Energy of Brain Potentials Evoked During Visual Stimulus: A New Biometric?

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Abstract. We further explore the possibility of using the energy of brain potentials evoked during processing of visual stimuli (VS) as a new biometric tool, where biometric features representing the energy of high frequency electroencephalogram (EEG) spectra are used in the person identification paradigm. For convenience and ease of processing of cognitive processing, in the experiments, simple black and white drawings of common objects are used as VS. In the classification stage, the Elman neural network is employed to classify the generated EEG features. The high recognition rate of 99.62% on an ensemble of 800 raw EEG signals indicates the potential of the proposed method.

1 Introduction

Over the last decade or so, there has been ongoing research into the possibility of employing some alternative biometrics for identifying individuals, instead of the standard one based on fingerprints [1]. These include techniques which focus on:- face [2], palm print [3], hand geometry [4], heart signal [5], iris [6], odor [7], and brain signals [8-10]. The brain *fingerprints* have also been studied for aiding criminal investigations [11]. Methods based on the use of brain electrical signals (electroencephalogram (EEG)) as a biometric are relatively recent compared to the other established biometric tools. Paranjape *et al* [8] achieved the classification accuracy ranging between 49% and 85%, by using autoregressive (AR) modelling of EEG in combination with discriminant analysis. Poulus *et al* looked at the problem of distinguishing between individuals, based on a set of EEG recordings [9]. Their objective was to find an individual as distinct from other individuals as possible [9]. Their method was based on AR modelling of EEG signals and Linear Vector Quantisation neural network (NN), with 72-80% of classification success. However, this method was not tested on the task of recognition of individual subjects.

In this paper, we provide further perspective on the possibility of EEG based person identification. This is an extension of our approach proposed in [10], where features computed from 61 EEG channels, were used for person identification. The fact that it is virtually impossible that different persons will have similar activity in all parts of the brain, and that brain responses cannot be faked, makes this method suitable for the use in biometric applications. The extracted EEG biometric features are processed with the Elman NN (ENN) to classify (that is recognise) different persons.

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Despite its relative simplicity and high success ratio, the method proposed in [10] suffered from several drawbacks, such as a decrease in the accuracy with the increase in the size of the recorded dataset and number of individuals to classify, and a relatively narrow frequency range used in the processing of signals. This paper therefore introduces several improvements in order to increase the success rate of person identification. This is supported by a comprehensive analysis and experimentation tackling all the aspects of the method, such as pre-filtering, usable frequency range, postprocessing and dimensionality reduction.

2 Data and Experiment

EEG biometrics as a data fusion problem: The processing of EEG recordings coming from multiple electrodes may be considered as a multi-channel signal processing problem. Notice, however, that the electrodes on the scalp of a subject are located so as to record the electrical activity of different brain areas. These areas in the cortex are responsible for a variety of cognitive and motor tasks, and the brain electrical activity recorded from these spatially distributed electrodes reflects the nature of the task being processed. For instance, the P3 area is responsible for decision making processes arising from visual stimuli [12]. Therefore, the processing of multi-channel EEG recordings represents a data fusion problem, since we combine the data coming from different information processing mechanisms within the brain.

Data used: We use a non-invasive technique based on the EEG signals recorded from the scalp. EEG signals are potentials exhibited by neuronal excitations in the cortex [13], and were recorded with the subjects observing drawings of common black and white objects.

Data processing: To obtain high frequency EEG signals in the gamma band range (30-70 Hz), filtering was performed, and the energy of these signals was used as a set of features (after some preprocessing) to be classified by the Elman neural network (ENN) [14] trained by the resilient backpropagation (RB) algorithm. This frequency band was suggested by other studies [15, 16] which have, for instance, successfully used gamma band spectral features to differentiate between alcoholics and non-alcoholics. Gamma band is suitable as EEG oscillations in this frequency band are believed to be involved in feature binding process during visual perception [16].

Data acquisition: The subjects (totalling 40) 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, sampled at 256 Hz. The electrode positions were according to the extension of Standard Electrode Position Nomenclature, recommended by the American Encephalographic Association.

Visual stimuli: The EEG signals were recorded from subjects while being exposed to a stimulus, which consist of drawings of objects chosen from Snodgrass and Vanderwart picture set [17]. These pictures represent common black and white objects, such as, for instance, airplane, banana, and ball. These were chosen according to a set of rules that provides consistency of pictorial contents. They have been standardised based in the variables of central relevance to memory and cognitive processing, for instance, objects can be named (definite verbal labels).

Mental task: The subjects were asked to remember or recognise the stimulus. Stimulus duration of every picture was 300 ms with an inter-trial interval of 5.1 s. All the stimuli were shown using a display located 1 meter away from the subjects. One-second EEG measurements after each stimulus onset were stored. Figure 1 illustrates the stimulus presentation. This data set used is a subset of a larger experiment designed to study the short-term memory [18].
Artifact removal: EEG signals contaminated with eye blink artifacts were not considered in the classification, and were detected using a 100 μV threshold. This is a common threshold value in EEG studies, and is used since blinking produces 100-200 μV potential lasting 250 milliseconds [19]. A total of 40 artifact free trials were considered for every subject, to make a total 1600 EEG data sets.

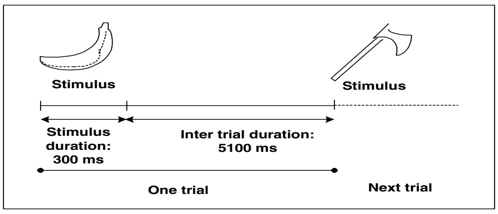

Fig. 1. Example of visual stimulus presentation

3 Method

Original method: In the original method proposed in [10], the EEG signals were filtered using a forward and reverse Butterworth band-pass digital filter, to obtain zero phase distortion. The 3-dB pass-band was chosen to be between 30 and 50 Hz, whereas the stop-band was fixed at 28 and 52 Hz. A model order of 14 was used to attain a minimum stopband attenuation of 20 dB. To form the EEG features, the energy of the EEG signal from each channel was computed and normalised according to the total energy from all 61 channels. These 61 EEG features were then classified by a multi-layer perceptron (MLP) NN trained by a standard backpropagation algorithm [20]. The training was conducted until the average error fell below 0.01.
Improved method: In the proposed method in this paper, several improvements were made for every aspect of the method:-

i) EEG signals were filtered (in the forward and reverse direction) using Elliptic filter as this required a lower order as compared to the Butterworth filter;

ii) frequency range was changed from 30-70 Hz because of the reported existence of gamma band oscillations in this range [21];

iii) order 5 was sufficient to obtain a 3-dB passband of 30-70 Hz with minimum stopband attenuation of 30 dB below 25 Hz and above 75 Hz. The ripple in the passband was kept below 0.1 dB;

iv) energy of the filtered EEG signal from each channel were computed and normalized with the total energy from 61 channels to form the EEG features;

v) EEG features were normalised to unit variance and zero mean;

vi) principal component analysis (PCA) was used to reduce the feature set by selecting the more discriminating features.

The PCA setting: The standard PCA method [21] was used, where variable **z** represents the extracted signal, for which its covariance matrix is computed as

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

where **E(.)** is the mathematical expectation operator. Next, matrices **V** and **D** were computed, where **V** is the orthogonal matrix of eigenvectors of **R** and **D** is the diagonal matrix of its eigenvalues, that is $D=diag(d_{1,\ldots,}d_n)$. The features with reduced dimensionality **y** were then found as

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

where $\mathbf{V_r}$ denotes the reduced eigenvector matrix corresponding to the selected principal components (PCs). In our work, the PCs that contribute to 99.9% of the total variance were selected, which amounted to 52 features. These features were normalised to the range [-1,1], using maximum and minimum values of each feature, with the idea to improve the NN training.

Neural network classification: ENN was used for feature processing. The ENN is effectively a MLP in which the hidden layer outputs are delayed and fed back into the network, thereby providing a state feedback. A three-layer network was used here, with the hyperbolic tangent activation function in its hidden layer, and a sigmoid activation function in its output layer. As compared to the standard MLP network, only one hidden layer, but with more hidden neurons is needed for the function approximation task. Network weights and biases were initialised following the Nguyen-Widrow algorithm [22]. This algorithm distributes the active region of each neuron in the layer evenly across the layer's input space, which is advantages to speed up training and to efficiently use the available neurons. After some preliminary simulations, the resilient-backpropagation (RB) algorithm [23] was used to train the ENN, and the training was conducted until the mean-square error fell below a threshold of 0.0001.

4 Results and Discussion

Table 1 shows the classification results based on the original and improved methods. For both the methods, 800 EEG patterns (20 from each subject) were used to train the NNs, while the previously unseen 800 EEG patterns were used to test the classification performance (%).

In the original method [10], the numbers of hidden units were varied from 10 to 50 in steps of 10 but using the current dataset, the classification performances were less than 93% (except for 50 hidden units) using these numbers of hidden units and are therefore not reported here. The poorer classification performance is most likely due to the increase in the complexity of the dataset, due to an increase in the number of subjects and patterns. In addition, to ensure a fairer comparison with the proposed improved method, the numbers of hidden units were varied from 50 to 300 in steps of 50. The ENN required a higher number of hidden units due to the increased state feedback (outputs of hidden neurons). The number of epochs (iterations), training and testing times (in seconds) for 800 EEG patterns are also shown in the Table. We chose to compare the execution times, rather than the number of operations needed, which is done for convenience. Since the algorithms were run on the same code, using Matlab, this still provides a fair comparison of the complexity of the algorithms. From the Tables, it can be seen that the proposed improved method gives better classification performance in addition to fewer training epochs and a decrease in the training duration. This applies for all the cases and sizes of hidden units.

Table 1. Classification results using the original and improved methods

Original method					Improved method				
Hidden units	Epochs	Train time (s)	Testing time(s)	%	Hidden units	Epochs	Train time (s)	Testing time(s)	%
50	191	51.85	0.19	95.50	50	40	4.26	0.06	98.75
100	161	54.52	0.20	95.50	100	32	6.81	0.10	99.12
150	217	96.75	0.25	95.87	150	25	8.29	0.14	99.62
200	151	83.59	0.29	96.13	200	32	14.12	0.19	99.00
250	185	122.21	0.35	95.37	250	28	17.29	0.26	99.00
300	157	120.67	0.39	95.75	300	31	24.48	0.33	99.00
Average	177.0	88.27	0.28	95.69	Average	31.3	12.54	0.18	99.08

5 Conclusion

In this paper, we embark upon the results from [10] and propose an improved method for employing EEG features as a biometric to identify individuals. This is achieved in a data fusion setting, where the energy of high frequency EEG signals has been used as a classification criterion, and has obtained when subjects were seeing a common black and white line drawing of common objects. The features have undergone several pre- and post-processing operations, to be used as features for classification by Elman neural network. The results obtained have shown the potential in applications such a stand alone individual identification system or as a part of a multi-modal individual identification system.

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