Journal of VLSI Signal Processing 49, 243–250, 2007
© 2007 Springer Science + Business Media, LLC. Manufactured in The United States.
DOI: 10.1007/s11265-007-0078-1

EEG Based Biometric Framework for Automatic Identity Verification

RAMASWAMY PALANIAPPAN
Department of Computer Science, University of Essex, Colchester, Essex CO4 3SQ, UK
rpalan@essex.ac.uk

DANILO P. MANDIC
Department of Electrical and Electronic Engineering, Imperial College London, London, UK

Received: 24 April 2006; Revised: 26 October 2006; Accepted: 2 April 2007

Abstract. The energy of brain potentials evoked during processing of visual stimuli is considered as a new biometric. In particular, we propose several advances in the feature extraction and classification stages. This is achieved by performing spatial data/sensor fusion, whereby the component relevance is investigated by selecting maximum informative (EEG) electrodes (channels) selected by Davies–Bouldin index. For convenience and ease of cognitive processing, in the experiments, simple black and white drawings of common objects are used as visual stimuli. In the classification stage, the Elman neural network is employed to classify the generated EEG energy features. Simulations are conducted by using the hold-out classification strategy on an ensemble of 1,600 raw EEG signals, and 35 maximum informative channels achieved the maximum recognition rate of 98.56±1.87%. Overall, this study indicates the enormous potential of the EEG biometrics, especially due to its robustness against fraud.

Keywords: biometric, Davies–Bouldin index, electroencephalogram, identity identification, neural network

1. Introduction

A number of biometrics has been in use for identifying individuals, in addition to the standard one based on fingerprints [1]. These include techniques that relies on: DNA, hand geometry, palm print, face (both optical and infrared), iris, retina, signature, ear shape, odor, keystroke entry pattern, gait, and voice [2]. Other emerging biometrics such as ear force fields [3], heart signals [4], and brain signals [5–7] have been proposed in recent years. As signal recording from the brain is rather complicated, biometrics based on brain signals has not been studied extensively though it is one of the most fraud resistant biometrics.

There are only a handful of studies that have utilised this brain signal based biometric. These include results by Paranjape et al. [6] who studied autoregressive (AR) modelling of EEG in combination with discriminant analysis and achieved a classification accuracy ranging between 49 and 85%, while Poulus et al. [7] studied the problem of distinguishing an individual from the rest using a set of EEG recordings. Their method was based on AR modelling of EEG signals and Linear Vector Quantisation (LVQ) neural network (NN), which gave 72–80% classification accuracy. However, this method was not tested on the task of recognition of individual subjects.

Our aim in this paper is to provide further perspective on the possibility of EEG based person identification. The approach here is an extension to the one proposed in [5], where person identification was achieved using features from 61 channels. Different persons will have dissimilar activity in some or all parts of the brain even for the same mental task, and this combined with the fact that brain responses cannot be faked, makes this method suitable for the use in biometric applications. The Elman NN is used to classify (that is recognise) different persons using the extracted EEG biometric features.

1.1. The Proposed Method

The method proposed in [5], despite its relative simplicity and high success ratio, 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.

Several improvements are introduced in order to increase the success rate of person identification. This is supported by a comprehensive analysis tackling all the aspects of the method, such as pre-filtering, usable frequency ranges and postprocessing. Further, a reduction in the number of required channels is also sought out. The experimental results support the analysis.

2. Experimental Study

2.1. 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 component from midline parietal is responsible for decision making processes arising from visual stimuli [8]. 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.

2.2. EEG Data

EEG signal data recorded non-invasively from the scalp were used. EEG signals are electrical potentials exhibited by neuronal excitations in the cortex [9]. For this study, the EEG signals were recorded with the subjects observing drawings of common black and white objects.

2.3. Data Processing

To obtain EEG signals in gamma frequency range, filtering was performed, and the energies of these filtered signals were used as a set of features (after some preprocessing) to be classified by the Elman neural network (ENN) [10] trained by the resilient backpropagation (RB) algorithm [11]. The use gamma band was suggested by other studies [12] 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 [13].

2.4. 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 active 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 En cephalographic Association.

2.5. 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 [14] picture set. 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 on the variables of central relevance to memory and cognitive processing. These objects had definite verbal labels, i.e. they could be named.

2.6. 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 m away from the subjects. One-s EEG measurements after each stimulus onset were stored. Figure 1 illustrates a stimulus presentation. This data set used is a subset of a larger experiment designed to study the short-term memory [15].

2.7. 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 ms [16]. A total of 40 artifact free trials were considered for every subject, to make a total 1,600 EEG data sets.

3. Original Method

In the original method proposed in [5], 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 NN trained by a standard backpropagation algorithm. The training was conducted until the average error fell below some prescribed threshold, in this case, it was 0.01.

4. Improved Method

In the proposed method in this paper, several improvements were made for every aspect of the method:

1. The EEG signals were re-referenced to common average using

$$z[n] = x[n] - \frac{1}{61}\sum_{i=1}^{61} x_i[n], \tag{1}$$

   where $x[n]$ is the original signal, while $z[n]$ is the new re-referenced signal. This would be useful in reducing the intra-subject variance of the EEG signals;
2. Here, the gamma range was extended from 20 to 50 Hz, i.e. a wider range was used.
3. 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. Orders 4 were sufficient to obtain a 1 Hz stop-band beyond the pass-band on both sides. Stopband attenuation was set to a minimum of 30 dB with maximum pass-band ripple set at 0.1 dB.
4. Energy of the filtered EEG signal from each channel were computed and normalised with the total energy from 61 channels. Therefore, a total of 61 values formed the EEG features.
5. Davies Bouldin index (DBI) was used to reduce the feature set by selecting the more discriminating features from different channels.
6. ENN was used instead of the standard MLP NN.

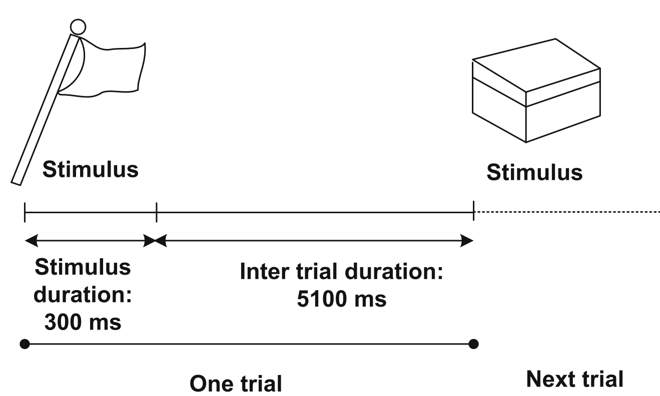

Figure 1. Example of visual stimulus presentation.

Table 1. Classification results using the original method.

Hidden units	Training time (s)	Testing time (s)	Classification (%)
50	33.59	0.19	93.44±2.17
100	42.83	0.20	93.25±2.13
150	61.47	0.25	93.69±1.60
200	81.26	0.29	94.00±1.58
250	96.17	0.35	93.75±1.88
300	126.93	0.39	91.38±1.69

4.1. Davies Bouldin Index

DBI is basically a method to determine the number of clusters in the data [17]. Here, it was used to select the important features from different channels to optimise the recognition accuracy. DBI could be computed as follows:

$$DBI(i) = \sum_{j=1}^{40} R_j(i), \tag{2}$$

where i representing the feature, i=1,.....61 and R_j is

$$R_j(i) = \max k_{(j \neq k)} \frac{S_j(i) + S_k(i)}{d_{jk}(i)}, \tag{3}$$

while S_j and S_k, j,k=1,....,40 are the dispersion of features from each of the 40 subjects. The dispersions are given by

$$S_j(i) = \frac{1}{|C|} \sum_{y \in C} \left\| y - m_j \right\|, \tag{4}$$

where C is all the feature vectors from the particular subject j, y is a feature in C and m_j is the mean of C. The distance d_{jk} is given by

$$d_{jk}(i) = \left\| m_j - m_k \right\|. \tag{5}$$

All distances as Euclidean distances. All the 61 features were sorted in descending order using the computed DBI.

4.2. Neural Network Classification

The ENN was used for feature processing. ENN was chosen as it gave improved results in preliminary simulations as compared to MLP. A three layer ENN 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, ENN requires more hidden neurons for the function approximation task [18].

Network weights and biases were initialised following the Nguyen–Widrow algorithm. This algorithm aims at distributing the active region of each neuron in the layer evenly across the layer's input space. Advantages of this initialisation over purely random weights and biases are faster training and the more efficient use of the available neurons. After some preliminary simulations, the RB algorithm was used to train the ENN, and the training was conducted until the mean-square error fell below a threshold of 0.0001.

Table 2. Classification results using the improved method.

Hidden units	Training time (s)	Testing time (s)	Classification (%)
50	7.26	0.06	98.13±2.02
100	8.59	0.11	98.06±2.00
150	10.71	0.13	98.56±1.87
200	14.82	0.16	98.31±1.91
250	20.16	0.21	98.38±2.01
300	23.99	0.27	98.31±1.91

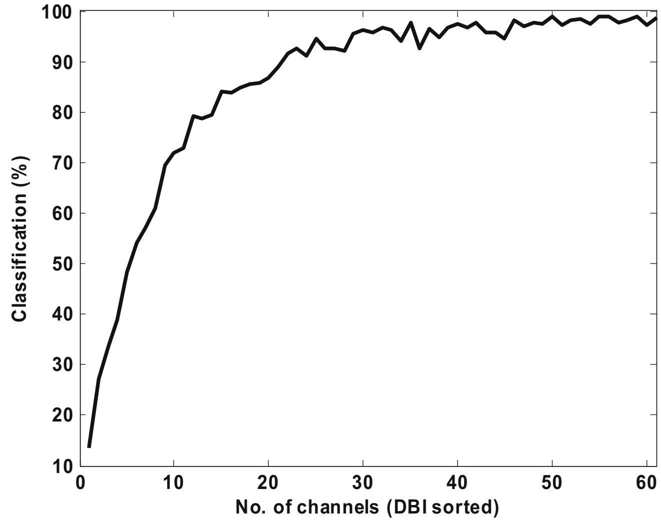

Figure 2. Classification (%) vs no. of channels (DBI sorted).

5. Results and Discussion

Table 1 shows the classification results based on the original method. In the original method used in [5], the numbers of hidden units (HUs) 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 HUs) using these numbers of HUs 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

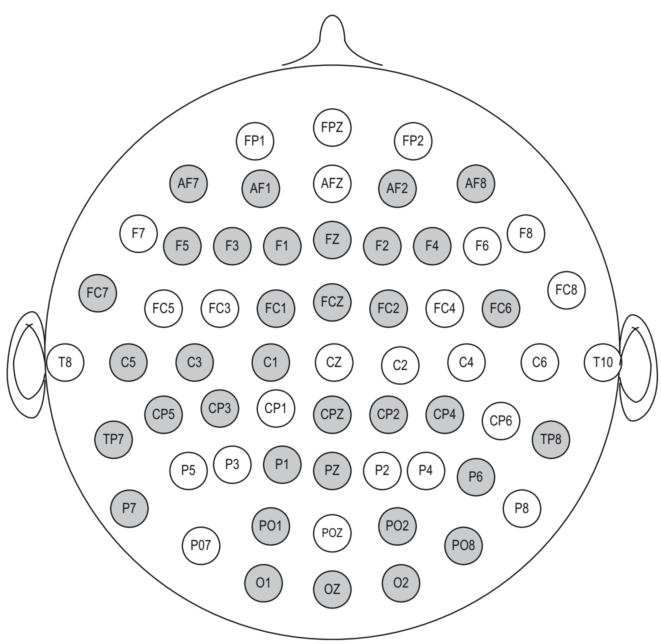

Figure 3. Optimal channel locations (*shaded*).

ensure a fairer comparison with the proposed improved method, the numbers of HUs were varied from 50 to 300 in steps of 50. The ENN required a higher number of HUs due to the increased state feedback (outputs of hidden neurons). For both the original method and improved method proposed here, an extreme case of hold-out strategy was employed. Using this method, 1,560 EEG patterns (39 from each subject) were used to train the NNs, while the previously unseen 40 EEG patterns (one from each subject) were used to test the classification performance. This procedure is repeated for 40 times, each with different training/testing pattern set and the averaged classification (and standard deviation) results are reported in Tables 1 and 2.

For the improved method, only optimal features were used. Features from different number of channels (using DBI sorted in ascending order) in incremental steps of 1, 2, 3,...., 61 were used to run ENN classification in a preliminary experiment. ENN was run once with 50 HUs, which was chosen for convenience of speed. This experiment would be useful in giving the approximate optimal number of features to use. Figure 2 shows the ENN classification results. As could be seen from the figure, using feature from a single channel gave classification accuracy of 13.63% while using features from 50 channels gave 99.0% accuracy. The classification accuracies using the features from all channels were sorted and the optimal number of channels was chosen as the number of channels that gave accuracy up to the 75th percentile of the accuracy obtained using 61 channels. It is a fact that the accuracy could increase with inclusion of channels beyond the optimal number but the marginal increase would not be worthy of the increase in complexity. The median accuracy was 97.62% and the optimal number of channels was 35. Figure 3 shows these optimal channels. The channel locations are of importance but a study of these is beyond the scope of this paper.

Using these 35 features from optimal channels, ENN classification was run with HUs of 50 to 300 in steps of 50. The results are reported in Table 2.

The training and testing times (in seconds) for 1,560 and 40 EEG patterns, respectively are also shown in the Tables. 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 (Mathworks Inc.), 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 a decrease in the training duration. Further, a reduction in the number of features for the improved method allows faster testing. This applies for all the cases and sizes of HUs. As the classification performance for the improved method did not vary significantly for the different HUs, 50 HU could be utilised in future studies as this would minimise computation time and complexity.

Figure 4 shows the classification results on a subject by subject basis (using 200 and 150 HU values for the original and improved methods, respectively), which shows that improvements were obtained for all the subjects excluding subjects 22,

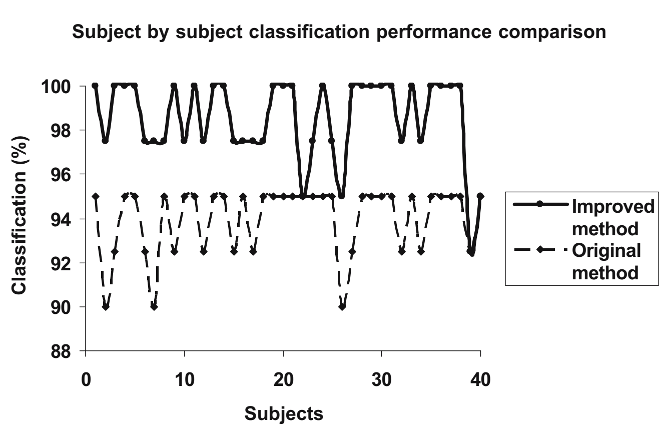

Figure 4. Classification results (subject by subject basis).

39 and 40 where the classification performances were the same.

6. Conclusion

In this paper, we embark upon the results from [5] and propose an improved method for employing EEG features as a biometric for automatic individual identification. This is achieved in a data fusion setting, where the energy of high frequency EEG signals has been used as a classification criterion, and were obtained when subjects were seeing common black and white line drawing of common objects. The features have undergone several pre- and post-processing operations, to be used as improved features for classification by ENN. Further, DBI was used to reduce the size of the features by selecting the optimal channels. The results obtained have shown the potential in applications such as stand alone individual identification system or as a part of a multi-modal individual identification system.

Acknowledgement

We thank Prof. Henri Begleiter at the Neurodynamics Laboratory at the State University of New York Health Centre at Brooklyn, USA who generated the raw EEG data and Mr. Paul Conlon, of Sasco Hill Research, USA for assisting us with the database.

References

1. S. Pankanti, R.M. Bolle, and A. Jain, "Biometrics, the Future of Identification," *IEEE Computer* (Special Issue on Biometrics), vol. 33, no. 2, 2000, pp. 46–49.
2. A.K. Jain, A. Ross, and S. Prabhakar, "An Introduction to Biometric Recognition," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 14, no. 1, 2004, pp. 4–20.
3. D. Hurley, M. Nixon, and J. Carter, "Force Field Feature Extraction for Ear Biometrics," *Comput. Vis. Image Underst.*, vol. 98, no. 3, 2005, pp. 491–512.
4. L. Biel, O. Pettersson, L. Philipson, and P. Wide, "ECG Analysis: A New Approach in Human Identification," *IEEE Trans. Instrum. Meas.*, vol. 50, no. 3, 2001, pp. 808–812.
5. R. Palaniappan, "Method of identifying individuals using VEP signals and neural network," *IEE. Proc.- Sci. Meas. Technol.*, vol. 151, no. 1, 2004, pp.16–20.
6. R.B. Paranjape, J. Mahovsky, L. Benedicenti, and Z. Koles, "The Electroencephalogram as a Biometric," *Proc. CCECE*, vol. 2, 2001 pp. 1363–1366.
7. M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, "Person identification based on parametric processing of the EEG," *Proc. IEEE ICECS*, vol. 1, 1999, pp. 283–286.
8. J. Polich, "P300 in Clinical applications: Meaning, method, and measurement," in *Electroencephalography Basic Principles, Clinical Applications, and Related Fields*, E. Niedermeyer and F.L. da Silva (Eds.), William and Wilkins, Baltimore, 1993, pp. 1005–1018.
9. K.E. Misulis, "Spehlmann's Evoked Potential Primer: Visual, Auditory and Somatosensory Evoked Potentials in Clinical Diagnosis," Butterworth-Heinemann, UK, 1994.
10. J.L. Elman, "Finding structure in time," *Cogn. Sci.*, vol. 14, 1990, pp. 179–211.
11. M. Riedmiller and H. Braun, "A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm," *Proc. IEEE ICNN*, vol. 1, 1993, pp. 586–591.
12. R. Palaniappan, P. Raveendran, and S. Omatu, "EEG optimal channel selection using genetic algorithm for neural network classification of alcoholics," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, 2002, pp. 486–491.
13. E. Basar, "Memory and Brain Dynamics: Oscillations Integrating Attention, Perception, Learning, and Memory," CRC, Boca Raton, 2004.
14. J.G. Snodgrass, and M. Vanderwart, "A Standardized Set of 260 Pictures: Norms for Name Agreement, Image Agreement, Familiarity, and Visual Complexity," *J. Exp. Psychol. (Hum. Learn)*, vol. 6, no. 2, 1980, pp. 174–215.
15. X.L. Zhang, H. Begleiter, B. Porjesz, W. Wang, and A. Litke, "Event Related Potentials During Object Recognition Tasks," *Brain Res. Bull.*, vol. 38, no. 6, 1995, pp. 531–538.
16. A.M. Halliday (Ed.), "Evoked Potentials in Clinical Testing," Churchill Livingstone, New York, 1993.
17. D.L. Davies and D.W. Bouldin, "A Cluster Separation Measure," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 1, no. 4, 1979, pp. 224–227.
18. D.P. Mandic and J.A. Chambers, "Recurrent Neural Networks for Prediction," Wiley, New York, 2001.

Ramaswamy Palaniappan received his first degree and M.Eng.Sc. degree in Electrical Engineering and Ph.D. degree in Microelectronics/Biomedical Engineering in

1997, 1999 and 2002, respectively from University of Malaya, Kuala Lumpur, Malaysia. He is currently a lecturer with the Department of Computing and Electronic Systems (formerly known as Computer Science), University of Essex, United Kingdom where he is the coordinator of Biosignal Analysis Group. Prior to this, he was the Associate Dean and Senior Lecturer at Multimedia University, Malaysia and Research Fellow in the Biomedical Engineering Research Centre-University of Washington Alliance, Nanyang Technological University, Singapore. He has been a referee to the Industry Grant Scheme managed by Ministry of Science, Technology & Environment, Malaysia. He helped to set-up the Biomedical Engineering Department in University Malaya, Malaysia and founded and chaired the Bioinformatics division in Centre for Bioinformatics and Biometrics in Multimedia University, Malaysia. His current research interests include biological signal processing, brain-computer interfaces, biometrics, artificial neural networks, genetic algorithms, and image processing. To date, he has published over 100 papers in peer-reviewed journals, book chapters, and conference proceedings. Dr. Palaniappan is a member of the Institute of Electrical and Electronics Engineers, IEEE Engineering in Medicine and Biology Society, Institution of Engineering and Technology, and Biomedical Engineering Society. He also serves as Editorial Board member for International Journal of Computer Science and Network Security, and International Journal of Information Processing. His pioneering work on using brain signals as biometrics has received international recognition.

Dr. Mandic received the Ph.D. degree in nonlinear adaptive signal processing in 1999 from Imperial College, London, London, U.K. He is now a reader with the Department of Electrical and Electronic Engineering, Imperial College London, London, U.K. He has previously taught at the Universities of East Anglia, Norwich, Norfolk, U.K., and Banja Luka, Bosnia Herzegovina. He has written over 150 publications on a variety of aspects of signal processing and a research monograph on recurrent neural networks. He has been a Guest Professor at the Catholic University Leuven, Leuven, Belgium and Tokyo University of Agriculture and Technology (TUAT), and Frontier Researcher at the Brain Science Institute RIKEN, Tokyo, Japan. Dr. Mandic has been a member of the IEEE Signal Processing Society Technical Committee on Machine Learning for Signal Processing, Associate Editor for IEEE Transactions on Circuits and Systems II, and Associate Editor for International Journal of Mathematical Modeling and Algorithms. He has won awards for his papers and for the products coming from his collaboration with industry.