Classifying Brain Prints Using Grow And Learn Network

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Abstract - **In this paper, a method to recognise persons using brain signal features classified by Grow and Learn (GAL) network is proposed. The features are obtained from brain signals and consist of gamma band spectral power. These brain signals are recorded from 61 electrodes located on the human scalp while the subjects are seeing a visual stimulus in the form of a picture. The experimental results using 800 brain signals from 40 subjects gave an average classification rate of 85.09 % using GAL network. This pilot investigation shows that the proposed method of recognising persons using their brain signals is worth further study.**

Keywords - **Biometrics, Electroencephalogram, Grow and Learn Networks, Person Identification, Visual Evoked Potential**

1. INTRODUCTION

The most common biometric method of recognising (identifying) or authenticating persons is through fingerprint recognition [1], [2]. In recent years, there has been active research to employ alternative biometrics either as stand alone or in addition to fingerprints for identifying individuals [1]. This is caused by the possibility of forging fingerprints and for added security purposes, which is a serious issue after the 911 incident. In this regard, other biometrics like palmprint [3], hand geometry [4], iris [5], face [6], and electrocardiogram [7] have been proposed.

However, using the brain signals or electroencephalogram (EEG) as a biometric is relatively new compared to the other biometrics. Poulus et. al. [8] proposed a method using autoregressive (AR) modeling of EEG signals and Linear Vector Quantisation (LVQ) NN to classify an individual as distinct from other individuals with 72-80% success. But the method was not tried to recognise each individual in a group. Paranjape et. al. [9] used AR modeling of EEG with discriminant analysis to identify individuals with classification accuracy ranging from 49 to 85%. Both the methods used EEG signals recorded while the subjects were resting with eyes closed [8] and with eyes closed or open [9].

The main advantage of using EEG signals as biometric is the difficulty in forging the brain's output. This will very useful in high security applications (like military use). Other biometrics have easier possibility of forgery. For example, fingerprint could be severed and used in scanners. However, EEG biometrics are more cumbersome to capture. But this is a price to pay for added security.

In this paper, a novel person identification method using Visual Evoked Potential (VEP) signals is proposed. VEP signals are EEG signals that are evoked during a particular visual stimulus, like seeing a picture. They are normally recorded from the scalp and are potentials (in micro Volts range) exhibited by neuronal excitations in the cortex. Here, the spectral powers in gamma band range of 30-50 Hz computed from the 61 recorded VEP electrodes are used as biometric features. Gamma band is specifically chosen instead of alternative frequency bands because other studies [10], [11] have successfully used gamma band spectral features to classify alcoholics and non-alcoholics. Basar et. al. [12] have also discussed the existence of the relationship of gamma band with focused arousal.

Because the method uses features computed from 61 VEP channels, it is unlikely that different persons will have similar activity in all parts of the brain. Thus, it is suitable for use in biometric applications. These VEP biometric features are trained with GAL to classify (i.e. recognise) different persons.

2. METHODOLOGY

The proposed method could be divided into 3 stages.

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The first stage involved the recording of 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 and extract spectral power features and normalisation. The third stage involved classification using GAL. The first stage, i.e. recording was done in Neurodynamics Laboratory, State University of New York for their studies on short term memory [13], [14].

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 Figure 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.

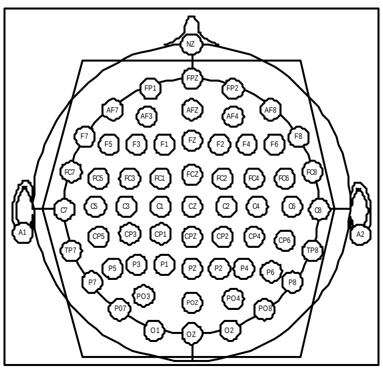

Figure 1: Locations of electrodes

(61 active channels inside hexagon)

The VEP signals were recorded from subjects while being exposed to a stimulus, which consisted of pictures of objects chosen from Snodgrass and Vanderwart picture set [15]. These pictures are common black and white line drawings like an airplane, a banana, a ball, etc. that are chosen 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 2 shows some of these pictures.

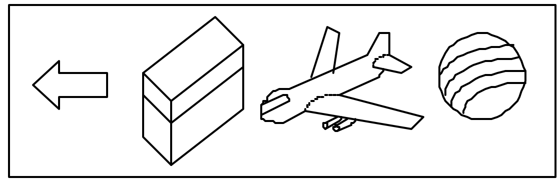

Figure 2: Some pictures from Snodgrass and Vandervart

The subjects were asked to remember or recognise 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. One-second measurements after each stimulus onset were stored. Figure 3 shows an illustrative example of the stimulus presentation. This data set was actually a subset of a larger experiment designed to study the short-term memory differences between alcoholics and non-alcoholics [13], [14].

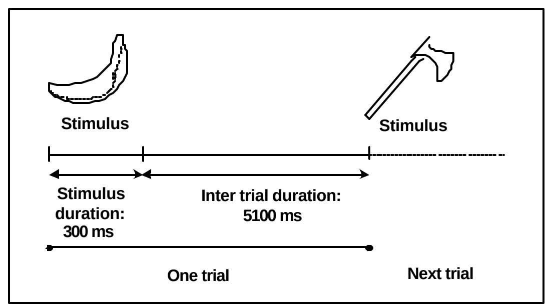

Figure 3: Example of visual stimulus presentation

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 milliseconds [16], [17]. 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. Next, mean from the VEP signals were removed. This was to set the pre-stimulus baseline to zero.

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

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

where N is the total number of data in the filtered signal. These VEP spectral power values from each of the 61 channels were concatenated into one feature array representing the particular VEP pattern. This power was normalised with the total spectral power from all the 61 channels, i.e. the power value from each channel was divided by the sum of all power values from the 61 channels.

2.3. *Grow and Learn Network*

These VEP feature arrays were classified by Grow and Learn (GAL) neural network into the different categories that represent the persons. GAL was chosen instead of other NN due to its high speed training and testing ability [18], [19]. In addition, GAL algorithm can be used to learn categories in an incremental manner, i.e. class definitions can be extended if need arises [18]. GAL is a new algorithm that learns an association at one-shot due to being incremental and using a local representation [18]. The network has a dynamic structure; nodes and their connection (weights) are added during learning when necessary [19]. In the forgetting phase the units that were previously stored but which are no longer necessary due to recent modifications are removed to minimize network complexity. The structure of the GAL is shown in Figure 4 [19].

The procedure for GAL learning and forgetting is as follows [19]:

Step 1: Initially choose a number of vectors randomly from the training set as many as the number of classes. Each vector represents only one class. Initialize each chosen vector as an output node of the GAL. Initialize the iteration number to zero value.

Step 2: Increase the iteration number. If the iteration number is equal to the chosen maximum value, terminate the algorithm. Otherwise, go to step 3.

Step 3: Choose one vector denoted by X_i randomly from the training set. Compute the distances between each output node of the GAL and the input vector, and find the minimum distance as follows.

$$d_o = \sum_{j=1}^{N}(x_j - w_{oj})^2 \tag{2}$$

$$d_m = \min_o (d_o)$$

where x_j is the j^{th} element of the input vector X, W_{oj} is the j^{th} element of the o^{th} node of the GAL, and N is the present number of input nodes. Compare the classes of the input vector and the m^{th} node nearest to the input vector. If their classes are the same, go to Step 2. Otherwise go to Step 4.

Step 4: Include the input vector in the GAL network as a new output node. The elements of the input vector are assigned as the associated weights of the new output node of the GAL. Go to step 2.

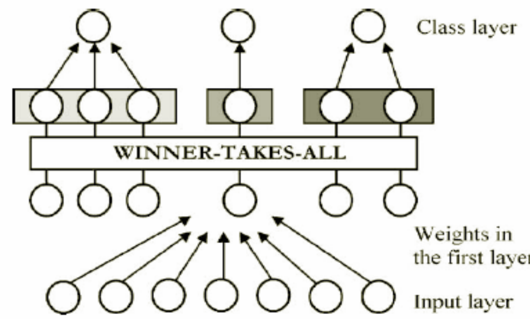

Figure 4: Structure of GAL Network

During the GAL learning stage, nodes generated depend on the order of the input vectors. A node previously stored may become useless when another node nearer to the class boundary is generated. When a useless node is eliminated from the GAL network, the classification performance of the network does not change. In order to decrease the network size, these nodes are extracted from the GAL by the forgetting algorithm, which is as given below [19]:

Step 1: Select the maximum iteration number as the number of output nodes in the GAL. Initialize the iteration number as zero.

Step 2: Increase the iteration number. If the iteration number is equal to the maximum value, terminate the algorithm. Otherwise, go to Step 3.

Step 3: Choose the next node from the GAL in an order. This node is extracted from the network and is given as an input vector to the GAL network.

Step 4: Compute Equations (2). Compare the classes of the input vector and the m^{th} node of the GAL. If there classes are not the same go to Step.5. Otherwise Step 3.

Step 5: Include the input vector again in the GAL. Go to Step 2.

3. EXPERIMENTAL STUDY

The VEP features are used to train and test the GAL classifier to recognise persons. The various steps involved are shown in figure 5. In the experiment, the total VEP patterns were split into 4 datasets. Each dataset contained 200 patterns. Different combinations of the four datasets were used as training and testing sets (i.e. similar to cross validation procedure). Forty patterns from the training set were given as initial class to the GAL network because of 40 subjects (classes) in the dataset. This is a requirement of GAL network.

4. RESULTS

Table 1 shows the classification performance (i.e. recognition rate) using the proposed method. The algorithm was tested with and without forgetting (sleep) phase. The performance of GAL was better without the forgetting algorithm due to the availability of additional number of nodes. From the table, we could see that the classification performances did not vary much with different datasets, which shows that the proposed method is independent of the dataset. The low train and test times mean that the proposed method could be implemented close to real time. The simulation was run using Pentium M processor running on Windows XP with programming done using MATLAB (Mathworks Inc). The average recognition rate is 85.09%, which should be improved further for practical applications. However, being a pilot study, the results suffice to show promise for the method to be developed further.

5. CONCLUSION

In this paper, a novel method using GAL neural network for classification of VEP features has been proposed as a biometric tool to recognise persons. The VEP features consisted of spectral power values computed from 61 channels extracted while the subjects were seeing a picture. The positive results obtained in this paper show promise for the method to be studied further as a biometric tool to recognise or identify different persons. The method could be used as a uni-modal (stand alone) or in part of a multi-modal person identification system. The method proposed is advantageous because of the difficulty in establishing another person's exact VEP output (i.e. difficult to forge) but the changes of VEP signals over longer periods of time requires further investigation.

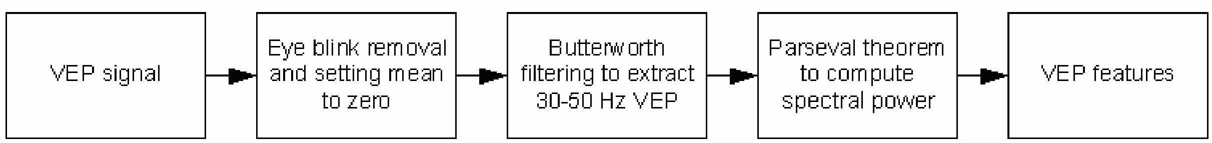

Figure 5: Steps in the feature extraction process

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TABLE 1: CLASSIFICATION USING GAL

Datasets (Train-Test)	**Train time (s)**	**Test time (s)**	**Nodes before forgetting**	**Nodes After forgetting**	**Recognition rate (%) with forgetting**	**Recognition rate (%) without forgetting**
I-II	1.77	0.73	105	88	83.0	83.5
II-III	1.29	0.73	111	90	84.5	85.6
III-IV	1.34	0.75	116	95	82.3	84.5
I-III	1.17	0.74	105	88	86.0	86.5
II-IV	1.31	0.75	111	90	85.5	86.2
I-IV	1.13	0.70	105	88	83.5	84.2
Average	**1.33**	**0.73**	**108.8**	**89.8**	**84.13**	**85.09**

Note: I, II, III, IV- Different datasets used for training and testing

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