EEG-based Person Recognition: *Analysis and criticism*

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***Abstract*— In recent years, researchers give a large interest to automatic person recognition using electroencephalogram (EEG). This paper is an overview on EEG biometrics. It reviews some recent research contributions over last years and discusses the challenges facing EEG-based person recognition systems. Finally, we draw our expectations for the future of EEG-based biometrics especially with the emergence of BCI applications and the development of Internet of Thing.**

***Keywords*— biometrics, EEG, identification, authentication.**

I. INTRODUCTION

Nowadays, a worldwide interest in security and safety keeps growing; systems require identifying their authentic users from intruders. For this issue, possible solutions could be based on something we know (such a password) or something we have (such a smart card). However, these solutions do not guarantee users' identities due to the possibility of sharing passwords or losing smart cards. Thus, biometric based methods, also known as "something we are", overcome this problem by recognizing automatically living people using their unique physiological traits (including fingerprint) or behavioral traits (including voice) [7]. These traits are continuously attached to the appropriate user (no share, no lose). Bio-signals such as EEG (electroencephalogram) is potentially rich in identity information [2]. One of the first investigations of EEG as a biometric trait was proposed in [29].

EEG (electroencephalogram) is the electrical recording and measurement of brain activity on the surface of the human skull using electrodes. This measurement reflects the summation of small electrical impulses emitted by the huge amount of brain's neurons [14]. EEG signal is obtained by placing electrodes on the scalp according to a given map such as the 10-20 international system for placement of electrodes. EEG measurement using EEG sensor requires the collaboration of users by executing a given task to ensure consistence and reliability of measured signals to recognize their identity [2, 17]. Thus, EEG is recorded either when users are in relaxation with Eyes Opened or Eyes Closed without having any mental or physical activity (resting state) or in presence of stimulus or events (sensor stimuli) or while users are performing cognitive tasks (cognitive activities). The most relevant cerebral activities are in the range of [0.5, 40 Hz]. There are typically five EEG waveforms, each associated with a specific bandwidth: Delta (0.5-4Hz), Theta (4-8 Hz), Alpha (8-14 Hz), Beta (14-30Hz) and Gamma (over 30 Hz).

The storage of features extracted from biometric traits in databases leads to the separation of the biometric traits from their associated users. In that case, if the biometric-based system is attacked, and databases are successfully compromised, these biometric traits could never be used again [7] because they cannot be changed or replaced: as mentioned in [8], we only have 10 fingers, two iris images and a single set of face features. To avoid this problem, researchers propose to encrypt features extracted from biometric traits before storage. EEG signal is unique by individual while performing a given task; when the performed task changes, the EEG signal changes too. Thus, if EEG databases are compromised, EEG traits can be used again by changing the task used in enrollment. Hence, EEG offers the advantage of using biometric traits that are associated to individual (advantage of something we are), and at the same time it is possible to change the stored EEG when EEG-based biometric system is corrupted just like changing passwords (advantage of something we have). Authors in [7] mentioned the usability of EEG as a "pass-though": instead of using a vocal password (voice recognition), user can keep the secret in her/his mind, and imagine saying the secret while EEG is recorded. Besides, EEG-based biometric systems are more secured because EEG is not exposed like fingerprint or face. Moreover, it is difficult if not impossible to spoof EEG (not like fingerprint where a gummy finger can be used). Finally, intruder cannot force user to provide EEG, because under-stress brain activity changes.

Recently, EEG has been widely used in BCI (Brain Computer Interface) and BMI (Brain Machine Interface). Besides, machine-learning techniques have been increasingly developed which considerably facilitates EEG processing. For all these reasons, investigating in EEG as a biometric trait becomes easier nowadays and more accepted by users compared with its first use in [30].

Two review papers were presented in [18, 19], they cover EEG-biometric research contributions until 2014. In this paper, we introduce the most recent contributions in EEG-biometric field and draw our expectations for the nearest future.

This paper is organized as followed: in section II, we introduce research contributions classified according to the different parts of EEG-based biometric system and objective issues of these contributions. The section III presents the remaining issues in EEG-biometric filed. The last section (section IV) lists the expected future works for EEG-biometric.

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II. RESEARCH CONTRIBUIIONS

In this section, we describe how researchers contribute in EEG-biometrics. We review several EEG-based biometrics studies and we describe a global map about how researchers explored this field. Figure 1 presents three main components in an EEG-based biometric systems which are: data description, measurement issues and recognition process. These components jointly influence the recognition performance in order to study a specific research objective issue.

A. Data description

Data description describes parameters and characteristics of EEG signal, and defines how EEG data are manipulated. Some of these parameters are the *number of participants* involved in EEG person recognition system, *EEG sampling frequency* and *description of sessions*. EEG can be recorded in several sessions, each session lasts in a period of time, and sessions are separated with a duration too. In some research contributions, a session involves several EEG records. It that case, session duration depends on number of records, time separating two records and record's duration. Moreover, the manipulation of EEG data depends on:

1) *Training and tests data:* EEG data are randomly divided into training data (for learning) and tests data (for validation). This data division is function of:

   - Number of data for training and test: generally, most of data are used for training such in [8] where 66% of data are for training. However, in [10], only 10% of data were used for training.
   - Training and tests through sessions: training and tests data can be from the same session [8], from disjoint sessions [4, 5] or training data include data from several sessions [4].
   - Training and tests through performed tasks: when we consider the fact of having several performed tasks while measuring data, training and test data can use data of the same task [10], data of distinct tasks such as in protocol 2 of [2] or training data can use data of several tasks such as protocol 3 of [2].

2) *Authentication or identification:* the purpose of person recognition is either identifying a person from a group of people (a comparison of one to many) or verifying the identity of a person that he is claiming to be (a comparison of one to one). Some researchers study both identification and authentication [2], only identification [4] or only authentication [10].

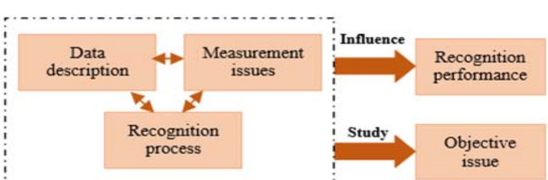

Figure 1. Components of EEG-based Person recognition system

B. Measurement issues

Users perform tasks while EEG is recorded. The choice of task defines the channels to select (number and placement) and frequency bands of EEG signal related to the performed task.

1) *Performed task:*

The study in [2] investigates the task sensibility in EEG biometrics. Several scenarios were tested: (a) Testing the sensibility of using several task in training: results show that performance could be improved in that case (increasing data volume); (b) Testing the sensibility of using mismatched motor movement/mental imagery tasks in training and tests: results show that performance are not sensitively affected by the mismatched training/tests tasks; (c) Variating task and three electrodes combination from three brain regions (frontal lobe, motor cortex and occipital lobe), to find the best task/region paring. Results show that there is no clear difference in performance amongst scalp regions.

The other propositions choose a task to perform as a step of EEG person recognition to study a main issue.

2) *EEG Frequency bands*

Although Brain waveforms are characterized by their standard frequency bands, many researchers define their own frequency bands according to their experiment's context. In [8], frequency bands were calculated for each channel and were defined as: delta (1-4) Hz, theta (4-8) Hz, alpha (8-12) Hz, beta (12, 30) Hz and gamma (30-44) Hz. These frequencies are used jointly while extracting features. The study in [4] considers four spectral components: $\delta - \gamma = [0.5, 40]$ Hz, $\delta - \beta = [0.5, 30]$ Hz, $\theta - \beta = [4, 30]$ Hz, and $\alpha - \beta = [8, 30]$ Hz. However, these frequencies are used one by one to analyze the permanence dependency on the selected EEG sub bands (a comparison study). Their results show that the subbands γ and δ worsen significantly the recognition permanence and the θ - β sub band gives the best performance.

3) *Channels selection*

EEG consists of a set of multi-channel signals. Channels selection is needed to reduce the computational complexity of EEG processing. There are three ways to select channels. In the first way, several combination of electrodes are tested to find the best combination. Seven electrodes from three brain regions (frontal, central and occipital) are chosen in [4]. Results show a preferable choice of electrodes of the occipital area. The second way consist of selecting a specific number of electrodes such in [8], where six channel placements C3, C4, P3, P4, O1, and O2 specified by 10–20 electrode placement are selected; In [9], 19 channel EEG signals were derived by using the average of the mastoid channels as reference. In [10], six channels (C3, C4, P7, P8, O1 and O2) were selected according to the literature. The impact of channel selection for lower-cost sensing was addressed in [11] where authors show how to use some channels that are not accessible from low cost sensor. In the third way of channels selection, some algorithms are used to determine channel's number. In [5], PCA is used to identify channels that carry the most discriminatory information across individuals. Additionally, the problem of channel selection was modeled by a meta-heuristic based optimization task in [14].

C. Recognition process

The recognition process allows to extract or validate user's identity from an EEG signal. A detailed description of each step of recognition process is presented in [17].

1) Preprocessing

This step consists of enhancing the measured EEG signal to be ready for features extraction. Some preprocessing techniques are presented in [16], particularly methods based on blind source separation and sample entropy estimation. One of the preprocessing techniques could be the detection of eye blinks considered as a source of artifacts for EEG. In [8], BAJWA et al detect eye blinking using a separate channel of data recorded from two electrodes placed above and below the subject's left eye. However, recently, eye blinking is used as a biometric modality [1, 31]. Moreover, a multi-level approach for person recognition using both EEG and EOG (eye blinking Electro-Oculo-Gram) is proposed in [32]; authors claim that significant improvement is achieved while using EOG and EEG instead of using EEG only. Hence, serious studies need to be conducted to improve the use of eye blinking in biometrics instead of removing it in preprocessing step.

2) Features extraction

Feature extraction is a crucial step in person recognition system, where a set or vector of information is extracted from the EEG signal to be used in the classification step. Several methods proposed in literature have been used such as using wavelet features [2, 5], autoregressive model [10] or Common Spatial Pattern (CSP) method [15]. We should mention that CSP can be used to convert multichannel EEG data into a lower-dimensional spatial subspace. Additionally, various feature extraction methods were also compared, e.g. the work in [4] compared AR modeling, power spectral density features (PSD) and coherence (spectral coherence). Results show that in resting state AR features have higher discriminative capacity than PSD or COH features. Additionally, work in [12] selected the optimal EEG feature sets using mutual information.

3) Classification

The classification step sets boundaries between the different features set by defining either "n" classes (identification) or two classes (authentication). Several methods have been used such as LDA classifier [2], K-Nearest Neighbors (kNN) [5] or Support Vector Machine (SVM) [10].

D. Objective issues

Research contributions aim to resolve a specific issue in EEG person recognition such as:

1) EEG performance

EEG is unique for each person, and has been widely used in many applications and games. However, the stability of EEG over time is still a problem. In fact, EEG signal measured in two different periods are different, though features extracted from these EEG signals should be sufficiently close to each other with a tolerant error. For permanence issue, some parameters of data description component make proposals of researchers different from each other, in particular number of sessions (at least two sessions because studies on one session do not reflect the EEG permanence [4, 5]), duration separating sessions (as long as possible to attest EEG permanence across longer period of time), duration of sessions (as short as possible to facilitate enrollment step for users), number of users (as high as possible to attest the EEG permanence across a large number of subjects) and finally the strategies defining training and tests data across sessions (the best is to keep enrollment and recognition session disjoint [4, 5] and significant improvement of recognition rates are reached if training set includes EEG recordings from multiple sessions [4]). Moreover, we noticed in [5] that duration of manipulated records is very short (2 seconds compared to 240 second in [4]). However, in [5] the number of electrodes is very high, the number of users is very low and the covered period of time separating sessions is short compared to [4]. We suppose that a degradation in performance is expected if reducing electrodes number, increasing number of users or increasing duration between sessions. Indeed, performance badly degraded in [5] when the number of channels was reduced from 128 to 48 in tests across two sessions. Besides, the authors in [9] have been studying the EEG permanence issue over 6 sessions separated with 1 month, when EEG is combined with ECG (electrocardiogram) through the use of binaural brain entrainment. Experiments show very high performance (near to 99%). However, the number of users is limited to 5 subjects and data were recorded from 19 channels during 2 min per recording. Thus, we suppose that a dependency may exist between channels selection, number of subjects and description of sessions.

2) Multi-modal biometric systems

Several studies presented the fusion of EEG with other modalities to get a multimodal biometric system such as in [33, 34, 13, 6]. The difference between these contributions consists in the kind of biometric modality merged with EEG, the level of fusion: in feature-level or score level and the strategy of fusion. One of the fusion methodologies that system in [6] offers is the fusion of EEG and ECG signal performed at score-level by means of the weighted sum, a simple and efficient approach. In [13], authors merged two EEG features extracted using Fraschini-Marcialis and La Rocca-Campisi Algorithms. The fusion in feature level and in score level are tested. Results show that fusion in score level is the best solution in terms of computational cost and performance trade-off.

3) EEG-based cryptographic key generation

Cryptographic systems strongly depend on the cryptographic algorithms (public) and cryptographic keys (secret). Biometric traits such as fingerprint, iris and voice have been used to generate unique keys for cryptography systems. These keys are not stored but generated when users are correctly authenticated. A biometric key generation using EEG was proposed in [8], where a consistent unique key is generated for each task and subject (Neurokeys). It is a solution to the permanent loss of cryptographic key generated using other biometric trait (possibility of cancelation if generated keys are corrupted). Authors claim that this work is the first investigation of EEG signal in biometrics-based cryptographic systems.

4) *EEG biometric in practice*

Most EEG biometrics contributions are studying EEG-issues in laboratory conditions, which do not necessary match with a practical case of EEG biometrics (such as using medical sensor for data collection). The authors in [7] implement a system for authenticating users within a smartphone application using EEG signal recorded with wireless EEG sensor, connected to the smartphone application via Bluetooth. The users are asked to recognize a personal image they have chosen before, from nine other images randomly selected from Internet while EEG is measured. Results show that a detectable change exists in the brain activity of a user who recognizes a personal photo.

5) *Computation issues*

EEG analysis is time intensive for large datasets. Therefore, the cost of EEG analysis should be reduced to provide a near real-time interaction with datasets. A thesis in [3] designs and implements a system for interactively analyzing large electroencephalogram (EEG) datasets to determine if a patient has experienced an epileptic seizure. This system has three optimized layers handling the storage, computation, and visualization of data. Such an implementation to analyze EEG datasets for person recognition issue would be desirable. In addition, The authors in [10] have examined EEG as a biometric characteristic for large number of subjects in resting state with closed and opened eyes (104 subjects), using AR features representation and SVM classier. The proposed system for EEG person authentication achieved more than 97% accuracy using 10% of data in training. However, the authors didn't mention the computation-cost which is important when the number of users is large (especially for person identification).

E. *Recognition performance*

In one of the first investigation of EEG in biometric field [29], the recognition performance obtained were less than 80% to identify four people only. Seventeen years later (in 2016), Binghamton University researchers have developed a biometric identification method called Cognitive Event-RElated Biometric REcognition (CEREBRE) to identify the "brainprint" of 50 participants [34]. This system could identify each volunteer's "brainprint" with 100 % accuracy. Many press and media all over the word talked about this achievement which reflects how EEG-based biometrics progressed nowadays. However, this study can be improve by increasing the number of users, reducing the number of selected channels (less than the selected 26 channels), studying the EEG permanence of CEREBRE protocol (across different sessions) and using low-cost sensor to collect data. Later, researchers of Binghamton University attest the biometric permanence of the CEREBRE protocol across 516 day inter-session lag by identifying 20 participants with 100% accuracy [36].

III. Remaining issues

Although several contributions have been done in EEG-biometrics field, there are some remaining issues that need researcher's attention. Firstly, most parameters of "Data description" component are determined at the beginning experiments, although we cannot try by experiments all possible cases such as determining EEG sampling frequency. Actually, some signal processing research try to minimize sampling frequency and show that classification accuracy are enhanced when some system parameters are optimized including sampling frequency [20]. Secondly, for measurement issues, we noticed that across the different researcher's contributions, we still have experiments protocol which are not suitable for biometric context, for instance using medical sensors to record EEG or including only healthy volunteers though they can develop brain illness. In addition, to our best knowledge, there is no public available database measured for biometric issues. Providing such a datasets would be useful to consolidate and intensify researchers' efforts. Besides, several studies have investigated the channels selection issues. However, few studies model this problem as an optimization one. The channels selection problem need to be studied across different sessions (conditions of EEG permanence issue), where the dependency between the number of channels and number of users need to be clarified. Moreover, the discriminant mental signature need to be clearly defined for each mental task, by providing the relative frequency subbands for each appropriate selected electrode. Thirdly, the recognition process as we describe involves three steps: preprocessing, feature extraction and classification. Each combination of three methods of these steps gives a new recognition process that affects performances. Finding the optimal combination of the three methods that maximizes recognition performance and minimizes computation performance is a remaining issue. Additionally, the combination of several methods in the same step need to be optimized too. Finally, for objective issues component, most of research studies don't mention the computation cost, although EEG signal processing is time consuming. Besides, more studies on EEG biometrics in practice conditions need to be performed. The study of EEG permanence over a longer time is also required; the optimal number of session to ensure the stability of EEG features across time need to be clearly defined; Although several studies have been done on EEG multi-modal systems, a comparative study is needed to find the biometric modality which complements EEG modality.

IV. EEG person recognition in the future

Several studies have been investigating EEG biometrics and their relative issues. As perspective for using EEG-based biometric systems, we can expect:

A. EEG biometrics in BCI applications

Nowadays EEG is used in a wide range of applications such as Brain computer interface (BCI). BCI is a communication system that **recognizes user's commands** only from his or her brainwaves and reacts according to them [21]. EEG person recognition is a biometric system that **recognizes users** only from his or her brainwaves. Thus, using EEG both user's commands and user's identity can be recognized. Furthermore, BCI systems can require the identification of users before commanding any object (such as in smart cities). Hence, EEG as a biometric modality can be used in that context instead of any other person recognition protocol. For this issue, the design and implementation of a combined model of BCI system and EEG-based biometrics system is needed. In both systems, recognition process proceeds through data collection, preprocessing, feature extraction and classification (figure 2). The "Decision" indicates if the distant object can be commanded by user: only if user's identity AND user's command are well identified. The simplest solution is considering the fact that the two systems are independent (process separately) but it is a time-consuming solution. The challenge is to ensure a parallel processing of the two systems. Several issues may exist, such as: "do the two systems choose the same Channels or same EEG frequency bands?"

B. EEG biometrics in Internet of things

Internet of Thing (IoT) is considered as a part of the Internet of the future and will comprise **billions** of intelligent communicating 'things' [22]. It should be able to interact without human intervention [23]. IoT needs to face a lot of security challenges such as authentication and access control [24]. In order to authenticate users (human), control there access to IoT and ban unauthorized users (human) to access to the system, EEG person recognition can be used. For this issue, several considerations should be taken into account:

1) Standardization of EEG collection and research:

Consumer Technology Association (CTA) raises the challenge of standardizing EEG brain signal collection to allow data exchange via **internet** and facilitate big data analysis [25].

2) Real time EEG person recognition

The use of EEG in IoT may involve the transmission of EEG data for distributed processing on a huge network. Hence, a real time EEG person recognition should be guaranteed.

3) Reducing cost of EEG person recognition treatments

Objects connected to IoT might have a lack in computing resources such as processing power and storage [24]. Hence, EEG person recognition processing should be alleviated in computing and storing costs to be adapted to IoT context.

4) Uniqueness of EGG in largest data

Neuroscientists attest the uniqueness of EEG due to both morphological and anatomical traits, and functional plasticity traits [35]. However, studies carried in EEG-based biometrics systems concern less than 120 subjects. In order to use EEG biometrics in IoT context, the uniqueness of EEG should be ensured when huge number of users are interconnected to the IoT.

5) Development of EEG sensors

Industry should fabricate more sophisticated EEG sensors

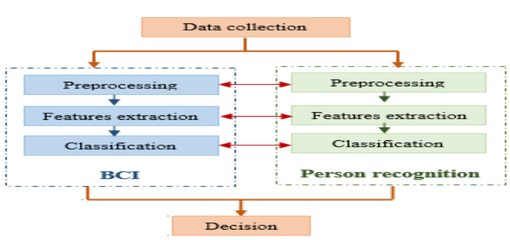

Figure 2. Recognition process for user's command and user's identity recognition

suitable to be used with technology of communication used in IoT.

Future = BCI + EEG biometrics + Internet Of things

C. Encrypting EEG

EEG data reveal the cognitive functions of users, their mood swings and if they are affected of some illness such as Epilepsy [26]. Thus, EEG data should be encrypted before storage on databases. Moreover, EEG encryption protects the biometric system against any non-noticed attack. Biometric data (including EEG) are unstable: it is difficult to obtain a single biometric template by user. A certain error threshold is tolerated during recognition, but this error threshold does not allow the use of conventional encryption techniques [33]. Some error-tolerant techniques are used to encrypt biometric data such as Fuzzy Vault method proposed firstly by Juels and Sudan in [27]. To our best knowledge, EEG was never encrypted before for biometrics issue. Therefore, encrypting EEG using Fuzzy vault or any other suitable encryption method may be one of perspectives for EEG biometrics.

D. Multi-granular computing in EEG

Wang et al in [28] presented a study on the Granular computing with multiple granular layers for brain big data processing. This study shows the possibility of applying multi-granular computing on Brain Big Data. Since EEG is part of brain big data, the use of multi-granular computing in EEG person recognition may improve the performance. The challenge is to define a framework of multi-granular representation to describe EEG.

V. CONCLUSION

In this paper, we reviewed the most recent researchers' contributions in EEG-based person recognition field. Our main contribution consists in classifying research works according to the different parts of EEG-based biometric system and the objective issues of these works. For each part of EEG biometric system, we listed several factors that make the difference between researchers' contributions. This description leads to a fair comparison between research works regarding the whole process of EEG person recognition: considering all aspects that affect recognition and computation performance. Besides, after analyzing the existing state of EEG-based person recognition contributions, we listed the remaining issues that need to attract researcher's attention. Moreover, we draw our exportations for the future of EEG-based biometric systems with the emergence of BCI application and the development of Internet of Things. Thus, we studied the feasibility of using EEG as a biometric modality in a big data context. Finally, we discussed the issues of EEG encryption with error-tolerant techniques and EEG processing with Multi-granular computing.

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