



SURVEY ON BIOMETRIC APPLICATION IN MEDICAL FIELD

YASHA.N@1, SUBIYA SHAHARIN.N@2, MALASHREE.N@3

UG STUDENT UG STUDENT ASST PROFESSOR

Department Of CSE, Visvesvaraya Technological University

CBIT, Kolar, Karnataka, India

1yashadhigu@gmail.com

2subi91075@gmail.com

3malachinmail195@gmail.com

ABSTRACT

With the advent of IoT and growing health awareness, the applications of wearable ECG & EMG sensors have grown manifold. These applications demand the sensors to be low-cost, low-power and highly portable. These requirements put several limitations on the wearable ECG & EMG sensors design and development. Brain signals have been investigated within the medical field for more than a century to study brain diseases like epilepsy, spinal cord injuries, Alzheimer's, Parkinson's, schizophrenia, and stroke among others. They are also used in both brain computer and brain machine interface systems with assistance, rehabilitative, and entertainment applications. Despite the broad interest in clinical applications, the use of brain signals has been only recently investigated by the scientific community as a biometric characteristic to be used in automatic people recognition systems. However, brain signals present some peculiarities, not shared by the most commonly used biometrics, such as face, iris, and fingerprints, with reference to privacy compliance, robustness against spoofing attacks, possibility to perform continuous identification, intrinsic liveness detection, and universality. The inherent characteristics of the ECG make it an interesting biometric modality, given its universality, intrinsic aliveness detection, continuous availability, and inbuilt hidden nature.

Keywords: Electromyography (EMG), Electrocardiography (ECG), biometrics, electroencephalographic (EEG)

I. INTRODUCTION

IN the last decade, an always growing interest towards these biological signals, like electroencephalogram (EEG), Electrocardiogram (ECG), electro myogram (EMG), electro dermal response (EDR), blood pulse volume (BPV), to cite a few, for the purpose of automatic user recognition is being witnessed. Within this framework the so-called "cognitive biometrics" refer to biometric traits which are detected during cognitive and/or emotional brain states. Therefore, while conventional biometrics rely on the use of either physiological or behavioral characteristics, that is on some biological characteristics the individual "possesses" or on the "way the individual behaves" respectively, cognitive biometrics are based on the measurement of signals directly or indirectly generated by the "way the individual thinks" as a distinctive characteristic for automatic user recognition.

The study of brain activity during specific mental states has been explored by means of different methodologies in order to extract discriminating features for the purpose of user recognition. Specifically, brain activity can be recorded either by measuring the blood flow in the brain or by measuring the neurons' electrical activity. To the first category belong approaches like functional magnetic resonance imaging (fMRI), which measures the concentration of oxygenated and deoxygenated hemoglobin in response to magnetic fields; near-infrared spectroscopy (NIRS), which measures the concentration of oxygenated and deoxygenated hemoglobin by means of the reflection of infrared light by the brain cortex through the skull; positron emission tomography (PET), which measures neuron metabolism through the injection of a radioactive substance in the subject.

To the second category belong approaches like magneto-encephalography (MEG), which is sensitive to the small magnetic fields induced by the electric currents in the brain, and electroencephalography (EEG), which is sensitive to the electrical field generated by the electric currents in the brain. EEG recordings are acquired with portable and relatively inexpensive devices when compared to the other brain imaging techniques. Specifically, signal amplifiers with high sensitivity and high noise rejection are used to measure the voltage fluctuations on the scalp surface, resulting from the electric field generated by the firing of collections of pyramidal neurons of the cortex.



The EEG amplitude of a normal subject in the awake state, recorded with scalp electrodes, is in the range 10 – 200 μV , and a healthy human brain has its own intrinsic rhythms falling in the range of 0.5 – 40Hz. EEG based brain imaging techniques present a limited spatial resolution due to the physical dimension, in the range of several millimeters, of the surface electrodes usually employed in the acquisition setup, which limits the possible number of the electrodes covering the whole scalp. A limited spatial resolution is also due to the dispersion of the signals, generated by the sources on the cortex, within the head structures before they reach the scalp. On the contrary, EEG techniques have a high temporal resolution, in the range of milliseconds, which allows dynamic studies to understand the underlying mechanisms by means of computational methods.

Different methodologies can be used to sense brain activity, by either measuring the blood flow or sensing the neuron electrical activity. Functional magnetic resonance imaging (fMRI), near-infrared spectroscopy (NIRS), and positron emission tomography (PET) belong to the first category. Magnetoencephalography (MEG) and electroencephalography (EEG) are methodologies belonging to the second category. Among such techniques, electroencephalography can be performed with portable and relatively inexpensive devices.

Fig. 1. The 10-20 international system seen from left (A) and above the head (B). The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes. Even numbers identify electrodes on the right hemisphere, odd numbers those on the left hemisphere, and “z” (zero) refers to electrodes placed on the midline. (C) Location and nomenclature of the intermediate 10% electrodes, as standardized by the American Electroencephalographic Society (Jaakko Malmivuo and Robert Plonsey, Bioelectromagnetism, Oxford University Press, 1995, WEB version).

II. EEG SIGNALS

The EEG recording procedure is performed using contact electrodes placed on the scalp surface. The 10-20 International System [4] shown in Figure 1 is the de-facto standard montage. The EEG time series reflect the superposition of specific oscillatory modes that are typical of brain functioning [3].

Since the earliest studies on the EEG, five main brain rhythms are commonly observed: Delta ([0.5, 4] Hz), Theta ([4, 8] Hz), Alpha ([8, 13] Hz), Beta ([13, 30] Hz) and Gamma (Over 30 Hz).

More in details, some main features for each rhythm can be identified:

- Delta rhythm is predominant during the so called deep or slow wave sleep (SWS) and in newborns. In this stage, Delta waves usually have relatively large amplitudes ([75,200] μV) and show strong coherence all over the scalp. Delta EEG activity has shown to be related to subjects' attention to internal processing [5].
- Theta rhythm shows an increased activity (Theta-band power synchronization) when comparing a resting state to test conditions. In particular, Theta band power increases in response to memory demands, selectively reflecting the successful encoding of new information [6].
- Alpha band activity is the most dominant rhythm in normal subjects during rest, most pronounced in the parieto occipital region. It is characteristic of a relaxed but wakeful state with closed eyes, and attenuates with eyes opening or mental exertion. Moreover there is evidence that attentional and semantic memory demands lead to a selective suppression of Alpha in different sub bands [7].
- Beta activity is characteristic for the states of increased alertness and focused attention. Phase synchrony in Beta band is detectable mainly in specific cortical areas, including Somatosensory, frontal, parietal and motor regions, depending on the task [8].
- Gamma components are difficult to record through scalp electrodes and their frequency components usually do not exceed 45Hz [3]. Components up to 100 Hz, or even higher, may be registered in electrocorticogram (ECOG).

III. EEG SIGNALS AS BIOMETRIC IDENTIFIERS

In , back in 1980, the basis for automatic people recognition using EEG signals were posed. However, only in the last the study of EEG based recognition systems has received a significant development. EEG signals present some peculiarities, which are not shared by the most commonly used biometrics, like face, iris, and fingerprints, and that make the investigation on the use of EEG signal as biometric identifier not a mere academic exercise but an analysis with potential dramatic effects on the design of the next generation biometric systems, namely the cognitive biometrics based systems.



Specifically, brain signals are more privacy compliant than commonly used biometrics like face, iris, and fingerprints, since they are not exposed and therefore cannot be captured at a distance. Moreover, they cannot be left on a crime scene, not even a digital one, and being brain signals the result of a cerebral activity, they are less likely to be synthetically generated and fed to a sensor to spoof it, like it can happen when using gummy fingers to spoof a fingerprint sensor. This also helps in addressing the liveness detection issue. Furthermore, when using EEG based recognition systems, it is impossible for an intruder to force a user to authenticate. In fact stress signals would be present in the measured brainwaves, thus resulting in a denial of access [39]. On the other hand, the use of brain signals poses new challenges. In fact, being the brain continuously and spontaneously active, there is a background electrical activity upon which the signals of interest, which come from the firing of specific collections of neurons responding accordingly to a variety of tasks, are superimposed. Part of this difficulty is the understanding of the brain areas where the response originates. These findings would drive an optimal or suboptimal choice about the number of electrodes to use and their location. Furthermore, due to the weakness of the signal detected on the scalp while generated on the cortex, the EEG acquisition process results very sensitive to endogenous and exogenous noise, that is artifacts generated by physiological processes and by external sources respectively. Therefore, the basic mechanisms which are behind the physiological process of brain signal generation, the signal stability in time, the acquisition protocols, the optimal sensors location depending on the employed acquisition protocol, the amount of the discriminative information, as well its frequency localization, need a much deeper understanding. In this Section the different characteristics of a biometric identifier, namely universality, uniqueness, permanence, collectability, performance, acceptability, and circumvention, are detailed with respect to EEG biometrics. It is worth pointing out that the analysis that follows has different depth levels for the different desired characteristics, since EEG biometrics is still in its infancy and an exhaustive analysis of the aforementioned issues is still missing in literature.

IV. SENSOR SPECIFICATIONS

The desired specifications of ECG & EMG sensor based on the requirements of various wearable applications, viz., heartbeat, eye blink, muscle movements etc. are given in Table I.

TABLE I. SENSOR SPECIFICATIONS

parameters	Values/range
Supply voltage	+1.8V to +3.3V
Current consumption	300 to 500 μ A
Common Mode Rejection Ratio (CMRR)	≥ 100 dB
Gain	100-15000
Low-Frequency Cutoff	0.15 Hz
High-Frequency Cutoff	400 Hz
Weight	≤ 10 g
Price	\leq USD 10

V. ECG Biometric System

These systems rely on the detection of notable ECG complexes for segmentation and extraction of a sequence of individual heartbeats. Typically, the QRS complex is used for that purpose.

Our ECG biometric system, designed with hand ECG signals in mind, starts with the acquisition of raw data, in this case the lead I ECG signal. The acquired signal is then submitted to a data preprocessing block, which performs a digital filtering step (band pass FIR filter order 150, and cutoff frequencies [5;20] Hz) and the QRS complex detection. The outputs of this block are segmented individual heartbeats, and a RR interval time series.

Given that segmentation algorithms are not perfect, especially for noisy signals like the ones obtained from the hands, we implement an outlier detection block, which performs detection and removal of anomalous ECG heartbeats. We follow the DMEAN approach described in which computes the distance of all templates in a



recording session to the mean template for that session, with templates being considered outliers if the computed distance is higher than an adaptive threshold.

The pattern extraction block takes the preprocessed input signals, and starts by aligning all the heartbeat waveforms by their R-peak instants, and by clipping them in the interval $[-200; 400]$ ms around that instant. In the scope of this work, we consider the features to be all the amplitudes within this interval. Finally, a k-NN classifier (with $k=3$) is used together with the cosine distance metric, to produce a decision on the recognition of the individual (either in

Authentication or identification), as it was found to be a good compromise between performance and computational cost (Silva et al., 2012). Altogether, our biometric system is fairly simple, being computationally light and opening the possibility of integrating it into embedded systems, which have limited processing power.

CONCLUSION

In this paper we have given an extensive and critical review on the state-of-the-art of EEG based automatic recognition systems. An overview of the neurophysiological basis, which constitute the foundations on which EEG and ECG biometric systems can be built, has been given. Employed acquisition protocols, features extraction algorithm database structure, classification algorithm used in state-of-the-art approaches have been detailed. The major obstacles towards the deployment of EEG based recognition systems in everyday life in the near future have been presented and some challenging research lines for the interested researchers have been suggested.

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