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A Survey on Cognitive Biometrics: EEG based approach to user recognition

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Abstract**—** Recent advances in signal processing have made possible the use of brain waves or EEG signals for user recognition and also for communication between human and computers. Electroencephalography (EEG) is sensitive to electrical field generated by the electric currents in the brain, and EEG recordings are acquired with portable and relatively inexpensive devices when compare to the other brain imaging techniques. EEG signals are representative signals containing the information about state of human brain. EEG signals are sometimes uses for clinical applications for medical diagnostics. The shape of the wave may contain useful information about the state of the brain. It has been known that different regions of the brain are activated according to the associated mental status, for example, emotional status, cognitive status, etc. Since the difference in activities of the brain causes the difference in characteristics of EEG, it has been attempted to investigate the brain activity through analyzing EEG.

Keywords**—** Electroencephalography (EEG), brain rhythms, biometrics, Brain Computer Interfacing (BCI), Feature Extraction, Auto-regression, Classification.

I. INTRODUCTION *(HEADING 1)*

Recording human brain activity in the form of electrical signals dates back to 1924, when German physiologist and psychiatrist Hens Berger placed some electrodes on a patient's scalp and by means of a galvanometer recorded the first electroencephalogram. Since then, research on electro-encephalography (EEG) has progressed dramatically, providing a valuable instrument for use in the diagnosis and treatment of spinal cord injuries, strokes, and brain disorders including epilepsy, Alzheimer's disease, schizophrenia, and Parkinson's disease. EEG signals also form the basis of brain-computer and brain-machine interfaces, with both rehabilitative and entertainment applications. In recent years, interest has grown in also using EEG for biometric recognition.

In the last decade, associate continually growing interest towards the Use of biological signals, like Electroencephalogram (EEG), Electrocardiogram (ECG), Electromyogram (EMG), Electrodermal Response (EDR), Blood Pulse Volume (BPV), to cite a few, for the aim of automatic user recognition is being witnessed. Among this framework the supposed "cognitive biometrics" talk over with biometric traits that are detected throughout cognitive and/or emotional brain states. Therefore, whereas typical biometrics admit the utilization of either physiological or behavioral characteristics, that is on some biological characteristics. The individual "possesses" or on the "way the individual behaves" severally, psychological feature bioscience are supported the measurement of signals directly or indirectly generated by the "way the individual thinks" as a particular characteristic for Automatic user recognition.

The study of brain activity throughout specific mental states has been explored by suggests that of various methodologies so as to extract discriminating options for the aim of user recognition. Specifically, brain activity may be recorded either by measuring the blood flow within the brain or by measuring the neurons' electrical activity. To the primary class belong approaches like functional resonance imaging (fMRI), which measures the concentration of oxygenated and deoxygenated haemoglobin in response to magnetic fields; near-infrared spectroscopy (NIRS), that measures the concentration of oxygenated and deoxygenated hemoglobin by suggests that of the reflection of infrared light by the brain cortex through the skull; positron emission imaging (PET), that measures neuron metabolism through the injection of a radioactive substance within the subject. To the second class belong approaches like magneto-encephalography (MEG), which is sensitive to the small magnetic fields induced by the electrical currents within the brain, and electroencephalography (EEG), which is sensitive to the electrical field generated by the electric currents within the brain. encephalogram recordings square measure non-inheritable with portable and comparatively cheap devices in comparison to the opposite brain imaging techniques. Specifically, signal amplifiers with high sensitivity and high noise rejection square measure used to live the voltage fluctuations on the scalp surface, resulting from the electrical field generated by the firing of collections of pointed neurons of the cortex. The EEG amplitude of a traditional subject within the awake state, recorded with scalp electrodes, is within the range 10 – 200 μV, and a healthy human brain has its own intrinsic rhythms falling within the range of 0.5 – 40Hz. encephalogram based mostly brain imaging techniques gift a restricted spacial resolution attributable to the physical dimension, in the vary of many millimeters, of the surface electrodes usually used within the acquisition setup, that limits the possible variety of the electrodes covering the full scalp. A restricted spacial resolution is additionally attributable 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, within the range of milliseconds, that permits dynamic studies to know the underlying mechanisms by suggests that of procedure strategies. In fact, info regarding for example psychophysiological state, neurologic and contractor health, emotions, memory, the course of concentration, attention, levels of arousal, mental fatigue or workload during special tasks, and sensitiveness to external stimulation can be extracted from EEG inspection and manipulation. Such a kind of evidence has led in last decades to use brain signals to convey conscious volition in EEG-based systems, like brain computer interface (BCI) , and brain machine interface (BMI) , aiming at controlling remote devices by means of the interpretation of the brain electrical activity.

The rest of the paper is organized as follows. This paper present and discuss some related works in section II. Section III describes the EEG-based recognition system. In section IV EEG brain rhythms are described and basic steps in brain signal processing is given in section V. Finally last section conclude the paper.

II. RELATED WORK

-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. These peculiarities make the use of brain signals appealing. On the other hand, there are many challenges which need to be properly addressed. The understanding of the level of uniqueness and permanence of brain responses, the design of elicitation protocols, and the invasiveness of the acquisition process are only few of the challenges which need to be tackled. In this paper, we further speculate on those issues, which represent an obstacle toward the deployment of biometric systems based on the analysis of brain activity in real life applications and intend to provide a critical and comprehensive review of state-of-the-art methods for electroencephalogram-based automatic user recognition, also reporting neurophysiological evidences related to the performed claims.[1]

-This paper presents an online semi-supervised P300 BCI speller system. After a short initial training (around or less than 1 min in our experiments), the system is switched to a mode where the user can input characters through selective attention. In this mode, a self training least squares support vector machine (LS-SVM) classifier is gradually enhanced in back end with the unlabeled EEG data collected online after every character input. In this way, the classifier is gradually enhanced. Even though the user may experience some errors in input at the beginning due to the small initial training dataset, the accuracy approaches that of fully supervised method in a few minutes. The algorithm based on LSSVM and its sequential update has low computational complexity; thus, it is suitable for online applications. The effectiveness of the algorithm has been validated through data analysis on BCI Competition III dataset II (P300 speller BCI data). The performance of the online system was evaluated through experimental results on eight healthy subjects, where all of them achieved the spelling accuracy of 85% or above within an average online semi-supervised learning time of around 3 min , This technique has advantages of reduced training effort, low computational complexity, low latency. But has Major computational burden of this system is obtaining on the inversion of Model matrix.[2]

-This article presents the development of a mobile biometric authentication system based on electroencephalogram (EEG) recordings with the technologies such as facial detection and near field communication (NFC). The overall goal of this work is to fill the gap between mobile Web technologies and wireless EEG devices and to develop a new authentication technique and a feasible application. Therefore, we review the relevant literature. We conduct several EEG measurement experiments, and discuss the procedure and results with experts in the EEG and digital signal processing (DSP) fields. On the basis of these results, we build and present a mobile prototype system capable of authenticating users based on the uniqueness of their brain waves.[3]

-This paper propose an Independent Component Analysis (ICA) based EEG feature extraction and modeling approach for person authentication. Five dominating Independent Components (DIC) are determined from five brain regions represented by EEG channels, then univariate autoregressive coefficients of DICs are extract as features.

Based on AR coefficients of DICs . Results from a real EEG motor task study suggest that the proposed ICA-based approach is promising and may , open new directions in the emerging EEG biometry area.[4]

-Brain waves are used in a biometric for verification of the identities of individuals or user in a small group. The approach is based on a novel two-stage biometric authentication method that minimizes both false accept error (FAE) and false reject error (FRE). These brain waves (or electroencephalogram (EEG) signals) are recorded while the user performs either one or several thought activities. As different individuals have different thought processes, this idea would be appropriate for individual authentication.[5]

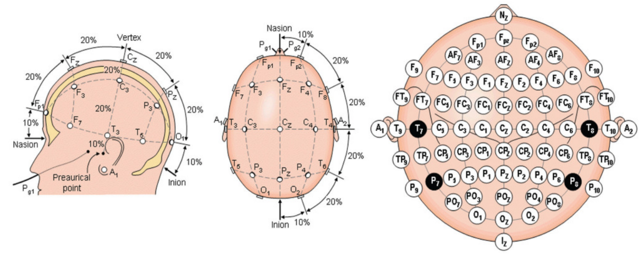
III. EEG BASED RECOGNITION SYSTEM

A generic EEG-based automatic recognition system consists of an acquisition module that senses a subject's EEG signals, a preprocessing module that removes noise and artifacts from the signals, a feature extraction module that separates the signals' representative elements, and a matching module that generates a score. The system uses the score to rank the most probable subjects or to make a decision about the subject's claimed identity.

The system can acquire EEG signals during spontaneous brain activity—for example, while the subject is at rest with open or closed eyes. It can also collect the signals in the presence of visual, auditory, or tactile stimuli (including real-world stimuli such as music, speech, or video) or during the execution of real or imagined tasks such as body movements or speech. The signals induced by such stimuli originate in different parts of the brain and vary significantly in bandwidth and amplitude.

An EEG acquisition device consists of a set of amplifiers, a multichannel analogue-to digital converter, and a set of electrodes, placed on the scalp, that sense the brain's electrical activity. Traditional passive electrodes require the use of conductive gel to reduce the electrode skin impedance, which can be uncomfortable to the user and takes time to apply, but newer active electrodes with built-in circuitry don't require gel.

Electrode positioning tradition-ally follows the 10-20 system recommended by the International Federation of Societies for Electro-encephalography and Clinical Neuro-physiology. The "10" and "20" indicate that inter-electrode distance is 10 or 20 percent of the distance between select longitudinal line segments connecting two reference points, the nasion (point between forehead and nose) and the inion (bump at back of skull).



(a) (b)

(c)

Figure 1. EEG electrode positioning. Arrangement of 21 electrodes, as seen from (a) the left of and (b) above the head, according to the international 10-20 system. (c) A 75-electrode extension of the 10-20 standard that provides higher spatial resolution. The letters F, T, C, P, and O stand for frontal, temporal, central, parietal, and occipital lobes. Even and odd numbers identify electrodes on the right and left hemispheres, respectively, and "z" (zero) refers to electrodes placed on the midline.

Figures 1(a) and 1(b) show a standard 21-electrode arrangement, while Figure 1(c) shows a 75-electrode extension of the standard that provides higher spatial resolution. The most relevant cerebral activities fall in the range of [0.5, 40] Hz.

IV. EEG BRAIN RHYTHMS

There are five main rhythms that can be distinguished within EEG signals: delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ). Table 1 lists the bandwidth range and characteristics of these rhythms, while Figure 2 provides an example of each. EEG signal amplitude is about 100 μV when measured on the scalp and about 1-2 mV when measured on the brain's surface. Background noise caused by continuous and spontaneous cerebral activity usually contaminates EEG signals and can obscure the electrical effects a cognitive stimulus produces. Signals also contain biological artifacts related to eye movements, the heart beat, muscle activity, and so on. Several techniques can remove such noise and artifacts, including adaptive filtering, principal component analysis, and blind source separation.

Table 1. EEG signal rhythms.

Rhythm	Bandwidth	Description
Gamma (γ)	[30, 40] Hz	Low in amplitude; can indicate event brain synchronization and be used to confirm some brain disorders.

Beta (β)	[13, 30] Hz	Indicates an alert state, with active thinking and attention.
Alpha (α)	[8, 13] Hz	Indicates a relaxed state, with little or no attention or concentration.
Theta (θ)	[4, 8] Hz	Indicates creative inspiration or deep meditation; can also appear in dreaming sleep (REM stage).
Delta (δ)	[0.5, 4] H	Primarily associated with deep sleep or loss of body awareness, but can be present in the waking state.

V. BASIC STEPS IN BRAIN SIGNAL PROCESSING

Propose system will recognize a certain set of patterns in brain signals following five consecutive stages: signal acquisition, preprocessing or signal enhancement, feature extraction, classification, and the control interface [6]. The signal acquisition stage captures the brain signals and may also perform noise reduction and artifact processing. The preprocessing stage prepares the signals in a suitable form for further processing. The feature extraction stage identifies discriminative information in the brain signals that have been recorded. Once measured, the signal is mapped onto a vector containing effective and discriminant features from the observed signals. The extraction of this interesting information is a very challenging task. Brain signals are mixed with other signals coming from a finite set of brain activities that overlap in both time and space.

CONCLUSION

Brain waves should be unique for automatic biometric-based user recognition. The major obstacles towards the deployment of brain waves based recognition systems can be enhance by focusing on classification and feature extraction techniques. An overview of the neurophysiological basis, which constitutes the foundations on which EEG biometric systems can be built, has been given. EEG measures electric potentials EEG signals can be used in many ways: ERP, Frequency, Time/Frequency EEG are best-suited to hypotheses about time .EEG can provide spatial information. Digital EEG is the paperless recording of an EEG using computer-based instrumentation. The data are stored on electronic media, such as magnetic drives or optical disks and displayed on a monitor. There are several waves that can be differentiated from the EEG signal alpha, beta, gamma, theta etc.

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