Biometrics from Brain Electrical Activity: A Machine Learning Approach

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Abstract—The potential of brain electrical activity generated as a response to a visual stimulus is examined in the context of the identification of individuals. Specifically, a framework for the Visual Evoked Potential (VEP)-based biometrics is established, whereby energy features of the gamma band within VEP signals were of particular interest. A rigorous analysis is conducted which unifies and extends results from our previous studies, in particular, with respect to 1) increased bandwidth, 2) spatial averaging, 3) more robust power spectrum features, and 4) improved classification accuracy. Simulation results on a large group of subject support the analysis.

Index Terms—Biometrics, EEG gamma band, Elman neural network, MUSIC, k-nearest neighbors, visual evoked potential.

1 Introduction

The recent progress in machine learning and computing power has been instrumental in the development of modern interdisciplinary research areas, such as biometrics. The goal of biometrics is to recognize and differentiate between humans based on their physical and behavioral characteristics [1], the most common example is the fingerprint. We have witnessed an increasing number of fingerprint biometric systems [2], most typically in various government-run person identity databases [2]. Despite its widespread use, the limitations of this approach (e.g., its intrusiveness), have motivated research on alternative biometrics; these include approaches based on signature [3], face features [4], palmprint [5], hand geometry [6], iris [7], and voice [8]. The potential benefit of using these alternative biometric modalities is two-fold: 1) they are potentially less prone to forgery and 2) they can be used within a multimodal biometric system. Some of the emerging biometrics techniques include those based on keyboard dynamics [9], ear force fields [10], heart signals [11], odor [12], and brain signals [13], [14], [15], [16], [17], [18].

Brain electrical activity has become the de facto standard in the diagnosis of brain related diseases, but there are very few reported studies on brain electrical activity-based biometrics; these can further be classified into electroencephalogram (EEG)-based and Visual Evoked Potential (VEP)-based. The advantage of using brain electrical activity in this context is its uniqueness; the recorded brain response cannot be duplicated, and a person's identity is therefore unlikely to be forged or stolen. In addition, some important practical issues, such as the size of the feature vectors needed for such biometrics and the associated database storage requirements are much less prohibitive as compared to the image-based methods (e.g., face recognition). Despite the somewhat cumbersome data collection procedures, there are clear indications that future improvements in the brain activity-based biometrics will relax this problem, and that the discrimination ability of this approach has great potential in highly secure environments.

Some early work on EEG-based biometrics includes the work by Paranjape et al. [13] who examined the use of autoregressive (AR) models of various orders computed from EEG signals recorded from the subjects with eyes open and eyes closed. They examined 349 EEG trials from 40 subjects, and the subsequently employed discriminant analysis gave the classification accuracy of about 80 percent. Poulos et al. [14] used a Learning Vector Quantizer[1] network to classify AR parameters describing the alpha rhythm EEG feature, where the classification performance of 72-84 percent was obtained based on the experiments involving four subjects and 255 EEG patterns. In another study, Poulos et al. [15] utilized the same data set but a different classification technique, which was based on computational geometry (convex polygon intersections) and gave an improved average classification of 95 percent. These experiments were conducted for a relatively small number of subjects.

In our previous studies, we used VEP-based biometrics [16] whereby the energy of the gamma band VEP potentials was used as a feature. The underlying hypothesis underpinning this approach was that the perception of a visual stimulus (black and white drawings of common objects) evokes brain activity related to recognition and memory, which is known produce a significant change in gamma band oscillations [19]; these are known to be distinct among humans and, therefore, a candidate for biometrics.

Applications of this kind of biometrics include those related to access to classified documents and situations where fingerprints could be easily forged. Most of other biometrics modalities, such as the palmprint, face, and iris are also prone to forgery, whereas it is not possible to duplicate mental activity within the brain.

We here present a framework for brain electrical activity-based biometrics, where our emphasis is on revealing the potential of this biometric modality. We first introduce the VEP-based biometrics and propose several modifications of our previous work, in order to improve the classification accuracy. These include a much more comprehensive data set and a rigorous analysis of the classification performance. Techniques used include those based on the k-Nearest Neighbors (kNN), Elman Neural Network (ENN) classifiers, and 10-fold Cross Validation Classification (CVC).

2 Experimental Setting

The VEP signals were recorded from the subjects being shown black and white drawings of common objects, extracted from the Snodgrass and Vanderwart picture set [20]. Fig. 1 shows some of these pictures, which were displayed on a computer monitor located 1 m from the subject. The mental task was to recognize and remember the picture shown. This is a well-known experiment, originally designed to study short-term differences in human memory [21], whereby a second picture is subsequently shown where the object belongs either to the same class of objects or different. For the purpose of this study, we shall only use the VEP signals recorded during the presentation of the first picture.

We have analyzed the VEP measurements (sampled at 256 Hz) coming from 61 active channels, where the electrodes were placed on the scalp according to the extension of the 10-20 electrode positioning system (Standard Electrode Positioning Nomenclature, American Encephalographic Association), as shown in Fig. 2. The stimulus duration of every picture was 300 ms. One second measurements after each stimulus onset were stored for analysis.

1. In the paper, it is referred to as Learning Vector Quantizer, though the common name is Learning Vector Quantization.

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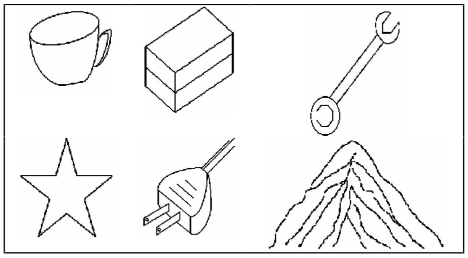


Fig. 1. Examples of pictures from the Snodgrass and Vanderwart data set [20].

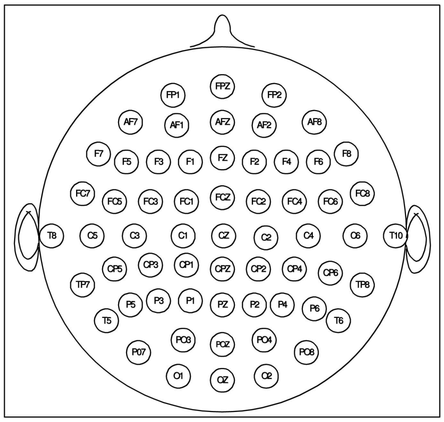


Fig. 2. Electrode locations for the 61 channel EEG recording system.

3 DATA LEVEL PROCESSING OF RAW EEG DATA

In technical terms, biometrics analysis after data extraction consists of three stages:

1. signal conditioning,
2. feature extraction, and
3. classification (decision making).

We shall now briefly summarize some previous approaches to the EEG-based biometrics and indicate the machine learning techniques used at the different processing stages.

In [16], the sum and difference (SD) finite impulse response (FIR) filter was used to extract gamma band VEP signals in the 3 dB range of 32-48 Hz. VEP data from 10 subjects with 40 artifact free[2] VEP signals from each subject were used. The features were produced by normalizing the signal power of every of the 61 channels with the total power from all the channels, and then concatenating the obtained features into a single feature vector. Based on this, a Simplified Fuzzy ARTMAP neural network (NN) gave classification accuracy of 90.95 $\pm$ 2.24 percent when tested on 20 previously unseen VEP patterns from every subject. The vigilance parameter was varied from 0 to 0.9 in steps of 0.1.

The approach presented in [17] was similar to that of [16] except that a Butterworth Infinite Impulse Response (IIR) filter was used to extract gamma band VEP in the 3dB range of 30-50 Hz. Also, a slightly larger VEP data set from 20 subjects (with 40 artifact free VEP signals from each subject) was used. Filtering in both the forward and reverse direction was performed in order to remove phase distortion. The power of the filtered VEP signal from each channel was normalized with the total energy from 61 channels to form the VEP features. A multilayer-perceptron (MLP) trained by the standard backpropagation (BP) algorithm gave classification accuracy of 99.06 $\pm$ 0.08 percent when tested on the unseen half of the data set. The number of hidden units (HU) in the single hidden layer ranged between 10 and 50 in the increments of 10. The features

2. Eye blink artifacts contaminated VEP signals were discarded. Eye blink were detected if the amplitude of VEP signals exceeded 100 μV. A similar procedure was followed for the improved method in this paper.

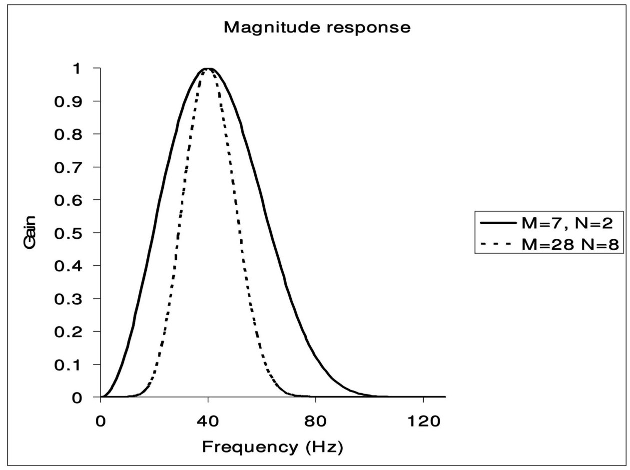


Fig. 3. Gain response of the SD filters with different orders.

used in [18] were similar to those from [17] except that an Elliptic IIR filter was used (since it requires a lower order than a Butterworth filter) with an ENN employed in the classification stage.

4 PROPOSED VEP BIOMETRICS METHOD

The proposed method involves a number of improvements on the methods presented in Section 3, and these are applied to every level of the data analysis.

4.1 Signal Conditioning—SD Filtering over Increased Bandwidth

Raw EEG data are notoriously noisy and difficult to analyze. Feature extracted from these raw data would not be robust and reliable enough for further processing. An SD filter with the 3dB bandwidth of 25-56 Hz (rounded to the nearest integer) was used for the initial filtering of VEP signal. This filter, which consists of a cascade of a sum (low-pass) and difference (high-pass) filter, can be expressed by the following difference equation:

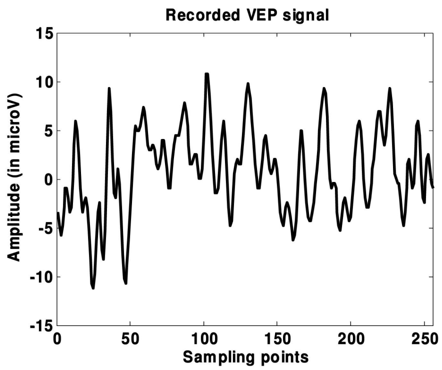
$$\begin{aligned} y[n] &= \sum_{k=0}^{M} \frac{M!}{k!(M-k)!} x[n-k], \text{ and} \\ z[n] &= \sum_{k=0}^{N} (-1)^k \frac{N!}{k!(N-k)!} y[n-k], \end{aligned} \tag{1}$$

where x[n] is the input at time instant n, and y[n] and z[n] are respectively, the outputs of the sum and difference filters. The filter length parameters were $\mathrm{M} = 7$ and $\mathrm{N} = 2$, and objective of the filter order selection was to include a relaxed gamma band spectral range, that is, to obtain a wider bandwidth. The advantage of this filter over the Butterworth or Elliptic filter is that the coefficients are integers and the phase response is linear. Also, the symmetry (for low pass) and antisymmetry (for high pass) properties reduce the computational complexity by half. Fig. 3 shows the SD filter gain responses, while Fig. 4 shows an example of VEP signal before and after filtering.

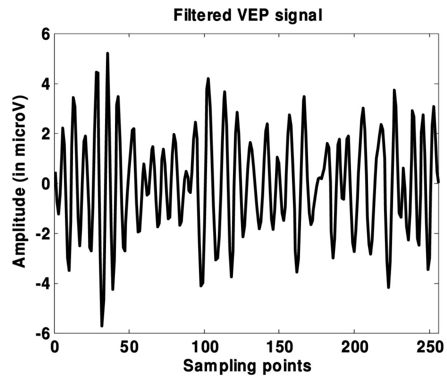
4.2 Signal Conditioning—Spatial Averaging

To reduce the intraclass variance, we adopt standard spatial averaging. In this method, an average of the filtered VEP signals from all the channels is computed and used as a baseline measure. This operation produces a new data sequence xx[n], whose elements are calculated as

$$xx[n] = z[n] - \frac{1}{61} \sum_{i=1}^{61} z_i[n]. \tag{2}$$



(a)



(b)

Fig. 4. Example of VEP (a) before filtering and (b) after filtering.

Notice that there is a possibility that the same subject exhibits similar gamma band energy patterns in different sessions, however, the recorded signal power is not likely to be the same. In order words, we have strong indications that the ratios among the gamma band energies across the channels do not vary over time but instead the subjects exhibit scaling of gamma band energies in all the channels. The baseline measure using common spatial average (2) serves to reduce this intraclass variance. Fig. 5 shows the reduction in intraclass standard deviation through the use of common spatial average as a baseline measure for one subject (from 50 VEP signals) over 61 channels. The sum of the standard deviation values over all the 61 channels was 0.215 for the case with spatial averaging, and 0.237 with no spatial averaging.

4.3 Feature Extraction: MUSIC Dominant Power

After the low-level signal processing (Sections 4.1 and 4.2), in the second stage of the proposed EEG data analysis, we perform feature extraction. These features will serve as unique descriptors of person's brain activity and will provide an input to the classification stage. In addition, by extracting features from raw data, the dimensionality of the problem is dramatically reduced. The Multiple Signal Classification (MUSIC) algorithm [22] was used to estimate the dominant frequency and power content for the cases where it was assumed that there was only one dominant sinusoid in each channel of the filtered VEP signal. The MUSIC algorithm belongs to the class of subspace methods, also known as high-resolution methods or superresolution methods, and is based on the eigenanalysis or eigendecomposition of the data correlation matrix. The choice of the MUSIC algorithm in order to produce feature vectors was also suggested by some previous studies on the analysis of EEG for sleep spindles [23]. In addition, in [24], it was shown that MUSIC-based spectral analysis is particularly suitable for spectral estimation of a combination of modulated sinusoidal signals; the VEP signal in gamma band exhibits exactly this behavior (as shown in Fig. 4b).

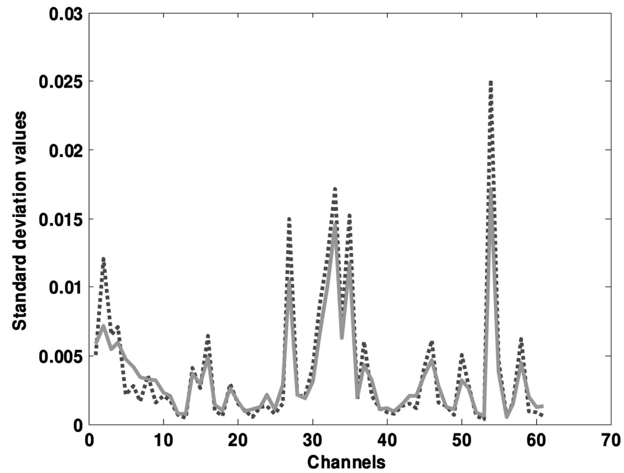


Fig. 5. Standard deviation values for 50 VEP signals over 61 channels. Solid line: standard deviation with spatial averaging as baseline measure. Dotted line: standard deviation without the use of spatial average.

Since the dominant frequencies within the VEP spectrum varied from subject to subject and from channel to channel, we only used the power spectrum component within the MUSIC spectrogram. These were subsequently normalized using the total power from all the 61 channels. These normalized power values from each of the 61 channels were concatenated into a feature vector.

4.4 Feature Vector Classification

In the third stage of our proposed framework for VEP-based person identification, the features extracted in the second stage were classified (decision making process). In the kNN algorithm [25], the classification is performed based on the class of k-nearest neighbors of the feature vector. Here, the kNN algorithm was implemented using the Manhattan distance metric to locate the nearest neighbors. The decision rule used as a discriminant criterion within kNN was the majority rule. The number of nearest neighbors used to classify the new VEP test vector was varied from 1 to 5 in integer increments.

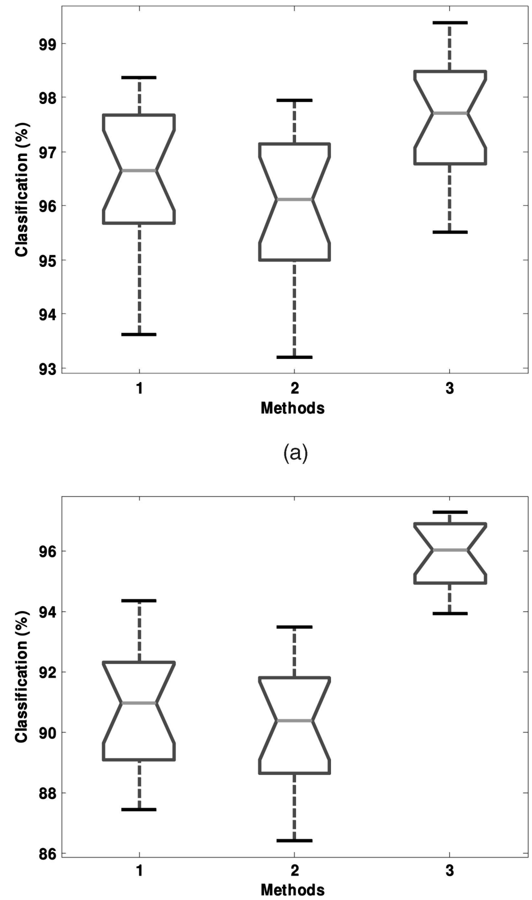
For comparison, an ENN with three layers of units was employed, with the hyperbolic tangent activation function in its hidden layer, and a sigmoid activation function in its output layer. The resilient-backpropagation (RBP) algorithm [26] was used to train the ENN, and the training was conducted until the mean-square error fell below a threshold of 0.0001. The ENN architecture and RBP training algorithm were chosen based on our previous experience, and also empirically after some preliminary experiments. These preliminary experiments (using a small subset of the data set) were conducted to decide the suitable training algorithm (fastest with available memory) among different types of backpropagation (BP) algorithms—standard BP, BP with momentum, BP with adaptive learning, Levenberg-Marquardt BP and RBP. Other preliminary experiments were also conducted using the standard MLP with three layers of units and ENN, which showed that ENN gave better classification performance. The number of input layer units was 61 as there were 61 normalized dominant frequency power features for each VEP signal. The inputs were normalized to fit within the range $[-1, 1]$ using the minimum and maximum value of each feature from all the VEP feature vectors, as this would improve the ENN training. The number of output layer units was 102 so that the ENN could classify into one of the 102 categories representing the subject. One-hot encoding was used for the target values (either 0 or 1). The number of hidden layer units was varied between 50 and 300 in steps of 50. These parameters of ENN were chosen based on the results from [18], where ENN was shown to be a suitable classifier for VEP biometrics.

TABLE 1
Averaged ENN Classification Results (Standard Deviation) Using EL, SMT, and Improved Features

	Previously used features		Improved
ENN HUs	EL	SMT	features
50	95.09 (1.48)	94.63 (1.34)	96.77 (1.26)
100	96.15 (1.53)	96.32 (1.10)	97.42 (1.06)
150	96.83 (1.16)	96.15 (1.80)	97.47 (1.48)
200	96.87 (0.96)	96.07 (1.08)	98.12 (1.26)
250	96.94 (1.44)	96.38 (1.43)	97.95 (0.87)
300	96.74 (1.03)	96.54 (1.23)	97.98 (1.25)
Maximum	96.94 (1.44)	96.54 (1.23)	98.12 (1.26)

TABLE 2
Averaged kNN Classification Results (Standard Deviation) Using EL, SMT, and Improved Features

	Previously used features		Improved
k	EL	SMT	features
1	92.87 (1.49)	91.94 (1.54)	96.13 (1.03)
2	89.97 (1.87)	90.08 (1.72)	95.00 (1.07)
3	90.96 (2.09)	89.66 (2.21)	96.01 (1.14)
4	89.97 (2.50)	89.13 (2.57)	96.08 (1.16)
5	89.75 (1.88)	88.48 (2.04)	96.03 (1.25)
Maximum	92.87 (1.49)	91.94 (1.54)	96.13 (1.03)



(a)

(b)

Fig. 6. Box plots of overall classification results using (a) ENN and (b) kNN. Method 1: EL features, Method 2: SMT features, and Method 3: improved features.

5 EXPERIMENTAL STUDY

In the experiments, we used a total of 3,560 VEP signals from 102 subjects. There was a minimum of 10 and a maximum of 50 eye blink free VEP signals from each subject (in multiples of 10). Three different experiments were conducted with features produced by the EL, SMT, and the proposed improved features. Two classifiers were used: ENN and kNN. For comparison, kNN was chosen due to its simplicity. A 10-fold CVC scheme was used to increase the reliability of the results. Using this scheme, the VEP feature vectors were split randomly into 10 sets, each containing equal number of VEP feature vectors from each subject. Training was conducted using nine sets of feature vectors, while testing was conducted using the remaining set. This was repeated for 10 times, each time using nine different sets for training and the remaining set for testing, whereby the averages and standard deviations of the classification performances were calculated.

6 CLASSIFICATION RESULTS AND DISCUSSION

From the results in Tables 1 and 2, we can see that the classification performances based on the proposed improved features were better than those based on EL[3] and SMT features. This is the case for both ENN and kNN classifiers. ENN classification performances were slightly higher than those of kNN, which proved true for all the different used feature extraction methods. The maximum ENN classification accuracy for the improved feature extraction method was 98.12 ± 1.26 $(\mathrm{HU} = 200)$, while the classification performances for EL and SMT methods were 96.94 ± 1.44 $(\mathrm{HU} = 250)$ and 96.54 ± 1.23 $(\mathrm{HU} = 300)$. For kNN, the corresponding maximum classification accuracies were 92.87 ± 1.49, 91.94 ± 1.54, and 96.13 ± 1.03 and were obtained for $k = 1$.

To perform statistical analysis of the classification results, the Kuskal-Wallis one way variance analysis was utilized, which gave $\mathrm{p} = 0.0016$ and $\mathrm{p} = 4.25e-7$ for ENN and kNN classifiers, respectively. This shows that the classification results were significantly different along the employed methods. Fig. 6 shows the box plots for each of the classifier (using all HU and k values), which clearly indicates the benefits of the proposed approach.

The ENN classification performances obtained here were slightly lower than previous studies reported in [16], [17], [18]. This was likely due to the significant increase in the size of the VEP data set. In terms of the algorithm complexity, ENN is much more algorithmically complex than kNN and requires tedious analysis in the design stage (architecture, learning algorithm) in addition to requiring longer training time. The kNN, in contrast, requires no explicit training. A major disadvantage of kNN is its longer computation time during testing, since in order to classify a test VEP feature vector, its distance to all the training VEP feature vectors needs to be calculated.

Notice that gamma band oscillations are evoked during visual perception, especially when a stimulus is being recognized and that these oscillations contribute to the feature binding process (which is necessary during stimulus perception [19]). The overall high classification results indicate that the feature binding process has different properties for different subjects. It is speculated in the

3. The previous method used in [16] will be denoted as EL, while the method used in [17] as SMT.

literature that this feature binding process could have a direct relation to the genetic material though only clinical trials would be able to give conclusive results.

7 CONCLUSION

This study has analyzed the potential of dominant frequency powers in gamma band VEP signals as a biometrics. A framework for the VEP data analysis has been established and the existing results in the signal conditioning, feature extraction, and classification stage have been summarized. The proposed approach was tested on a large group of subjects with a high number of VEP signals. The proposed framework, supported by the analysis and simulations has clearly indicated the significant potential of brain electrical activity as a biometrics.

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REFERENCES

[1] *Biometrics Systems: Technology, Design and Performance Evaluation,* J. Wayman, A. Jain, D. Maltoni, and D. Maio, eds. Springer-Verlag, 2004
[2] D. Maltoni, D. Maio, A.K. Jain, and S. Prabhakar, *Handbook of Fingerprint Recognition.* Springer-Verlag, 2003.
[3] Y. Jonghyon, L. Chulhan, and K. Jaihie, "Online Signature Verification Using Temporal Shift Estimated by the Phase of Gabor Filter," *IEEE Trans. Signal Processing,* vol. 53, no. 2, part 2, pp. 776-783, 2005
[4] R. Chellappa, C.L. Wilson, and S. Sirohey, "Human and Machine Recognition of Faces, a Survey," *Proc. IEEE,* vol. 83, no. 5, pp. 705-740, 1995.
[5] N. Duta, A.K. Jain, and K.V. Mardia, "Matching of Palmprint," *Pattern Recognition Letters,* vol. 23, no. 4, pp. 477-485, 2002.
[6] R. Sanchez-Reillo, C. Sanchez-Avila, and A. Gonzalez-Marcos, "Biometrics Identification through Hand Geometry Measurements," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 22, no. 10, pp. 1168-1171, Oct. 2000.
[7] R.P. Wildes, "Iris Recognition: An Emerging Biometrics Technology," *Proc. IEEE,* vol. 85, no. 9, pp. 1348-1363, 1997.
[8] W.J.J. Roberts, Y. Ephraim, and H.W. Sabrin, "Speaker Classification Using Composite Hypothesis Testing and List Decoding," *IEEE Trans. Speech and Audio Processing,* vol. 13, no. 2, pp. 211-219, 2005.
[9] J. Bechtel, G. Serpen, and M. Brown, "Passphrase Authentication Based on Typing Style through an ART 2 Neural Network," *Int'l J. Computational Intelligence and Applications,* vol. 2, no. 2, pp. 131-152, 2001.
[10] D. Hurley, M. Nixon, and J. Carter, "Force Field Feature Extraction for Ear Biometrics," *Computer Vision and Image Understanding,* vol. 98, no. 3, pp. 491-512, 2005.
[11] L. Biel, O. Pettersson, L. Philipson, and P. Wide, "ECG Analysis: A New Approach in Human Identification," *IEEE Trans. Instrument and Measurement,* vol. 50, no. 3, pp. 808-812, 2001.
[12] Z. Korotkaya, "Biometrics Person Authentication: Odor," http://www.it.lut.fi/kurssit/03-04/010970000/seminars/Korotkaya.pdf, 2003.
[13] R.B. Paranjape, J. Mahovsky, L. Benedicenti, and Z. Koles, "The Electroencephalogram as a Biometrics," *Proc. Canadian Conf. Electrical and Computer Eng.,* vol. 2, pp. 1363-1366, 2001.
[14] M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, "Person Identification Based on Parametric Processing of the EEG," *Proc. IEEE Int'l Conf. Electronics, Circuits, and Systems,* vol. 1, pp. 283-286, 1999.
[15] M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou, "Parametric Person Identification from the EEG Using Computational Geometry," *Proc. IEEE Int'l Conf. Electronics, Circuits, and Systems,* vol. 2, pp. 1005-1008, 1999.
[16] R. Palaniappan and P. Raveendran, "Individual Identification Technique Using Visual Evoked Potential Signals," *Electronics Letters,* vol. 138, no. 25, pp. 1634-1635, 2002.
[17] R. Palaniappan, "Method of Identifying Individuals Using VEP Signals and Neural Network," *IEE Proc.—Science, Measurement, and Technology,* vol. 151, no. 1, pp. 16-20, 2004.
[18] R. Palaniappan and D.P. Mandic, "Energy of Brain Potentials Evoked During Visual Stimulus: A New Biometric," *Proc. Int'l Conf. Artificial Neural Networks,* W. Duch et al., eds., pp. 735-740, 2005.
[19] E. Basar, *Memory and Brain Dynamics: Oscillations Integrating Attention, Perception, Learning, and Memory.* CRC Press, 2004.
[20] J.G. Snodgrass and M. Vanderwart, "A Standardized Set of 260 Pictures: Norms for Name Agreement, Image Agreement, Familiarity, and Visual Complexity," *J. Experimental Psychology: Human Learning and Memory,* vol. 6, no. 2, pp. 174-215, 1980.
[21] X.L. Zhang, H. Begleiter, B. Porjesz, W. Wang, and A. Litke, "Event Related Potentials During Object Recognition Tasks," *Brain Research Bulletin,* vol. 38, no. 6, pp. 531-538, 1995.
[22] M. Akay, *Detection and Estimation Methods for Biomedical Signals.* Academic Press, 1996.
[23] O. Caspary, M. Tomczak, N. Di Renzo, M. Mouze-Amady, and D. Henry, "Enhanced High Resolution Spectral Analysis of Sleep Spindles," *Proc. 16th Ann. Int'l Conf. IEEE Eng. Medicine and Biology Soc.,* vol. 2, pp. 1232-1233, 1994.
[24] O. Caspary and P. Nus, "Adaptive Spectral Analysis of Sleep Spindles Based on Subspace Tracking," *Proc. 18th Ann. Int'l Conf. IEEE Eng. Medicine and Biology Soc.,* vol. 3, pp. 976-977, 1996.
[25] K. Fukunaga, *Introduction to Statistical Pattern Recognition,* second ed. Academic Press, 1990
[26] M. Riedmiller and H. Braun, "A Direct Adaptive Method for Faster Backpropagation Learning: The RPROP Algorithm," *Proc. IEEE Int'l Conf. Neural Networks,* vol. 1, pp. 586-591, 1993.