A Survey of EEG Based User Authentication Schemes

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Abstract— **Electroencephalography (EEG) is the recording of electrical activity occurring in the brain, which is recorded from the scalp through placement of voltage sensitive electrodes. It has been repeatedly demonstrated that the brain emits voltage fluctuations on a continuous basis. These fluctuations are a reflection of the on-going brain dynamics, which present as a series of fluctuations that have characteristic waveforms and amplitude patterns, depending on the cognitive state of the subject. A number of published reports have indicated that there is enough depth in the EEG recording, rendering it suitable as a tool for person authentication. This idea has a solid underpinning in that recent evidence suggests much of the on-going EEG recordable activity within brains has a genetic component. This study presents the common steps for developing a human identification systems based on EEG signals. It will also present some of the important techniques used.**

Keywords-component; artificial intelligence; behavioral biometrics; cognitive biometrics; EEG; user identification;signal processing

I. INTRODUCTION

Biometrics is the process of uniquely identifying individuals based on one or more physical or behavioral characteristics. Physiological biometrics is related to the shape of the body such as finder print, face, and DNA; while behavioral biometrics is related to the person's behavior such as typing rhythm, gait and signature. There are several techniques of recording brain activities such as magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI), electroencephalography and Electroencephalography (EEG). EEG signals are brain activities recorded from electrodes mounted on the scalp. EEG is the most practical capturing method that can be used in biometrics due to the advances in its hardware devices; there are some a EEG signal capturing device that are equal in size to a mobile phone or computer headset. EEG is one of the physiological unique characteristics of an individual [1].

There are several requirements that need to be covered by any biometric system: [2]

a) Changeability: If the user's authentication information is compromised, we must be able to replace this information (and revoke any old password or access credential).

b) Shoulder-surfing resistanc: The scheme must not be vulnerable to shoulder-surfing, particularly in the presence of ubiquitous visual recording devices.

c) Theft protection: This includes physical theft and the computational infeasibility of guessing attacks. If we must rely on the entropy of an authentication scheme for protection against off-line dictionary attack, we require an authentication method whose entropy can scale with processor speeds

d) Protection from user non-compliance: To discourage unintended transfer to other parties, the user should not be able to write down (in a manner useful to an attacker) or share their authentication information "too easily".

The discovery of electrical currents in the brain was discovered in the 19th century, but understanding the meaning of such currents advanced in the past years more rapidly as the technology improved allowing researchers to capture more data accurately. Moreover, the advancement in the signal processing and data classification techniques helped researches to use the data captured in disease diagnosis, brain computer interface and finally user identification. Several classifiers were experimented for the use of EEG signals in user identification such as neural networks, fisher's classifier and linear classifier. In Each experiment the subjects were asked to do one or more mental tasks such as solving a mathematical problem, mental visual counting, composing a letter or even just resting. Depending on the tasks and the classifiers used several experiments were conducted that showed very promising results in the use of this characteristic as a behavioral biometric feature.

The need of a new behavioral biometric is derived from the need of securing important facilities and important information. Most of the market available secure systems can be penetrated by hacking or by a mistake of one the authorized personnel. The good thing about using EEG is that it covers all the above mentioned requirements unlike other techniques. Users can change their password by selecting a different mental tasks, its prone to shoulder surfing no one can view your thoughts, Users have to do the authentication their selves, they can't give a copy of the password and they have to be alive. One of the most common used authentication techniques is finger print recognition; if the user fingerprint is captured by an intruder, when the system administrators discover this breach the user and the intruder will be prevented from entering the system, The benefits of EEG based authentication system is enormous, it have all the benefits of different authentication methods.

In this paper we investigate the various techniques and experiments that were developed for using EEG signals as a user identification characteristic. In the next section we present a brief summary on the medical aspects of the EEG signals In section three we describe the methods of capturing EEG signals and user identification methodology. In section four we discuss the techniques used to identify the users. Finally, we present a brief discussion.

II. MEDICAL ASPECTS OF EEG

The electrical currents in the brain was discovered in 1875 by an English physician Richard Caton. He observed the EEG from the exposed brains of rabbits and monkeys. In 1924 Hans Berger, a German neurologist, used his ordinary radio equipment to amplify the brain's electrical activity measured on the human scalp. He announced that weak electric currents generated in the brain can be recorded without opening the skull, and depicted graphically on a strip of paper. The activity that he observed changed according to the functional status of the brain, such as in sleep, anesthesia, lack of oxygen and in certain neural diseases, such as in epilepsy. [3]

EEG signals are generated from activities in the neurons. When the neurons are activated, local current flows are produced. EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. Differences of electrical potentials are caused by summed postsynaptic graded potentials from pyramidal cells that create electrical dipoles between soma (body of neuron) and apical dendrites (neural branches). See figure 1.

Brain electrical current consists mostly of Na+, K+, Ca++, and Cl- ions that are pumped through channels in neuron membranes in the direction governed by membrane potential [4]. The detailed microscopic picture is more sophisticated, including different types of synapses involving variety of neurotransmitters. Only large populations of active neurons can generate electrical activity recordable on the head surface. Between electrode and neuronal layers current penetrates through skin, skull and several other layers. Weak electrical signals detected by the scalp electrodes are massively amplified, and then displayed on paper or stored to computer memory [5]. The human brain electric activity starts around the 17-23 week of prenatal development. It is assumed that at birth the full number of neural cells is already developed, roughly 1011 neurons [6]. This makes an average density of 104 neurons per cubic mm. Neurons are mutually connected into neural nets through synapses. Adults have about 500 trillion (5.1014) synapses. The number of synapses per one neuron with age increases, however the number of neurons with age decreases, thus the total number of synapses decreases with age too. From the anatomical point of view, the brain can be divided into three sections: cerebrum, cerebellum, and brain stem (see figure 2). The cerebrum consists of left and right hemisphere with highly convoluted surface layer called cerebral cortex. The cortex is a dominant part of the central nervous system. The cerebrum obtains centres for movement initiation, conscious awareness of sensation, complex analysis, and expression of emotions and behaviour. The cerebellum coordinates voluntary movements of muscles and balance maintaining. The brain stem controls respiration, heart regulation, biorythms, neurohormone and hormone secretion, etc.[5]. The highest influence to EEG comes from electric activity of cerebral cortex due to its surface position.

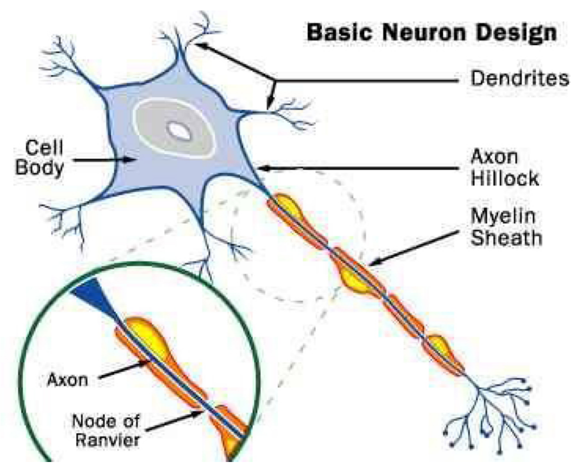

Figure 1. Basic structural features of a neuron, highlighting the three principal functions elements.

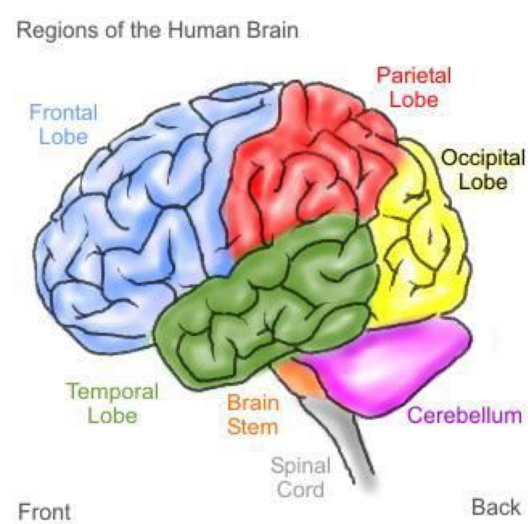

Figure 2. Regions of Human Brain, highlighting the major anatomical divisions (the Lobes). (http://msnowe.files.wordpress.com/2009/06/brain_witelson1.jpg).

. III. EEG signals are sinusoidal waves, their amplitude is normally between 0.5 and 100 µV. After applying a Fourier transform to the row signals and the power spectrum is generated, we have four groups of waves [7] see figure 3:

- Alpha 8-13 Hz, appears during relaxation without attention and concentration.
- Theta 4-7.5 Hz, theta waves in adults while awake is abnormal, they are generated by access to unconscious material, deep inspiration and meditation
- Beta 14-26 Hz Usual working rhythm
- Delta 0.5-4, usually happens during deep sleep

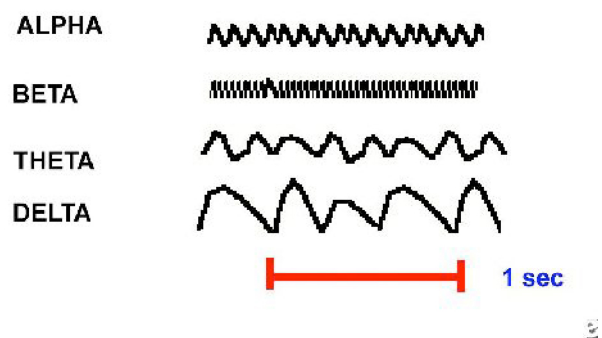

Figure 3.Samples of EEG demonstrating the major frequency bands that are presented at various stages of cognitive activity.

III. EXPERIMENT ASPECTS

A. Task Definition

Each part of the brain is responsible for a certain mental or physical activity. The identification technique will require that the user perform a certain mental task. Accordingly this task will trigger neurons in a certain parts of the brain that is responsible for handling such task. Different tasks have been used; the most used task was just letting the user stay still in a quite environment and relax; then capture the signal for a period of time to identify the user. Several tasks were later introduced; R. Palaniappan used the following five different tasks in his experiment [8]:

- Baseline task. The subjects were asked to relax and think of nothing in particular. This task was used as a control and as a baseline measure of the EEG signals.
- Geometric figure rotation task. The subjects were given 30s to study a particular three-dimensional block object, after which the drawing was removed and the subjects were asked to visualize the object being rotated about an axis. The EEG signals were recorded during the mental rotation period.
- Math task. The subjects were given nontrivial multiplication problems, such as 79 times 56 and were asked to solve them without vocalizing or making any other physical movements. The tasks were non-repeating and designed so that an immediate answer was not apparent. The subjects verified at the end of the task whether or not he/she arrived at the solution and no subject completed the task before the end of the 10s recording session.
- Mental letter composing task. The subjects were asked to mentally compose a letter to a friend or a relative without vocalizing. Since the task was repeated for several times the subjects were told to continue with the letter from where they left off.
- Visual counting task. The subjects were asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subjects were instructed not to verbalize the numbers but to visualize them. They were also told to resume counting from the previous task rather than starting over each time.

B. Signal Capturing

A typical EEG Signal capturing device consists of electrodes with conductive media, filters and amplifiers and analogue/digital converters. Devices have up to 256 electrodes; nowadays exists commercial devices with much less electrodes, devices area available in with 4 or even 2 electrodes. Of course they capture much less information but data analyzing techniques are enhanced to be able to cope with such devices.

Electrodes are usually placed on the scalp using the 10-20 standards (see Figure 4). This method was developed to ensure standardized reproducibility so that a subject's studies could be compared over time and subjects could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull.

Each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for Frontal, Temporal, Central, Parietal and Occipital respectively. Note that there exists no central lobe, the "C" letter is only used for identification purposes only. A "z" (zero) refers to an electrode placed on the midline. Even numbers (2,4,6,8) refer to electrode positions on the right hemisphere, whereas odd numbers (1,3,5,7) refer to those on the left hemisphere. [3]

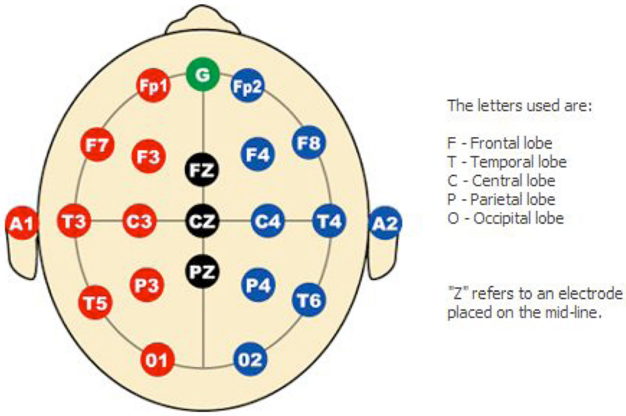

Figure 4. Standard electrode map, illustrating the commonly deployed 10-20 System (http://www.immrama.org/eeg/electrode.html)

Values at each channel is calculated by finding the difference in the reading of two electrodes based on one of the below methods

- Bipolar: calculating the difference related to a nearest electrode.
- Referential: calculating the difference with reference to the ear lobe so nodes at the right side of the head use reference of the right ear, and the left with the left ear.
- Common reference, calculating the difference to a single electrode reference for all electrodes.

Based on the mental tasks that the user will perform, activities should be expected at certain channels which reflect the part of the brain responsible for this activity.

IV. PROCESSING TECHNIQUES

In this section we will discuss various techniques used in human identification based on EEG Signals

A. Fisher's Discriminant Analysis

A. Riera et al. [9] have developed a multimodal authentication algorithm based on EEG and ECG signals. They conducted the test on 40 healthy subjects. Each subject was required to sit in a comfortable armchair, to relax, be quiet and close their eyes. Then three 3 minute takes are recorded to 32 subjects and four 3minutes takes are recorded to the 8 subjects. The 32 subject set are used as reference subject in the classification stage and the 8 subjects are the ones that are enrolled into the systems. Then several 1 minute takes are recorded afterwards to these enrolled subjects, in order to use them as authentication tests. Two electrodes were used to capture the EEG signals and 2 for the ECG. The data was divided to four seconds epochs. Two types of Features were extracted from the four seconds epochs, one channel features (Auto regression, Fourier Transform) and Synchronicity features. Three features were selected from the Synchronicity features namely; Mutual information (measures the dependency degree between two random variables given in bits, when logarithms of base 2 are used in its computation) , Coherence (quantizes the correlation between two time series at different frequencies), Correlation measures (measure of the similarity of two signals,). The classifier used in the authentication process is the classical Fisher's Discriminant Analysis, Four different discriminant functions were used (Linear, Diagonal Linear, quadratic, diagonal quadratic). The five best classifiers from the original 28 classifiers generated for each subject are selected during the enrollment and authentication of each subject.

The False Acceptance Rate (FAR) is computed taking into account both the intruder and the impostor cases (21.8%). The True Acceptance Rate (TAR) only takes into account the legal cases.(71.9%)

After combining the 2 signals (EEG and ECG) the TAR is 97.9% and the FAR is 0.82%.

B. Linear Discriminant Classifier

R Palaniappan[8] proposed a multiple mental thought identification modal. The experiment was conducted on four subjects The subjects were seated in an Industrial Acoustics Company sound controlled booth with dim lighting and noise-less fan (for ventilation). An Electro-Cap elastic electrode cap was used to record EEG signals from positions C3, C4, P3, P4, O1 and O2 defined by the 10-20 system of electrode placement. Each subject was requested to do up to five mental tasks. Signals were recorded for 10 seconds during each task and each task was repeated 10 times. Each recording was segmented into 20 segments, each 0.5s length. The five mental tasks performed by the subjects are baseline task (relaxed state), geometric figure rotation, math task (2 digit multiplication), mental letter composing task, and visual mental counting. The captured data features were extracted using AR modeling. Six AR coefficients were obtained for each channel, giving a total of 36 feature vector for each EEG segment for a mental thought. When two mental thoughts were used, the size of the feature vector was 72 and so forth when more mental thoughts were used.

Linear Discriminant Classifier was used to classify the EEG feature vectors, LDC is a linear classification method that is computationally attractive as compared to other classifiers like artificial neural network. Various results were presented showing the error rate using 1,2…5 five combination of the mental tasks. Using 1 task an average of error rate is 2.6%, while using the 5 mental tasks, the error rate was 0.1%.

C. LVQ Nerual Net

Cempírek et al. [10], proposed neural network classification technique for user identification. The algorithm was conducted on a datasets of 8 subjects. The subject was sat is a dim and silent room, eyes kept closed. Then the EEG recordings were segmented (segment length 180 sec, step 22.5 sec); the single segments were centered. Linear magnitude spectra of the single segments were computed by Fast Fourier transform (Hamming window was used).

The LVQ neural network is a self–organizing neural network, with added second layer for vectors classification intended to be used with unlabelled training data. The first network layer detects subclasses. The second layer combines these subclasses into one single class. Actually, the first layer computes distance between input and stored patterns; the winning neuron is the one with minimum distance. Hence LVQ network is a kind of nearest-neighbour classifier; it does not make clusters, but the algorithm search through the weights of connections between input layer neurons and output map neurons. These represent classes. The best classification rate was around 80% .

D. Neural Network

Sun [11] has developed a user identification system based on Neural Networks. The system was tested on 9 subjects. The task was to imagine moving his or her left or right index finger in response to a highly predictable visual cue. EEG signals were recorded with 59 electrodes mounted according to the international 10-10 system. Only Signals from 15 electrodes were used in the system. Totally 180 trials were recorded for each subject. Ninety trials with half labeled left and the other half right were used for training, and the other 90 trials were for testing. Each trial lasted six seconds with two important cues. The preparation cue appeared at 3.75 s indicating which hand movement should be imagined, and the execution cue appeared at 5.0 s indicating it was time to carry out the assigned response. The common spatial patterns (CSP) is employed to carry out energy feature extraction. As a result, each trial is modeled by an 8-dimensional vector (4 sources from each kind of mental task is assumed in this paper). Based on these features, neural network classifiers can be learned. Neural networks of one hidden layer and one output layer for experiments. The results showed that imagining left index finger movements is more appropriate for personal identification. Left index movement gave a classification accuracy of 95.6% and right index accuracy gave 94.81%. To summarize the above mentioned techniques', Table I presents a summary of these techniques.

V. CONCLUSION

This paper has summarised several techniques and implementations that have been published with respect to the deployment of EEG for human authentication and/or identification. The results are quite promising – with upwards of 95% accuracy. One of the major obstacles for deploying the EEG as a biometric is the signal acquisition process. In the clinical arena, large electrode caps with 128 or 256 electrodes are deployed. These caps require a significant effort to put on and setup. The impedance must be at a certain level, the skin requires preparation, conductive gels are often deployed to enhance the SNR. These steps preclude the deployment of EEG based approaches to biometrics for obvious reasons. Furthermore, the electrode wires are attached to cumbersome ADC boards, attached to a dedicated computer system. What is required is a small footprint, portable device – and these are being developed at a very rapid pace. As indicated in table I, authentication can be quite successful with a small number of electrodes(in fact 2 have provided significant success in several reported cases). Furthermore, dry electrodes are now becoming common place – these do not require significant skin preparation and obviate the need for messy conductive gels. Furthermore, an electrode cap is not required – the electrodes can be placed in a headband or a baseball cap. In addition, these devices transmit the data wirelessly (BlueTooth of WiFi) – making data collection a common place task. So the technology is developing – and will continue to do so, provided there is a market.

The studies selected for presentation in this survey are typical – and one notices that most studies deploy a small cohort of subjects. This is a significant design flaw – though it is not specific to biometrics. These studies should be reproduced on much larger scales, utilizing 100's of subjects within a study, in order to investigate the scalability of the classification ability of the EEG. If these studies provide results consistent with small scale studies, then scalability will not be a significant factor in the deployment of EEG based biometrics (this is a major assumption in Cognitive biometrics [12]). Other salient issues are the temporal stability of the EEG, and the effect of variations in mental state – such as stress and general arousal levels. These are the principal topics of the cognitive biometrics domain – which serves to investigate how cognitive and emotional states, in conjunction with basic genetic variability can provide unique signatures that will serve as an authentication vehicle. It would be interesting to simply put on a cap, and begin interacting with the device, without the need to remember which login ID and password is required for the current system. The system would present challenges to the user, to which they would respond naturally to – and based on the stimulus-response protocol, the user would be authenticated. Lastly, this approach provides a suitable mechanism for static and continuous authentication.

TABLE I. A SUMMARY OF SELECTED STUDIES DEPLOYING EEG FOR PERSON AUTHENTICATION, INCLUDING TASK MEASURE AND THE RESULTING CLASSIFICATION ACCURACY (TAR = TRUE ACCEPTANCE RATE AND FAR = FALSE ACCEPTANCE RATE). THE REFERENCES ARE LISTED IN THE RIGHT-MOST COLUMN.

Technique	**Channels**	**Subjects**	**Task**	**TAR**	**FAR**	
A	2	40	Rest	79.2%	21.8%	[9]
B	6	4	Rest, Math, Letter, Count, Rotation	-	0.1% avg combination using 5 features	[8]
C	-	8	Rest	80%		[10]
D	15	9	Left/Right Hand Movement	95.6% (left) 94.81 (Right)		[11]

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