

# A New Method to Identify Individuals Using Signals from the Brain

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## Abstract

A new method to identify individuals using signals from the brain is proposed. In the method, brain signals specifically known as Visual Evoked Potential (VEP) signals are recorded from 61 electrodes located on the scalp while the individuals see a picture. Next, spectral features are computed and classified by a Simplified Fuzzy ARTMAP (SFA) neural network (NN). The spectral features consist of power in gamma band (30-50 Hz). The experimental results using 800 VEP signals from 20 subjects show give average classification of 94.18%. This pilot investigation shows that the proposed method of identifying individuals using their brain signals is worth further study.

## 1. Introduction

The most common biometric method of identifying persons is through fingerprint recognition [8]. In recent years, alternative biometric methods to replace or augment the fingerprint technology have been researched. In this regard, biometrics like palmprint [4], hand geometry [5], iris [3], face [12], and electrocardiogram [2] have been proposed.

However, using electroencephalogram (EEG) as a biometric is relatively new compared to the other biometrics. Poulus et. al. [11] 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. [10] used AR modeling of EEG with discriminant analysis to identify individuals with classification accuracy ranging from 49 to 85%. The methods used EEG signals recorded while the subjects were resting with eyes closed [11] and with eyes closed or open [10].

In this paper, a new individual identification method using VEP signals is proposed. VEP signals are EEG signals that are evoked during a particular visual stimulus, like seeing a picture. Here, the spectral powers in gamma

band range of 30-50 Hz computed from the recorded VEP signals are used as biometric features. Gamma band is specifically chosen instead of alternative frequency bands because it is related to focused arousal and memory [1].

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

## 2. Methodology

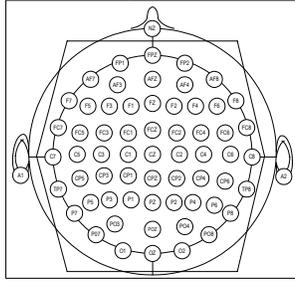
The proposed method could be divided into 3 stages. The first stage involves recording the VEP signals from the subjects. In the next stage, these VEP signals are processed to remove VEP signals with eye-blink contamination, setting mean to zero, noise removal through Principal Component Analysis (PCA) and extract GBP features. The third stage involves SFA classification experiment.

### 2.1 Data

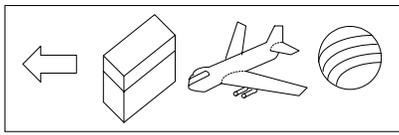
Twenty subjects participated in the experimental study. The subjects are seated in a reclining chair located in a sound attenuated RF shielded room. Measurements are taken from 61 channels placed on the subject's scalp, which are sampled at 256 Hz. The electrode positions (as shown in Figure 1) are located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

The VEP signals are recorded from subjects while being exposed to a stimulus, which consist of pictures of objects chosen from Snodgrass and Vanderwart picture set [13]. 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

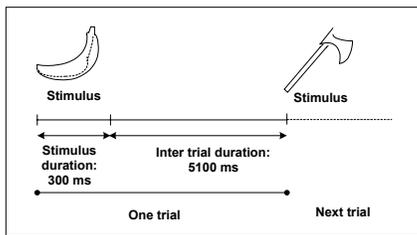


**Figure 1: Locations of electrodes (61 active channels inside hexagon)**



**Figure 2: Some pictures from Snodgrass and Vandervart**

The subjects are asked to remember or recognise the stimulus. Stimulus duration of each picture is 300 ms with an inter-trial interval of 5.1 s. All the stimuli are shown using a computer display unit located 1 meter away from the subject's eyes. One-second measurements after each stimulus onset are stored. Figure 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 [14].



**Figure 3: Example of visual stimulus presentation**

## 2.2 Feature Extraction

VEP signals with eye blink artifact contamination are removed using a computer program written to detect VEP signals with magnitudes above 100  $\mu\text{V}$ . These VEP signals detected with eye blinks are then discarded from the experimental study and additional trials are conducted as replacements. The threshold value of 100  $\mu\text{V}$  is used since

pictures.

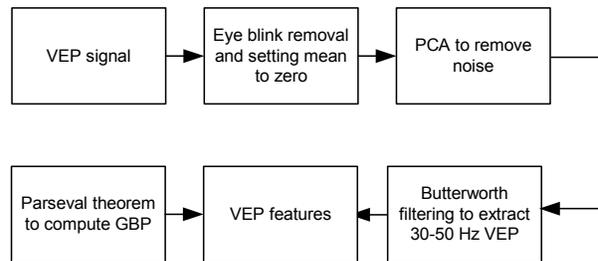
blinking produces 100-200  $\mu\text{V}$  potential lasting 250 milliseconds [7]. A total of 40 artifact free trials are stored for each subject. As such, a total of 800 single trial VEP signals are available for analysis. Next, mean from the data are removed. This is to set the pre-stimulus baseline to zero.

Noise is removed from the 61 channel VEP signals through the use of PCA. The method is described elsewhere [9].

A 10<sup>th</sup> order forward and 10<sup>th</sup> order backward Butterworth digital filter is used to extract the VEP in the 3-dB passband of 30 to 50 Hz, 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<sup>1</sup> *filtfilt* function is utilised for this purpose. 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

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

where  $N$  is the total number of data in the filtered signal. These GBP values from each of the 61 channels are concatenated into one feature array representing the particular VEP pattern. This power is normalised with the GBP values from all the 61 channels. Figure 4 shows the procedure of extracting VEP features.



**Figure 4: Method to extract GBP features from VEP signals**

## 2.3 Identification using SFA

These VEP feature arrays are classified by a SFA into the different categories that represents the individuals. SFA is chosen instead of other NN due to its high speed training ability in fast learning modes. SFA is a type of neural network that performs incremental supervised learning [6].

<sup>1</sup> The Mathworks Inc.

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 classes. Inter ART module works by increasing the vigilance parameter (VP),  $\rho$  of Fuzzy ART by a minimal amount to correct a predictive error at the category layer. Parameter  $\rho$  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  $\rho$  enable larger categories to form and lead to a broader generalisation and higher code compression.

The testing stage works similar to the training (i.e. learning) stage except that there will be no match tracking. This is because the input presented to Fuzzy ART will output a category in layer  $F_2$ , which will be used by the Inter ART module to trigger the corresponding category layer node that refers to the predicted class. Figure 5 shows the SFA network architecture as used in the experimental study. For further details on SFA, refer to [6].

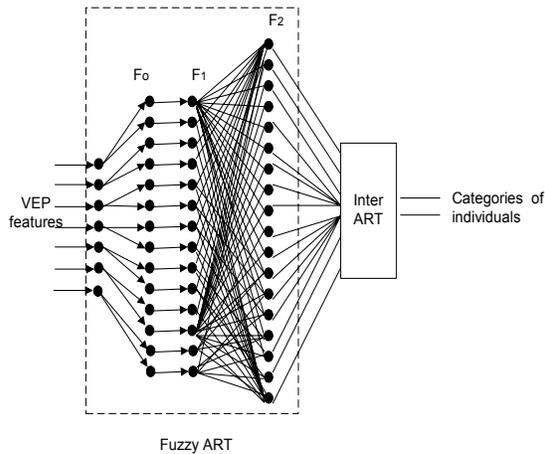


Figure 5: SFA network as used in the study

### 3. Experimental Study

As mentioned earlier, the VEP features consisting of GBP from 61 channels are used to train and test the SFA classifier to identify individuals.

In all the experiments, half of the available VEP patterns (i.e. 20 from each subject) are used for training while the rest half are used for testing. Therefore, a total of 400 VEP patterns are used in training, while the rest 400 VEP patterns are used in testing. The selection of VEP signals for the training and testing datasets are conducted randomly and

are fixed for the experiment. The order of training patterns to SFA for all experiments is conducted randomly.

Table 1 shows the results of the experimental study. The table give the Fuzzy ART cluster size, SFA training time for one pattern, SFA testing time for one pattern, and the SFA classification percentage. The results are tabulated for varying VP values from 0 to 0.9 in steps of 0.1, where the averaged classification percentage of 94.18% obtained is shown. The maximum classification percentage is 95.75%.

The average clusters required are 46.3, while the average train and test times are 0.019 s and 0.015 s. With additional NN training and improvements in VEP signal processing, it might be possible to increase the classification percentage.

### 4. Conclusion

In this paper, a new method using SFA classification of VEP features has been proposed as a biometric tool to identify individuals. The VEP features consist of GBP values computed from 61 channels extracted while the subjects are seeing a picture. The positive results obtained in this paper show promise for the method to be studied further as a biometric tool to identify different individuals. 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 persons exact VEP output (i.e. difficult to forge) but the changes of VEP signals over longer periods of time requires further investigation.

Table 1: SFA results

VP	Cluster	Train time (s)	Test time (s)	%
0.0	34	0.014	0.013	94.00
0.1	27	0.011	0.013	93.75
0.2	31	0.013	0.013	95.50
0.3	36	0.015	0.013	93.75
0.4	36	0.015	0.013	93.75
0.5	32	0.015	0.013	94.25
0.6	32	0.014	0.013	93.50
0.7	35	0.015	0.013	93.50
0.8	58	0.022	0.018	94.00
0.9	142	0.058	0.031	95.75
<b>Average</b>	<b>46.3</b>	<b>0.019</b>	<b>0.015</b>	<b>94.18</b>

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