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Biometric Based User Authentication Using EEG Signals

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Abstract— **Electroencephalography (EEG) is measuring of brain electrical activity which recorded from the scalp by attaching voltage-sensitive electrodes. The brain activities continuously create positive and negative voltage potential which is modeled using as a series of rhythmic wave forms. It has been shown that EEG oscillatory patterns depends on the state of cognition and the dynamics of the brain activity are reflected in these waveform. In the recent years, published reports show that there is strong correlation between the EEG signals and its owner, which explains why the EEG has been proposed as a usable tool for user identification and authentication. EEG based authentication methods require the user to perform a particular mental task. Every part of the brain is responsible for either mental or physical activity. Based on the tasks that the user does, it has to be expected that the activity of the neurons in parts of the brain responsible for this task increases, and these activities will be shown in the electrodes attached to these parts. To perform the user authentication, a set of appropriate feature should be extracted from the EEG signals which is used by classification algorithms to classify each user. In this paper, the EGG based authentication methods and required processes are reviewed.**

Keywords-component; *authentication, biometrics, electroencephalography* (EEG)

I. Introduction

Biometrics authentication is the process of identifying user based on one or some of their physical and behavioral characteristics. The physiological biometric is related to the body, such as fingerprints, faces, and DNA; while behavioral biometrics relate to the user behavior such as typing rhythms or walking. Brain activities is one of the distinguished physiological biometrics. There are several techniques of measuring brain activity such as EEG, MEG and fMRI. EEG is recording electrical potential, caused by the brain activities, through electrodes mounted on the scalp. Currently, thanks to the progress of EEG devices, it is the most practical recording method of brain activity, that can be used in biometrics and meanwhile, it contains a unique physiological feature of an individual.

Any biometric feature, for use in the authentication system, should meet the following requirements [4]:

1) "*Being universality*": Each user should have the required attribute to use the corresponding biometric;

2) "*Distinctiveness*": Each pair of users must be distinguishable enough in terms of the biometric feature;

3) "*Permanence*": This feature must be sufficiently stable over a period of time (according to the matching criterion);

4) "*Collecting*": This feature can be quantitatively measured.

Most of the biometric features satisfy these requirements sufficiently for authentication. Examples of these features include face, fingerprint, DNA, hand geometry, eye iris (mostly retinal replacements), speech and sound [4].

Given the great advances in neuroscience and technology over the past few years, and due to physiological and anatomical differences in the brain of individuals, EEG records have been recognized as an effective biometric feature [9] and it has attracted much attention in authentication systems. The EEG-based authentication system also meets the basic requirements of any biometric system, namely, collecting, distinctiveness, permanence, and universality. This method offers greater confidentiality benefits than other common biometric methods, such as fingerprint, face recognition, and so on. For example, the reproduction and imitation of the brain signals of one person by another is impossible [8] and much less likely to be artificially produced [10]. Also, brain waves are an intrusive and intrinsic property, and are not subject to intruders. Additionally, when using EEG-based authentication systems, it is impossible for a perpetrator to force the user to authenticate. In fact, stress affects the brain waves and leads to the denial of access [10]. This method is also very suitable for people with some disabilities who are unable to use fingerprints, retina scans, or other biometric methods [11]. It should be noted that in addition to the EEG method, there are other methods such as fMRI, MEG and fNIRS for measuring brain activity. But EEG offers a high-resolution, low-cost hardware, easy management, wireless connectivity and lower maintenance costs, and therefore has many biometric applications [7].

This paper reviews the EEG base authentication methods and required processes. The paper continues as follows. In the next EEG and its features are reviewed. The overall process of authentication using EEG is represented in section three. Sections four and five reviews the proposed works using shallow and deep learning respectively, and finally the paper end in section six with summary and open research challenges.

II. EEG and Its Features

From anatomical point of view, the brain can be divided into three parts: the cerebrum, the cerebellum and the brain stem (as seen in Fig. 1). The brain stem connects the brain to the spinal cord and controls the unconscious processes, such as breathing, digestion and heart rate. Cerebrum controls the balance and movement of the man and is responsible for certain cognitive functions such as attention, language, emotional functioning, processing and storage in memory. The cerebellum controls the body temperature and behavioral responses and plays a key role in memory, attention, thinking, awareness, language, and so on. Cerebellum in turn consists of four lobes; Frontal Lobe, Parietal Lobe, Occipital Lobe and Temporal Lobe.

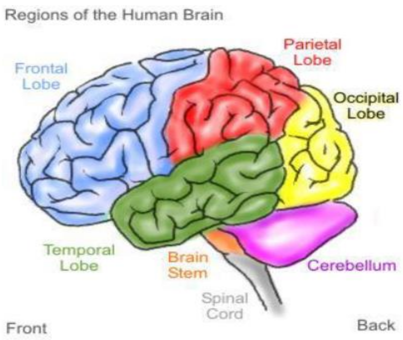

Fig. 1: Regions of the human brain.

Neurons connect to neural networks via synapses. They pass electrical potential when exchanging information between each other. But, given the very small dimensions of neurons, in order to be able to measure these fields, a significant number of neurons must be stimulated simultaneously and produce fields that are consistent [3]. These electric signals were firstly discovered in 1875 by the British physician Richard Cotton. He observed the electrical activity of the brain of rabbits and monkeys. In 1924, Neuroscientist Hans Berger used his usual radio equipment to enhance the electrical activity of the brain on the human skin. He declared that without opening the skull, the weak electrical currents produced in the brain could be recorded and displayed graphically on a paper tape. He observed that brain activity varies with respect to brain function, such as sleep, anesthesia, oxygen deficiency and some neurological diseases, such as epilepsy [3].

Today, electrical signals related to brain activity are measured and recorded by placing the electrodes on the scalp, which is called the Electroencephalogram (EEG). To connect these electrodes to the human head, some international standard is used. These standard systems are based on the relationship between the location of the electrode and the area of the cerebral cortex. For example, in 10-20 system, the actual distance between the adjacent electrodes is 10% of the total front and rear front, and 20% of the total left and right front, respectively. The weak electrical signals detected by the electrodes on the scalp are sufficiently amplified and then displayed on paper or stored in the computer memory [3].

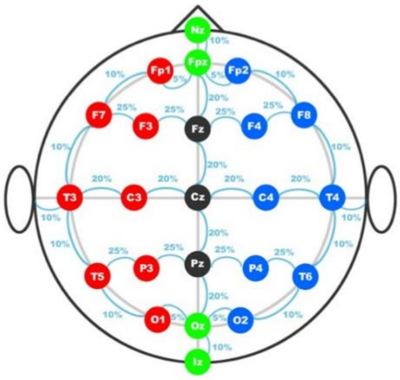

Fig. 2: Electrodeposition of EEG according to International Standard 10-20.

The electrical signals of the brain are typically described in terms of rhythmic activity waveforms, usually ranging from 0.5 to 100 μV in amplitude. These rhythmic waves are divided into five groups based on the frequency (Fig. 3):

1) Delta: 0-4 Hz, usually these waves appear when the person is in deep sleep. If the person is awake, the delta waves are not detected naturally, and if it is observed, it is probably due to artificial pulse waves caused by movement or because of a defect in the brain;

2) Theta: -5-7 Hz, Theta waves occur in adults during waking, which are generated through access to the subconscious, deep inspiration and meditation.

3) Alpha: 8-13 Hz, in a relaxed state without attention and concentration, drowsiness appears while the person is calm and conscious;

4) Beta: 14-26 Hertz, associated with alertness, a relaxed state of mind, focused and aware of itself and around. The solving of the mathematical task increases the beta level;

5) Gamma: 26-48 Hz, correlated with attitude, perception, and cognition.

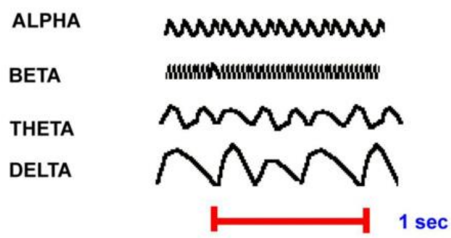

Fig. 3: Samples of EEG demonstrating the major frequency bands.

III. EEG based Authentication Process

EEG-based authentication methods require the user to perform a specific mental task. Each part of the brain is responsible for a specific mental or physical activity. Based on the mental tasks that the user is doing, one should expect that the activity of the neurons in the parts of the brain which are responsible for that task will be increased and these activities will be shown in the electrodes associated with these parts. In studies, several different tasks are examined for authentication with EEG, including resting with open or closed eyes, doing mental calculations or reading, imagining a picture, imagining motion, and watching or listening to known stimuli [4]. The most commonly used task is to ask the person to stay calm and comfortable in an environment; then the EEG signals are recorded in a period of time to authenticate the user [3].

After recording EEG signals, a step-by-step recognition processes are performed. The recognition process allows the user's identity to be extracted or verified from an EEG signal. Recognition processes include [1]:

1) **Preprocessing**: This step involves amplifying the measured EEG signal to prepare the extraction of the features. Some of its preprocessing techniques, in particular, methods based on "*Blind Source Separation*" and "*estimation of sample entropy*" are presented in the paper by Mayorana et al. [5].

2) **Feature extraction**: Feature extraction is an important step in any user authentication system, where a collection or vector of information is extracted from the EEG signal to be used in the classification stage. Methods for extracting features include "*wavelet characteristics*", "*automated regression model*", "*common space method*", "*spectral power density characteristics*".

3) **Classification**: Classification step defines the boundaries between the extracted features of different users by defining *n* distinguishable classes (for identification) or two classes (for authentication). For this aim, several methods including shallow and deep learning can be used. The shallow machine learning approaches such as LDA, KNN and SVM traditionally have been used by any researches. However, deep learning approaches are gaining more interest in recent years.

In continue, we have review both shallow and deep learning approaches in EEG based authentication methods.

IV. EEG BASED AUTHENTICATION USING SHALLOW LEARNING CLASSIFIERS

In a work proposed by Fallah et al. [12], an EEG-based authentication system is presented on a large data set of 104 healthy individuals. In this paper, the brain signals of users is re-evaluated in both opened and closed eyes. By extracting the "*Autoregressive*" coefficients as a feature set, the accuracy of the proposed system was 97.43% using only 10% of the data in the training phase.

In a paper by Chen [13], an EEG-based validation system was proposed with the instigation of a "*Rapid Serial Visual Presentation*", and used a knowledge-based approach to authentication. Data of 29 users were recorded and analyzed by wet and dry EEG electrodes. For all users, the "*true acceptance rate*" (TAR) is 100%, with the average time required for logging to be 13.5 seconds for a wet electrode and 27 seconds for dry electrodes. The mean error rate when using dry electrodes is estimated to be 3.33×10^{-5}.

Ashby et al. [4] proposed a low-cost EEG-based authentication system. In this work, EEG signals are recorded while individuals perform four mental tasks, including baseline measurement, referential limb movement, counting, and rotation. Each task takes 150 seconds. Three sets of features are extracted for each electrode, and these sets of features are combined into a feature vector and then classified by an SVM. The goal was to minimize both the "*false acceptance rate"* (FAR) and the "*false rejection rate*" (FRR). For each person in each task, accuracy of classification was 100%. Unlike the most expensive laboratory equipment, an inexpensive and commercially available EEG headset is used to make this way for consumer applications.

Vahid et al. [8] examine human identification using the EEG signal under different conditions. Previous studies have only reported proper channels and features in resting or mental tasks. But since the EEG signal is sensitive to emotions, the stability of reported features in emotional states is not well-established. The purpose of this article is to examine channels and features that have sustained results, regardless of emotional states. For this purpose, the training and test data were selected in three ways: 1) selection of different emotional states; 2) selection of a particular emotional state; and 3) selection of two different emotional states. Three experiments were carried out based on this division. 1728 features are extracted that map the properties of each user and then, SVM is used to classify individuals. 54 features from 32 EEG channels have been extracted in various emotional states. Finally, 5 best features are selected from 5 channels that can produce stable results in different emotional states. After selecting 5 better attributes, the "*correct classification rate"* (CCR) was obtained by using the "Support Vector Machine" (SVM) classification in the range of 88% to 99% for 3 experiments. In addition, it is shown that the properties extracted from the gamma frequency band in the Left-Posterior quantum of the brain provide more reliable information for user authentication, regardless of emotional states.

Thmas et al. [9] present superior performance of "*spectral density*" (PSD) characteristics of gamma band (30-50Hz) in biometric authentication, in contrast to delta, theta, alpha and beta bands at rest. The proposed method is based on the simple correlation values of the extracted PSD properties of 19 EEG channels, which are recorded in opened and closed eyes of 109 users and provide an EER of 0.01996.

Ahmed et al. [10] present a new multilevel approach for biometric authentication using brain wave signals and blinking signals (EOG). The main objective of this paper is to improve the EEG-based biometric authentication functions using the EOG; rather than considering these signals as an artificial source for EEGs. Both EEG signals (recorded in rest and relaxation or by visual stimulation) and the waveform blinking in the feature extraction process are used. Finally, the classification step is performed using "Linear Discriminant Analysis" (LDA). To evaluate, a database of 10 users who performed blinking task was collected using the Neursky Mindwave headset. Using eye-blinking features, in terms of correct detection rates and equal error rates, significant improvements are achieved in the proposed system.

Rodriguez [6] illustrates the possibility of using a unique hard forging feature as an absolute biometric identification feature. It utilizes signals generated by different regions of the brain when the subject is exposed to visual stimuli. In addition, it is shown that the use of logarithmic bandwidth processing in combination with the LDA as a machine learning algorithm is more accurate than the "*Common Space Patterns*" (CSP) or window tools processing in combination with "*Gaussian Mixture Models*" (GMM) and SVM machine learning algorithms.

Kumar [7] suggests a new framework for immunizing mobile devices using the EEG signal, along with existing model-based authentication. Here, pattern-based authentication passwords are considered as identifiers. The EEG signals was recorded and investigated when user draws a pattern on a mobile device screen. To evaluate the method, EEG signals are collected from 50 users while drawing different patterns. System efficiency was tested on 2,400 unauthorized attempts made by 30 intruder users who trying to access the device using known patterns from 20 real users. EEG signals are modeled using the "*Hidden Markov Model*" (HMM), and then, using a binary classification with a SVM machine.

The system developed by Sadeghi [14] is a security system for EEG-based authentication and authentication which target five common challenges: accuracy, timeliness, energy efficiency, usability, and robustness. They meet first four challenges by using low learning educational machine algorithms, multi-layered computing architecture, fog servers and, commercial EEG headsets and dry electrodes. In this system, by only using two minutes of training and performing a simple task (rest and relaxation), the accuracy of the authentication and identification functions are obtained by 55% and 81%, respectively, for 11 individual users.

V. EEG based authentication using Deep Learning Classifiers

Shallow classifiers and other classic machine learning approaches are giving over deep learning, and today deep learning approach has proven its efficiency in many areas. In EEG processing and authentication field, recent works have also focused on this approach. Therefore, it is necessary to pay special attention to this approach. In this section, we will review current works based on the deep learning approach.

Lan Ma et al. [11] proposed an EEG-based identification system model that uses "*Convolutional Neural Networks*" (CNNs) and automatically extracts and categorizes the best and most unique neurological features of a user. CNN is a famous multi-layer deep neural network which primary is proposed for image processing but also finds many useful applications in other fields. In this work, EEG data is recorded from 10 resting users, with both "*opened eyes*" (REC) and "closed eyes" (REO). The length of each recorded data per person is 55 seconds, which is divided into 55 sub-records of 1 second. 50 of these subsets are used for training phase and 5 ones are used for testing phases, and therefore there are a total of 500 training samples and 50 test pieces. Each of the EEG signals is normalized before consuming by CNN model. Network topology settings are empirical and require frequent analysis and computation. The proposed CNN network has five layers consisting of two layers of convolution, two pooling layers and a dens layer. The proposed neural network is optimized based on the gradient descend algorithm. The size of the CNN input matrix is: $N_{elec} \times N_t$, so that N_{elec} is the number of electrodes (64), and N_t gives the number of time points for each sample; and its value is 160. The results give 88% accuracy for the classification of 10 users.

Thiago Schons et al. [16] suggested an approach for EEG-based recognition based on deep learning. The approach uses a database including 109 subjects using 64 channels at 160 Hz sampling rate. Each user's signals were captured for both opened eyes and closed eyes for 60 seconds and over 14 sessions [22] Each data record is then divided into 5 sub-records of 12 seconds. However, since using 5 data records for each user is not enough to train a deep convolutional neural network, a data reinforcement method is proposed to generate new sample data. The architecture of this network has three layers of convolution, three-layer pooling and three-layer fully connected. The results of this study indicate that the use of the CNN network in the EEG biometric is a promising pathway, and this method significantly reduces the EER compared to other non-deep methods.

Wilaiprasitporn [15] with the aim of improving the accuracy of the EEG-based authentication proposed a model which is a combination of CNN and "*Recurrent Neural Networks*" (RNNs). CNN is used to extract spatial features and RNNs is used to extract time properties. Two types of RNN networks are investigated in this paper, which are "*Short-Term Memory Networks*" (LSTM) and "*Gateway Return Units*"(GRUs). The proposed model is evaluated on DEEP dataset [21], which relates to the various user's feelings. The results show that the CNN-GRU and CNN-LSTM hybrid models can perform a user's authentication according to different emotional states and achieve a correct detection rate of 99%. The average value of 100% for CRR is obtained for only 40 users in this dataset. To make this system operational, it reduces the number of 32 electrodes to 5 electrodes; in this case, the forehead shows the best CRR value (99.17%) (using the CNN-GRU model). Among the two deep learning models used in this paper, the CNN-GRU model is slightly better than the CNN-LSTM model and has less training time (faster training).

VI. Summary and Open challenges

In this paper, we have reviewed the current works on EEG based authentication in the literature. Table 1 represents a quick comparison between these works including the number of channels used, the number of participants in the experiment, and the task that each person performs.

Although various studies have been done on EEG based authentication, many challenges still remain with practical use of this method. For example, the accuracy of these systems is very low in the high number of users. Also, some methods require sampling of a significant number of channels (e.g. 64) that makes it harder to use them practically (or commercially). Hence, more research is needed to apply these methods in real world. After reviewing the state of the art works in this paper, we have concluded the following as the open challenges in this field:

- Although deep learning approaches are proposed in the very last proposed works, but this field is still in early stage and more researches are required to be applicable;

- The proposed works often use a wide number of channels to identify the user. Minimizing the set of required channels for authentication will simplify the hardware requirements and therefore make them more practical;
- The proposed methods have just been tested and evaluated on a limited set of users (in the best case 109 users). It seems that these methods in the real world will not be able to perform effectively authenticating users even within a few hundred or thousands of users. Extending systems to support more users with an acceptable accuracy is a critical requirement before using these systems.

TABLE 1. the list of the EEG-based authentication methods.

Paper	Channels No.	Participants	Task	Approach
[11]	64	10	REO and REC	Deep
[16]	64	109	REO and REC	Deep
[15]	5	40	different affective states (DEEP dataset)	Deep
[17]	6	32	REO	Shallow
[18]	2 for REO and 4 for REC	10	REO and REC	Shallow
[19]	2	10	stimuli of self-photos and non-self-photos	Shallow
[20]	1	23	REC	Shallow
[4]	14	5	REO and REC	Shallow
[9]	19	109	REO and REC	Shallow
[10]	1	31	REO and REC	Shallow
[12]	6	109	REO and REC	Shallow
[13]	16 for dry and 31 for wet	29	RSVP Stimuli	Shallow

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