A Generic Framework for EEG-Based Biometric Authentication

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***Abstract*— Biometric systems are a part and parcel of everyone's lives these days. However, with the increase in their use, the security risks associated with them have equally increased. Hence, there is an increased need to develop systems which use biometrics efficiently and ensure the authentication is integral and effective. This paper aims to introduce the concept of using Electro Encephalogram (EEG), commonly known as brain waves, as a biometric. A wavelet based feature extraction method is proposed, that uses visual and auditory evoked potentials. The future scope, pros and cons of this biometric are analyzed next.**

Keywords-EEG, brain wave, biometric, security, evoked potentials, wavelets, pros and cons

I. Introduction

Biometrics is a field of science which deals with the exploitation of the unique, identifiable and quantitatively measurable characteristics of humans in order to authenticate and validate their identity [1]. Since the time of their inception, biometric systems have been used in various applications across various domains ranging from medical to institutions to military bases. The key role of a biometric in any application is to provide identification and authentication. Traditional password-based mechanisms fail in current systems as they can be easily compromised by using standard hacking algorithms devised over years. Moreover, password-based systems require user intervention, good memory of the password and prevention of shoulder-surfing [2]. Passwords are typically obtainable by performing brute-force techniques which makes it all the more easy to intercept. Biometrics, however, offer an integrated approach to secure authentication where the human characteristics define what a person is gets exploited rather than what a person knows.

Following sections of the paper are organized as follows: Section II talks about the current biometrics and emphasizes on the need for introducing EEG as a biometric technology. Section III explores the concept of EEG and provides visionary ideas on how it can be exploited as a biometric before proposing the potential use of wavelets to extract features based on time-frequency analysis of the EEG and then compiling them into a template after pre-processing. Finally, Section IV throws light on the advantages and disadvantages of having this trait as a biometric.

II. Current Biometrics

A. Performance of existing biometrics

There are different biometrics in the market that have been integrated into different applications like smart phones, research labs, offices, hospitals and many more [3]. However, not all of them are reliable and offer least invasion of privacy. The quality of a biometric is measured by different factors like uniqueness, universality, permanence, collectability, acceptance and circumvention [4]. The technologies currently prevalent have been ranked in Table I as being high (H), medium (M) or low (L), in the corresponding criteria.

Universality refers to how a single biometric device can handle any type of input given to it and how it can produce accurate results for any person living anywhere in the world. Permanence refers to the time, preferably in years, for which the biometric is usable. However, since biometrics are basically body characteristics, there is a possible deterioration of performance of a biometric due to infliction of a disease of physical trauma [5]. Collectability refers to how easy it is to collect information from the biometric without involving much hardware, software, user intervention and/or time. Acceptance of a biometric is a measure of how approachable it is. Circumvention, on the other hand, talks of how apparently a biometric can be bypassed or circumvented by an impostor. Note from the below table below that the results are relative in nature and have been ascertained based on experimental observations and averaging the details.

B. EEG As a Biometric

An EEG defines the brain's response by recording the waveforms evoked by the excitation of neurons when subjected to stimuli [6]. The stimuli can be images, videos, sounds, or even reactions to certain events. Deoxyribonucleic acid (DNA) and ribonucleic acid (RNA) proteins are the driving source for uniqueness in an individual [7]. Therefore, one-dimensional signals such as EEG evoked by the excitation of tissues comprising these proteins exhibit the uniqueness characteristic, thus qualifying to be a potential biometric trait. The potential of using EEG as a biometric trait stems from the fact that it achieves a moderate to high performance on all the performance criteria considered in previous sub-section.

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TABLE I. PERFORMANCE OF DIFFERENT BIOMETRICS [4]

Biometrics	Characteristics					
	Universality	*Uniqueness*	*Permanence*	*Collectability*	*Acceptance*	*Circumvention*
DNA	H	H	H	L	L	L
Ear	M	M	H	M	H	M
Iris	H	H	H	M	L	H
Retina	H	H	M	L	L	H
Face	H	L	M	H	L	L
Fingerprint	M	H	H	H	M	M
Signature	L	L	L	H	L	L
Voice	M	L	L	M	H	L
Heart	H	H	H	M	L	H
Vein Pattern	H	H	H	M	H	H
Odor	M	M	M	H	H	L
Hair	H	L	M	H	H	H

EEGs can be recorded as long as the brain is functional and receptive, hence making it highly permanent. Collectability and acceptance are two areas where EEG currently has medium performance since measurement of EEG signals is not something that has reached the desired levels of sophistication and ease when compared to other seemingly non-invasive biometrics like face or fingerprint recognition. However, it is almost never possible to circumvent an EEG because spoofing a brainwave is not possible. Liveness detection is inherent in the measurement phase, and an impostor cannot force a person to generate the kind of brainwave the system looks for since aggression and fear tend to morph the brainwaves[8] [9].

There are five major bands in an EEG signal [6] [10] [11]. Alpha waves (8-13 Hz) are emitted when a person is awake but in a relaxed state of mind, perhaps with eyes closed or indulged in meditation or yoga. Beta waves (13-30 Hz) are prevalent when the person is awake but in an alert state of mind. These waves are emitted even when the brain is in a state of agony, panic, anger, frustration, tension, stress or depression. However, when a person is excited or sad, a mixture of alpha and beta waves are seen. Theta waves (4-8 Hz) are observed when a person is asleep. During deep sleep state that lasts for three to four hours a day on average, alpha waves diminish and the brain releases theta and sometimes delta waves. However, delta waves (1-4 Hz) are more common when a person is unconscious. Gamma waves (>30 Hz) are predominant with the movement of index finger, thumb or tongue. Among all the bands, alpha and beta waves are the most widely observable (and hence measurable) wave patterns because human mind emanates these two types of waves for most of the time during a day. However, when an individual is exposed to bimodal stimuli (visual and audio together for example), gamma waves are chiefly observed [12]. This paper goes beyond the initial challenges that are faced in measuring an EEG signal. It is still considered as an invasion of privacy for electrodes attached to the scalp for recording the EEG signals despite huge advancements in technology for the EEG acquisition to be as user-friendly and sophisticated as possible. Once the raw EEG data is obtained, a baseline template has to be generated.

C. *Importance of Biometric Template Security*

Templates form the backbone of biometric authentication. These templates stored in the database and are generated during the enrollment phase as a baseline. During the recognition phase, the live patterns obtained through the sensors are compiled into a second template and matched with the stored baseline template. The degree of matching leads to authentication or rejection of the corresponding user.

Secure templates satisfy all of the following properties: diversity: stored template should not allow matches from across databases; revocability: if compromised, the template should be easily destroyable and a new one should be easily issuable; securable: obtaining the original template from its secured version must be difficult; performance: the template protection scheme must not disrupt the system integrity or authentication power [13].

III. FEATURE EXTRACTION FROM EEG USING WAVELETS

Feature extraction is the process of deriving the important characteristics of the captured biometric data or information and the extracted features are used to represent the biometric trait, in this case, the EEG [14]. The features we aim to extract from an EEG are collectively called "Evoked Potentials" which will be explained in the following sub-section. Current literature predominantly uses pattern recognition for the purpose of feature extraction [6]. However, most of the pattern recognition algorithms such as linear support vector machine with cross validation [15], neural networks with spectral features [16], Gaussian mixture model with maximum a posteriori adaptation [17], auto regression coefficients with Principal Component Analysis [18], Auto regressive moving average model [19], and processing of EEG motor imagery from Brain Computer Interface model [20] are a few approaches, however, they do not perform well on non-stationary signals like the EEG. Hence, a more versatile

framework is required to perform feature extraction. As pointed out in [21], wavelets provide simultaneous time and frequency localizations which makes them a potential contender for feature extraction of EEG signals since higher resolution can be achieved at lower frequencies.

Before a step-by-step process of performing EEG biometrics is explained, it is important to understand the concept of Evoked Potentials (EPs).

A. Evoked Potentials

Evoked potentials are very specific brain activities that are measured when the brain is subjected to some kind of external stimulus, either visual or auditory. Accordingly, EPs can be classified as Visually Evoked Potentials (VEPs) or Auditory Evoked Potentials (AEPs) [22]. A third class of EPs that might be of particular interest are the Somatosensory EPs (SEPs) that are the EPs generated by the brain in response to the stimulation of peripheral nerves [23].

Evoked potentials are usually hidden in the EEG signals and their duration is typically between fifty to five hundred milliseconds [24]. These potentials are also called Event Related Potentials (ERPs) and have very low amplitude when compared to that of the actual EEG signal it is embedded in. In order to easily measure these signals which are essentially voltage fluctuations observed over the original EEG, multiple trials are performed and ensemble averaging [21] is done on them. However, performing multiple trials is not an option in biometrics because it is time-consuming, computationally complex and needs better processing power. Moreover, there are variations in every trial of the EEG and ensemble averaging assumes that the variations are minimal or trivial in nature, which essentially introduces error instead of reducing the same. Thus, extracting ERPs from the EEG in a single-trail brainwave response is the key.

Weiner filter has been used to extract the ERP from the background EEG information on single-trial responses. But, as pointed out in [24], it does not apply for the analysis of non-stationary, time-variant signals like EEG. Short Time Fourier Transforms (STFTs) perform time-frequency analysis on signals by computing Fourier transforms of signal components within a constant-width window that is moved through the full sample. However, due to the constant width of the sampling window, signals with different spectral components are treated with the same frequency resolution [25]. Time-frequency analysis using wavelet transforms overcomes these difficulties and hence has a better performance when compared with the previously cited algorithms.

B. Measuring the EEG

The first step is to measure the EEG and record it using electrodes connected to selected regions over the head along the scalp. This is a non-invasive procedure to an extent and with further advancement in technology; better ways to record EEG can be obtained. During the process of recording EEG, the subject is made to sit on a comfortable couch and some form of external stimulus is provided to him. This stimulus can be visual: the image of parents, pets, best friends or some object that the user is personally attached to; or it can be auditory: a personal favorite music that the subject can best relates to; or it can be a combination of visual and auditory components: a video with audio that the person is personally attached to. Since the biometric has to be universal, for the people who are visually challenged or have hearing impairments, a different stimulus can be used as input to evoke brainwaves. For example, the person might be asked to recall a particular incident in the past, or imagine doing some work, or even think about a particular topic. However, the same person can think of doing the same task in different ways at different times which will evoke different kinds of brainwaves but he will evoke the same signal when he recalls something that happened to him in the past because he is more likely to feel the same way about it.

During the enrollment phase, this person will upload the image, audio, video or the thought (through a question or phrase that the system will later use for matching). After this, the EEG is recorded and the brainwaves are obtained. Each electrode records the waves evoked in that area of the brain, but these individual waves have to be combined into one wave, usually called wave pattern. Hence, this represents a data fusion problem [26] [27] that can be optimized and enhanced with improved technology. However, the so-obtained wave pattern has a lot of background information, termed as noise, necessitating a pre-processing before feature extraction.

C. Pre-processing the measured EEG

Despite enough care being taken during the measurement of EEG, there is some noise that is bound to be interjected The most common noise is the additive noise of the potential due to blinking [25]. When the subject blinks his eyes, the motor movement of the eye muscles triggers an evoked potential that acts as a noise. Amplitude thresholding removes eye-blink artifacts since blinking causes a potential of 50 μV that can be easily filtered [8]. In order to effectively measure the evoked potentials, anything else that has been recorded is considered as noise. Hence, the background EEG that encompasses the EP is itself a noise. Energy from the high-frequency gamma brain waves can also be exploited in performing person authentication [12]. A three-layer Elman Neural Network (ENN) was employed over the data set recorded and de-noised before using Davies-Bouldin Index (DBI) [8] for optimal channel selection to reduce the number of parameters being computed, hence, reducing the training time of the ENN.

In [24], an automatic de-noising algorithm was proposed wherein "an automatic selection of wavelet coefficients based on the inter- and intra-scale correlation of neighboring wavelet coefficients" is used. Quadratic B-Spline Mother wavelet was used since it has compact support and is smooth, hence best for analysis of ERPs. Moreover, the wavelet has the same form as that of the ERP, hence achieving best time-frequency resolution. In the following sub-section, different forms of wavelets used to de-noise and extract the evoked potentials from the EEG are discussed briefly.

D. Different wavelets used for de-noising EEG

There are different wavelet functions that can be chosen for the purpose of feature extraction from an EEG. The important criterion to be satisfied by the wavelet function is that it should resemble the ERP that we are trying to extract from the EEG [24]. Though quadratic B-Spline has been shown to resemble

most closely to the evoked potentials, there are other wavelets that can be equally used without compromising on the resolution complexity. The only advantage of having a wavelet similar in shape to the ERP is faster resolution, but the accuracy is still achieved by many other transforms. Typically, irrespective of the wavelet chosen, three steps have to be performed in order to extract the required ERP from the EEG: decomposition of the wavelet, non-linear thresholding, and inverse wavelet reconstruction [21].

Continuous Wavelet Transforms (CWTs) result in information redundancy and huge computational complexity since they are computed at continuous time and frequency scales [28] [21], as shown in (1), where $x(t)$ is the one-dimensional signal, $\psi(t)$ is the mother wavelet considered and a and b are the scaling and translation parameters such that $(a,b) \in R$ and $a \neq 0$.

$$W_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

Discretization of translation and scaling parameters in the CWT is hence preferred. When the scaling parameters are chosen as powers of 2, we get the dyadic wavelet transforms [21] as represented in (2), where the mother wavelet is dilated by a factor of 2 at every decomposition step. Multiresolution decomposition algorithm is used to analyze the dyadic wavelet transforms by splitting them into a single approximation and different details at different levels of scale.

$$W_x(\mathrm{l},\mathrm{n}) = \frac{1}{\sqrt{2^l}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-n}{2^l}\right)dt \tag{2}$$

Traditionally, evoked potentials are estimated based on either hard or soft thresholding of the wavelets. While hard thresholding reduces the wavelet coefficients below the modeled threshold to zero, soft thresholding alters the coefficients but does not reduce them to zero. Hence to avoid the presence of spikes in the resolution, soft thresholding is preferred. In order to avoid the pseudo-Gibbs phenomenon that this method suffers from, translation-invariant EP estimator was developed in [21] that has higher Signal to Noise Ratio (SNR) and lower Root Mean Square Error (RMSE). The RMSE and SNR are defined for this method in (3) and (4) respectively.

$$\left\{\frac{1}{N}\sum_{n=1}^{N}(s(n)-s'(n))^2\right\}^{1/2} \tag{3}$$

$$10\log_{10}\left\{\frac{\sum_{n=1}^{N} s^2(n)}{\sum_{n=1}^{N}(s(n)-s'(n))^2}\right\}(dB) \tag{4}$$

Here, $s(n)$ is the true evoked potential and $s'(n)$ is the estimated evoked potential and N is the number of samples in each trial. Classical Discrete Wavelet Transforms (DWTs) are wildly used in estimating and/or analyzing the evoked potentials but despite the good quality de-noising capabilities, they tend to perform poorly when the SNR is low (less than 0dB) [21]. Moreover, DWT is shift-invariant implying that a small time-shift in the signal would cause a major disturbance in the energy distribution between sub-bands. Hence, Complex Discrete Wavelet Transforms (CDWTs) were proposed that overcome this flaw of the DWTs and scales the wavelet coefficients across successive sub-bands based on phase invariance. Donoho's wavelet thresholding employs a hard thresholding mechanism [21] where for each scale *j*, a threshold T_j is defined by (5) in which N is the number of wavelet coefficients and σ_j is the estimated standard deviation of the noise for that scale *j*.

$$T_j = \sigma_j \sqrt{2\log_e N} \tag{5}$$

However, in this method, the different wavelet coefficients are considered individually and the correlation of such coefficients with the neighboring wavelet coefficients is neglected. It was further observed that considering the correlation of neighboring coefficients provides better evoked potential estimation, as outlined by NZT De-noising in [24]. Besides including information from the neighboring coefficients, this algorithm uses the Zerotrees de-noising which states that when a particular coefficient has been decided to be removed for a particular threshold chosen, the coefficients in the same time locations but at lower levels should also be expunged. The similarity in resemblance between the quadratic B-Spline wavelets and the evoked potential responses implies faster time-frequency resolution, as shown in Fig.1 below.

E. Classification and authentication

Once the evoked potentials have been obtained from the EEG by the process of de-noising, the signal parameters are compiled into a biometric template and then stored in an encrypted format. This completes the enrollment phase. However, during the authentication phase, the user is subjected to similar classifiers that he was exposed to during the enrollment, and the EEG signals are recorded before removing artifacts and noise. The next step is the classification process. For the purpose of classification, personal One-Class Classifiers (OCCs) are used since they tend to perform better than neural networks or other genetic algorithms [8]. An OCC can have multiple features as inputs producing a single output TRUE or FALSE corresponding to a legitimate user and impostor respectively. Inherently, single-trial evoked responses are poor in quality because for the same person performing the same task, the recorded EEGs have minor imperfections at different times of the day. This might lead to an increased False Accept Rate (FAR) or False Reject Rate (FRR).

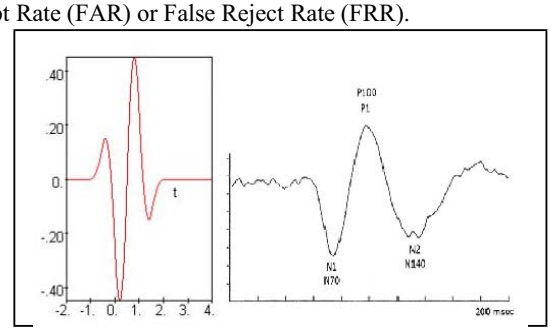

Figure 1. Comparing EP on the right with the Quadratic B-Spline wavelets [31] [32]

Hence, it is practically advisable to use multiple features averaged over the trials so that the recorded EEG is most similar to the stored template. Randomness can be introduced in the biometric authentication phase by exposing the user to different types of stimuli. For example, the user might be presented with a visual stimulus during one authentication phase while during the next time; he might be presented with an auditory disturbance to evoke the potentials. This ensures the biometric system as such is less predictable for an impostor to cause harm, but effectively increases the complexity.

Under this setup, the user has to undergo a laborious enrollment process by recording the EEG response to multiple stimuli and for each stimulus recording multiple trials of the EEG response to avoid inaccuracy of the data set. Computational complexity also increases since the system has to perform artifact removal and de-noising for each of these responses both during enrollment and every single time during the authentication. However, much of the computational complexity can be reduced by using a wavelet transform like quadratic B-spline as explained earlier.

IV. Pros And Cons of EEG As A Biometric

The feasibility of using EEG as a biometric has been studied for a decent amount of time. However, there are challenges in implementing this technology both due to lack of appropriate measurement tools that are completely or near-ideally non-invasive in nature, and due to inherent complexities in the EEG. This section sheds some light on the pros and cons of using EEG as a biometric trait.

A. Pros of EEG

There are numerous advantages of using EEG-based biometric technologies. As mentioned briefly in the first section of the paper, EEG has better performance than most of its counterparts existing in the market. Technically, every living brain emits some kind of brainwave in response to every stimulus—visual, auditory or tactile in nature. Abstract stimuli like dreams, imagination, perception, feelings, thoughts and answers to questions also trigger the generation of different forms of EEG responses. Embedded within each of these responses are stimulus-specific evoked potentials, also called event-related potentials since they depend on the kind of event the brain is exposed to. EEGs are privacy-compliant by nature unlike other biometrics like face, fingerprints, iris, retina or keystroke. The EEG-based biometric is inherently robust against spoofing and replay attacks. Even when an impostor forces the authentic user to provide the input, under stress and agony, the EEG tends to vary and the authentication would not be successful anyway. Further, EEGs are signals that can be generated only by live tissues of the brain. Synthetic versions of the signals will not match the original ones. Hence, the major drawback of liveness detection in other biometrics is easily handled by the EEG, making it a potential candidate for being exploited as a biometric trait [8].

Since EEGs are embedded intrinsically within the human body, even the physically challenged people can avail the use of this technology, which may not be the case with fingerprint or other forms of technology [6]. Given the technological and practical feasibility of the implementation of this technology, one can easily employ this technology in high-security environments.

B. Cons of EEG

Given the technological constraint of measuring and quantifying EEG, the prospects of implementing a physical system with EEG as a biometrics seem futuristic. Despite the universality professed by the EEGs, their exploitation is limited to people with healthy brains. People with mental challenges like autism, dyslexia, and other forms of illnesses might not find this form of biometric useful.

EEG is a low power signal. Hence, the measurement of these signals should be done in a careful manner under a well-controlled environment. Pre-processing of the recorded EEG signals is vital because the evoked potentials are usually embedded within the EEG and are measurable only for the first few hundred milliseconds after the subject is exposed to the stimulus. Current technology uses electrodes for measuring EEG along the scalp. This measure is, however, considered invasive by some people. Constancy is another drawback in the measurement process of EEG. An electrode records the EEG response around the region it is placed over the scalp. However, the response recorded by that electrode changes significantly even if its position changes by a minuscule fashion [29]. Hence, the positioning of electrodes should be fixed and deterministic during enrollment and every authentication phase.

Coherency between the EEG and EP before and after the stimulation is important. Spontaneous activities just prior to the exposure to external stimuli determine the frequency of the evoked responses [30]. Hence, the user's mental and physical state should be stabilized before beginning the measurement. Thus, the extracted EP will have an indelible component of the potential due to electrical activity as a consequence of events just before the stimulation. In addition to it, the EEG and hence the evoked potentials vary by large dimensions when the subject experiences a slight change in the mood or mental state during or just before the measurement. Thus, it is generally expected from the users or subjects to maintain a steady mental state prior to recording the EEGs. Posture of the person when the signals are measured is also important. Hence, they should be seated in a comfortable manner and they should have their eyes closed for a few seconds before the stimulus is presented to them. In this way, major distortions owing to the signal variance associated with mood and physical stimuli can be averted.

This consequently makes EEG-based biometrics a very elaborate technology. Considering its time-consuming nature, it is considered best to optimize the feature extraction and classification algorithms. However, most of these disadvantages can be overcome by improvisations in the technology. This emphasizes the reiterated fact that the EEGs could be a potential candidate for the biometrics market in the near future.

Conclusion

This paper has aimed to introduce the concept of using evoked potentials as a measure of uniqueness in a person and hence acts as a potential contender as a biometric. When the

brain is exposed to certain stimuli, visual, auditory, tactile or abstract, it reacts to the stimuli by emitting specific brainwaves.

Measurement of these signals is done through EEG by placing electrodes along the scalp and recording the brainwave response when the subject, initially in a relaxed state, is exposed to the stimuli. However, the ERPs occupy a very little portion of the EEG and are predominant only for the first hundred milliseconds of the EEG response. Thus, pre-processing of these signals by de-noising and artifact removal is of utmost importance. Wavelet transforms are best suited for signal de-noising since they can perform resolution in both time and frequency scales simultaneously unlike STFT or other conventional filters. The de-noising process using wavelets is threefold. Soft thresholding is preferred over hard thresholding. NZT and Zero-trees de-noising also show compact support. In order to achieve fast resolution or convergence, selection of mother wavelets that resemble closest to the ERP waveform is preferred. It has been observed that quadratic B-Spline wavelets qualify for this property.

Finally, the pros and cons of using EEG as a biometric has been briefly discussed. However, with appropriate advances in the near future, this visionary system with a quadratic B-spline wavelet based de-noising and OCC based classifier will have optimal performance.

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