SFA classification performance from 71.14% to 92.84%. In addition, Fuzzy ART size (i.e. F_0 nodes) was reduced from 140.02 to 53.91, which would reduce computational complexity and time. For kNN, the improvement in classification performance was from 70.88% to 92.04%.

TABLE 1: AVERAGE SFA CLASSIFICATION RESULTS

	Exp. 1		**Exp. 2**	
VP	**Cluster**	**%**	**Cluster**	**%**
0	126.78	70.88	41.43	92.25
0.1	126.78	70.88	41.43	92.25
0.2	126.78	70.88	41.43	92.25
0.3	126.78	70.88	41.43	92.25
0.4	126.78	70.88	41.43	92.25
0.5	127.98	70.63	41.43	92.25
0.6	129.13	70.50	41.43	92.25
0.7	133.48	71.00	51.55	94.25
0.8	151.28	73.00	70.05	**95.25**
0.9	224.43	71.88	127.50	93.13
Average	**140.02**	**71.14**	**53.91**	**92.84**

TABLE 2: AVERAGE KNN CLASSIFICATION RESULTS

k	**Exp. 1**	**Exp. 2**
1	70.50	91.00
2	67.38	89.50
3	70.38	92.13
4	70.88	92.00
5	71.00	92.88
6	71.00	92.50
7	71.38	92.50
8	71.50	92.38
9	72.38	93.13
10	72.38	92.38
Average	**70.88**	**92.04**

Application of PCA resulted in the selection of PCs that were more 'important' and discarded PCs that represented noise, thereby increasing the classification accuracy for both the classifiers. Normalization reduced the intra-class variances and increased the inter-class variances, which also resulted in increasing the classification accuracy for both the classifiers.

Though the raw VEP dataset used in the experimental study here was similar to [7], 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.

V. CONCLUSION

In this paper, an improved method using classification of VEP features has been proposed as a biometric tool to authenticate the identity of persons. The VEP features consisted of energy values computed from 61 channels extracted while the subjects were seeing a picture. Both the SFA and kNN classifiers gave improved results through the use of PCA and normalization. The positive results obtained in this paper show promise for the 40 Hz EEG oscillations to be studied further as biometrics.

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