EEG/ECG Signal Fusion Aimed at Biometric Recognition

Silvio Barra[1(✉)], Andrea Casanova[1], Matteo Fraschini[2], and Michele Nappi[3]

[1] Department of Mathematics and Computer Science, University of Cagliari, Via Ospedale, 40, 09124 Cagliari, Italy
silvio.barra@unica.it

[2] Department of Electrical and Electronic Engineering (DIEE), University of Cagliari, 09123 Cagliari, Italy

[3] University of Salerno, Via Giovanni Paolo II 132, 84084 Fisciano, Salerno, Italy

Abstract. The recognition of individuals based on behavioral and biological characteristics has made important strides over the past few years. Growing interest has been recently devoted to the study of physiological measures, which include the electrical activity of brain (EEG) and heart (ECG). Even if the use of multimodal approaches overcome several limitations of traditional uni-modal biometric systems, the simultaneous use of EEG and ECG characteristics has been scarcely investigated. In this paper, we present a set of preliminary results derived by the investigation of a biometric system based on the fusion of simple features simultaneously extracted from EEG and ECG signals. The reported results show high performance both from uni-modal approach (higher performance being EER = 11.17 and EER = 3.83 for EEG and ECG respectively) and fusion (EER = 2.94). However, caution should be considered in the interpretation of the reported results mainly beacuse the analysis was performed on a limited set of subjects.

1 Introduction

Biometric systems, which allow to automatically recognize individuals on the basis of their behavioral and biological characteristics, have made important strides over the past few years. These pattern recognition systems will play an increasingly relevant role in the future of highly reliable security systems.

During the last years, the interest in the identification of more robust subject-specific traits has widen the scenario of possible new relevant physical characteristics. In particular, growing interest has been recently devoted to the study of physiological measures, which include the electrical activity of brain and heart. Electroencephalography (EEG) and electrocardiography (ECG) have been indeed extensively investigated as possible markers of biometric traits.

The potential role of brain activity has been highlighted using both simple spectral measures [12] and more complex parameters such as functional connectivity [7] and network topology [5]; for a comprehensive review see [7].

Recently, it has also been shown that some features of ECG signals are very subject-dependent and thus, a high inter-subject variability can be observed [15].

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However, up to date there are several issues that hinder a clear interpretation of the reported results for both EEG-based and ECG-based biometric systems. In particular, the current literature is characterized by high variability in experimental protocols, dataset structure, number of subjects, features extracted, frequency components.

Multimodal biometric systems are characterized by the fusion of different biometric traits; in [16] it has been stated that such systems are able to overcome several limitations of traditional uni-modal biometric systems. Nevertheless, the simultaneous use of EEG and ECG characteristics has been scarcely investigated [[14], [15]].

In this paper, we present a set of preliminary results derived from the investigation of a biometric system based on the fusion of simple features simultaneously extracted from EEG and ECG signals. Uni-modal results are also reported. Our thesis is that the contemporary evaluation of such characteristics may represent an important advance towards the development of new efficient and robust authentication systems.

2 Related Works

In the last ten years, fusion of EEG and ECG signals has been extensively used in several fields. Definitely, diagnostic is the most covered purpose by this practice. In [1], the authors fused the signals in order to detect epileptic events in a patient, based on the fact that such events produce some alterations in the cardiac rhythm. In [8] and [9] a seizure detector is presented, which exploits Support Vector Machines for classification of time and frequency features. Further applications lie in the field of BCI (brain computer interface) systems. In [17], a two-stage hybrid BCI has been developed: first, a feature extraction process over the EEG and ECG signals, based on bispectrum, is achieved; then, a classification is applied to the normalized features, by means of the Fisher's Linear Discriminant analysis (LDA).

The simultaneous use of EEG and ECG characteristics for the development of a biometric system has been scarcely investigated. Some interesting and promising approaches are described in [[14], [15]].

However, it must be kept in mind that the physiological signals are always contaminated by several artifacts which strongly affect the recorded electrical activity; therefore, caution should be used in the interpretation of the results. The investigation of possible solutions for automatic artifact removal ([2], [3], [6], [11], [13]) still represents an important challenge.

3 The Proposed Approach

The idea behind our proposal is to construct a biometric system by composing characteristics and subject-specific traits extracted from the EEG and ECG signals.

In the following, we describe the acquisition process of EEG and ECG, the extraction of the corresponding features and finally the definition of the new biometric proposal by fusing the extracted EEG and ECG signals. In Fig. 1 the steps involved in the system are summarized.

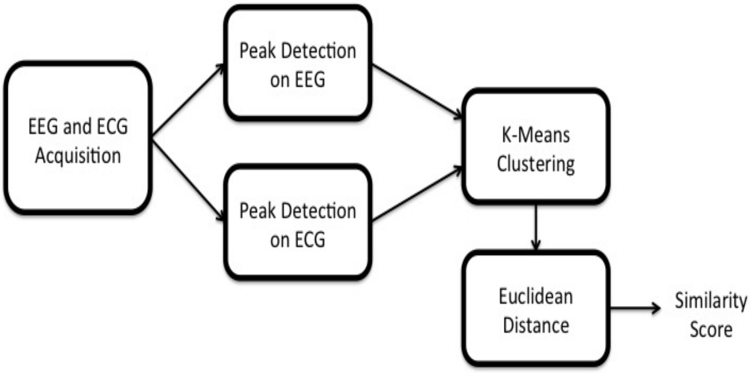

Fig. 1. The process starts with the acquisition of the signals which first are band pass filtered and then given as input to the peak detection method. The detected peaks are represented by a decreasing ordered 48-features vector. Finally, the fusion by clustering is computed. The Euclidean Distance is used to achieve the matching between the centroids of the clusters.

3.1 The Acquisition Process

EEG signals were recorded according to a standard protocol using a 64 channels EEG system. During the EEG recording, the subject involved in the acquisition was instructed to close his/her eyes, stay awake, and reduce eye movements as much as possible, in order to minimize the noise caused by the ocular muscles. The reference electrode was placed in close proximity of the electrode *POz*, with the ground electrode on the forehead. In Fig. 2, a schematic representation of the position of the electrodes placed on the head of the subject via a soft-helmet is shown.

The acquired signals were digitized with a sampling frequency of 1024 Hz and successively resampled to 256 Hz. Signals were band-pass filtered between 0.5 and 70 Hz. For each subject, five eyes-closed epochs of 16.384 samples (16 s) were selected. In the selection, periods indicating drowsiness were excluded from the analysis.Furthermore, in order to limit as much as possible the contamination of external sources (not neural), we decided to focus the analysis on epochs free from artifacts (blinks and eye movements) which can be visually detected. However, the possible impact of these artifacts on classification performance need investigation.

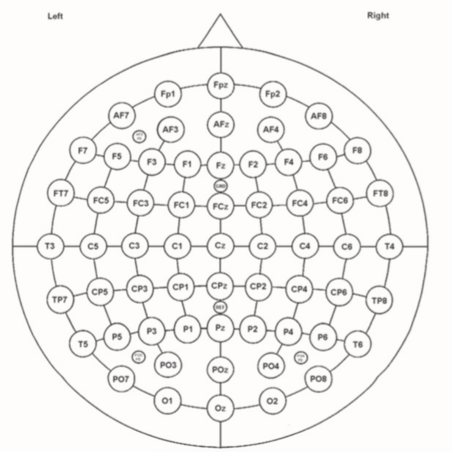

Fig. 2. Electrode position for the 64 channels Micromed system *BrainQuickSystem* by Micromed (Mogliano-Veneto, Italy).

EEG signals were successively band-pass filtered in the classical EEG frequency bands: *theta* (4-8 Hz), *alpha* (8-13 Hz), *beta* (13-30 Hz) and *gamma* (30-50 Hz). The broadband (0.5-50 Hz) signal was also included in the analysis. All the analyses were performed for each band separately.

ECG signals were band-pass filtered in the band 3-15 Hz to avoid noise contamination. Furthermore, since ECG signals show a baseline shift (not representing true amplitude) a detrend procedure based on a low order polynomial fitting was used.

3.2 Feature Extraction

At the end of the acquisition process, for each subject and each epoch, the EEG signals were obtained and represented by a set of 61 vectors, one for each channel, containing 16384 samples of the y-coordinate of the corresponding signal. The ECG signal were represented similarly, by a vector obtained by the potential difference, *ECG+-ECG-*, of the electrodes posed on the wrists. In Fig. 3, the first 61 signals are referred to the EEG, the last one is the *ECG+-ECG-* signal.

The description of the ECG signal has been based on the characterization of the most prominent repeating peaks, which consists of three major components: the Q, R, and S waves (QRS-complex).

The detection of QRS-complex still represents an important challenge. Main problems arise from differences in shape, low signal-to-noise ratio, artifacts and abnormalities. Many detection techniques have been proposed in the literature. These techniques include thresholding, neural networks, hidden Markov model, matched filters, zero-crossing, and singularity techniques. For a more detailed description of these techniques see [4].

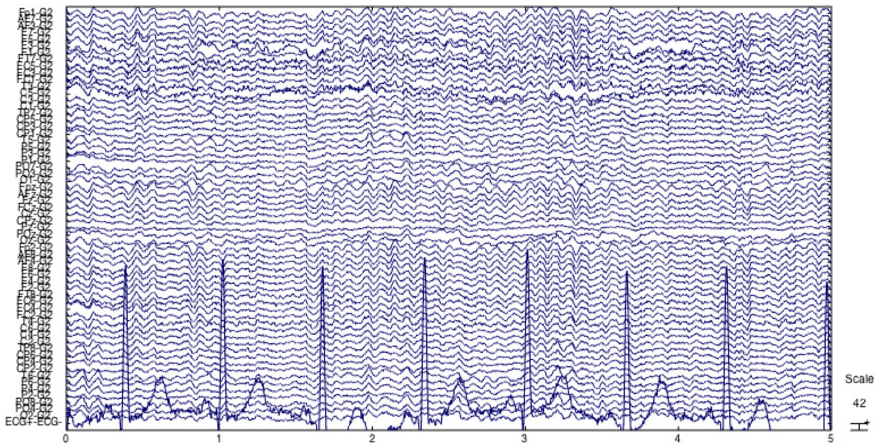

Fig. 3. A typical EEG/ECG acquisition: the first 61 signals are referred to the EEG. The last signal is referred to the ECG.

However, it is important to highlight that the aim of the present study was not develop a novel methods for QRS-complex detection. Therefore, in this study the feature extraction procedure was based on a simple peak detection method which is not accurate for detecting the QRS-complex. The extracted peaks were successively sorted in descending order (based on the peak amplitude) and a fixed set of k elements (most prominent peaks) were selected as features.

In order to avoid any arbitrary selection, the choice of the optimal k threshold was based on the assessment of the possible number of QRS-complex repetitions which could be identified on the selected time interval (16 seconds). All the subsequent analysis is therefore based on a fixed threshold k, with $k = 48$ (sixteen single peaks, one per second, for each of the three waves of the QRS-complex). The impact of the threshold k on the system performance should be further investigated.

The same procedure, with the same k value, was successively used to select the EEG features.

3.3 EEG and ECG Fusion

As for the EEG signal, the previous phase produced 61 vectors of 48 components for each of the five bands *theta* (4-8 Hz), *alpha* (8-13 Hz), *beta* (13-30 Hz) and *gamma* (30-50 Hz) and *broadband*. Analogously, the 62nd vector is obtained for the ECG signal. The fusion process of the two traits is done as follows:

- for each band separately, the 61 vectors for EEG and the one for ECG are clustered, using the well known *k-means* algorithm;
- then, for each cluster the centroid vector is evaluated;
- the biometric is then composed, grouping the centroid vectors of all the clusters.

All the signals share the same feature space and both EEG and ECG waves are band-pass filtered in such a way that the clustering process is done among similar vectors. The centroids of each cluster represent the fused vectors between EEG and ECG signal, as well as the entry point for that cluster. In our study, we considered different numbers of clusters in order to evaluate the better choice fitting our biometric system. Then, given the number of vectors, we evaluated different options, respectively with 4, 8, 16 and 24 clusters for each bandwidth. In a further analysis, we excluded the first option (i.e. 4 clusters) since we observed an excessive loss of information. Each cluster contains a subset of signals such that the intra variability is minimized, and only one of these contains the ECG signal.

4 Experimental Results

In the study, nine healthy (without cardiovascular or neurological complications) volunteer subjects were included in the experimental protocol; their informed consent was obtained. The EEG system used in the experimentation was the *BrainQuickSystem* by Micromed (Mogliano-Veneto, Italy).

The results use the equal error rate (EER), which refers to the intersection point between the false acceptance rate (FAR) and the false rejection rate (FRR) curves.

In Table 1, the results for the uni-modal EEG approach are summarized. Higher results were obtained using the broadband (0.5-50 Hz) EEG signal component.

From the uni-modal ECG approach an EER = 3.83% has been obtained.

Finally, in Table 2, we reported the results (in terms of EER) obtained from the fusion of EEG and ECG features.

Table 1. EEG signal: EER values for each band

Theta (4-8Hz)	Alpha (8-13Hz)	Beta (13-30Hz)	Gamma (30-50Hz)	Broadband (0.5-50 Hz)
16.67%	17.11%	15.83%	15.50%	**11.17%**

Table 2. EER values derived from the fusion of the signals

number of clusters	Theta(4-8Hz)	Alpha(8-13Hz)	Beta(13-30Hz)	Gamma(30-50Hz)	Broadband
8	**2.94%**	4,44%	**2.94%**	**2.94%**	11.11%
16	**2.94%**	8.94%	**2.94%**	4.44%	17.78%
24	**2.94%**	**2.94%**	**2.94%**	6.67%	4.50%

5 Further Works and Considerations

The reported results show good classification performance and then they seem to be promising. Probably the most relevant finding reported in this paper is that by means of a very simple and inexpensive procedure (peak detection and sorting), it is still possible to detect subject-specific traits extracted from both EEG and ECG activities. Furthermore, it seems that from the fusion of these specific traits the system is even more accurate.

However, caution should be used in the interpretation of the reported results, since it is needed to validate the proposed approach on a higher number of subjects. Nevertheless, it is quite interesting that EEG still has the capability to reduce the EER when fused with ECG features.

Moreover, the results obtained from the study of high-frequency (above 30 Hz), which include both gamma band and broadband analysis, should be considered potentially compromised by muscle artifatcs [10].

In conclusion, the results obtained suggest that the fusion of EEG and ECG characteristics show results of potential interest in the development of new biometric systems.

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