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Review

A Review Study of Brain Activity-Based Biometric Authentication

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Abstract: Biometrics is the process of identifying an individual among others by biological means. Concerning security, biometric system is one of the best options available in this technology driven era. Places such as nuclear facilities, airports, banks etc. are on the frontline of security threats. Therefore, biometrics such as Iris, face and fingerprint recognition is frequently used to avoid any security breach. However, the possibility of imitating, replicating or even the stealing of original data has made these tools unreliable. As a result, there has been a growing interest in finding a better biometric system and brain activity-based biometrics such as Electroencephalography (EEG) and Functional Near-Infrared Spectroscopy (fNIRS) come with the advantage of being quite impossible to mimic. This paper presents a thorough and in depth review of the state of the art studies and research on brain activity-based biometrics. These studies and selected research projects are reviewed based on their feature extraction, methods, classification and most importantly, performance. Reviewing the most recent studies and research, we have found that time and frequency based features are better to be considered together for a brain activity-based biometric system. Together they are effective and efficient and give us a higher performance rate. Furthermore, we have found that Support Vector Machine (SVM) classifier is the best classification option with 100% accuracy and it can be used for a higher number of users for a biometric system. Our review lays a foundation for future investigation into the use of a combination of EEG and fNIRS for a biometric based authentication system.

Keywords: Biometrics, Authentication, Classification, Features Extraction, EEG, FNIRS, Brain-Waves

Introduction

The interest in biometrics for the purpose of authentication systems has grown exponentially in the past years. There are many types of biometrics that which currently enjoy high usage, such as fingerprint, iris and face recognition (Bashar *et al*., 2016). However most recognition biometrics are less than secure and can be faked or stolen. Finger prints, for example, as reported were stolen when “a violent gang in Malaysia chopped off a car owner’s finger to get round the vehicle’s hi-tech system” (Gui *et al*., 2015). The fingerprint can also be duplicated through high resolution photography; there was an incident where “the finger prints of German Defense Minister Ursula von der Leyen were copied without her knowledge by a member of Chaos Computer Club (Blondet *et al*., 2015). Considering the unreliability of these biometrics, there is a new type of biometrics called brain activity-based biometrics. Brainwaves have remarkable properties that can be used against spoofing attacks (Fraschini *et al*., 2015). Brain activity-based biometrics are far more secure than the existing fingerprint or facial identification technologies, since it cannot be exposed or used without the user’s knowledge. It is also less likely to be artificially produced (Thomas and Vinod, 2016).

Encouragingly, the new Electroencephalogram (EEG) based biometrics, which represents human brain activities, has emerged as an approach to human identification (Gui *et al*., 2014). EEG records an individual's brain activity through some measurements. Electrodes are placed on the skin and measurements are taken using voltage fluctuations recorded on the surface of the scalp.

Gui *et al*. (2015) it is almost impossible for one individual to simulate the readings of another, as individual brain activities are unique, being patterns of neural pathways of any one human being; they are connected into a subject's unique memory and knowledge. In addition, because the brain signals are associated with an individual's emotions, it is very difficult to obtain them using threat and force.

Another method of brain activity biometrics is the Functional Near Infrared Spectroscopy (FNRIS); it uses frontal FNRIS signals for people's recognition (Heger *et al*., 2013). In FNRIS, neural activity implicit in various mental tasks causes changes in the blood flow. Such changes appear in light absorbed by the blood and can be measured accordingly. FNRIS has many advantages compared to EEG; it has an advanced level of practicality, higher "signal-to-noise ratio" and, most importantly, higher space resolution (Serwadda *et al*., 2015).

The rest of this review paper focuses on: 1. Related Work 2. Methodology 3. Performance Measurement 4. Related Work Comparison 5. Conclusion and Future Work 6. Acknowledgment.

Related Work

In order to gain in-depth knowledge of the issues concerning EEG and FNIRS-based biometrics, previous research work is reviewed in this section. Gui *et al*. (2015) proposed a novel framework based on stimuli-driven, non-volitional brain responses in order to identify an individual. Here the subject is not able to manipulate his/her brain activities for the good reason that they are not in fact aware of such activities. Thus is the non-volitional mechanism even more secure for biometric authentication systems. With a sample of 30 subjects in their study, these researchers used Euclidean Distance (ED) and Dynamic Time Warping (DTW) as their methods. The accuracy for identifying the 30 subjects using the ED method is more than 80%, while it is 68% using the DTW method.

Ruiz-Blondet *et al*. (2016) focused on the Event-Related Potential (ERP), arguing that it provides highly accurate biometric recognition. Describing Cognitive Event Related Biometric Recognition (CEREBRE) as an ERP protocol in their work, it is designed to extract unique individual responses from brain. Using this protocol and the cross-correlation classifier, they have achieved 100% identification accuracy using 50 subjects.

Bashar *et al*. (2016) made use of a new method, in which EEG signals are first preprocessed using Bandpass FIR filter in order to remove noise. After dividing the EEG signals into two separate sections, three extraction features-Multi-scale Shape Description (MSD), multi-scale Wavelet Packet Statistics (WPS) and multi-scale Wavelet Packet Energy Statistics (WPES) -are put to use in a time-frequency domain. Using a Support Vector Machine (SVM) classifier, these features are then used to train a supervised Error-Correcting Output Code multicast model (ECOC) which can be ultimately used to identify human beings from the test EEG signals. A true positive rate of 94.44% of the mentioned method is achieved using 9 subjects in an experiment.

Fraschini *et al*. (2015) presented a new way to look into the distinctive brain network organization based on phase synchronization. They suppose that individual identification can be accurately done by the nodal centrality. Using 109 subjects, they computed the nodal Eigenvector Centrality. For feature vector, they use nodal centrality. An Equal Error Rate (EER) of 0.044 was achieved in the gamma band and EER of 0.102 in the beta band as highest recognition rates. EER of 0.144 was achieved in the low beta band as lower recognition rate. Based on their results, it is shown that better classification performance is provided by the resting-state functional brain network topology than by using only functional connectivity. They also suggest that when interpreting results from biometric systems based on scalp EEG features of high-frequency, caution should be used.

Blondet *et al*. (2015) explored the stability of EEG signals for a biometric system over a long period of time. This project asked if non-volitional EEG brainwaves were stable over the course of time. Using 15 human participants, they studied the stability of EEG brainwaves over a six-month period. Based on their findings, it was shown that the accuracy of EEG signals for biometric systems and the stability of human brain activities could remain stable over a long period of time.

Hasan *et al*. (2016) proposed another methodology for identifying humans for an EEG-based biometric system. Using the most effective features, they build three multi-layer neural networks. After the relative comparison, they found that using the time domain features of EEG signals in designing the network gave the worst performance, whereas the best performance was achieved using frequency domain for individual identification for the designed network. Also by utilizing the EEG headset that contains more channels, the result would be much more precise.

Kang *et al*. (2016) focused on the developing of a new method for feature selection and on the possibility of nonlinear dynamic characteristics of EEG signals in order to identify an individual in an EEG-based biometric system. Using 7 subjects, they record 16 EEG channel signals in eyes closed resting state over several days. For individual EEG characteristics, Power Spectral Density (PSD) and the Lyapunov exponents were calculated. Achieving an accuracy rate of 94.9% for individual identifying, they use statistical t-tests and a linear Support Vector Machine (SVM) classifier. In addition, they found that the maximum Lyapunov exponents for an EEG-based biometric system were the most feasible features. Furthermore, this measurement indicates a solid candidate for person recognition through the combination of lower intra-subject variability and higher inter-subject discrimination.

Pham *et al*. (2015) focused on the stability of EEG signals for a biometric authentication system. The paper discussed how sensitive EEG is to emotions, results showing that in order to decrease changes of EEG signals on an EEG-based authentication system in the real-world, some emotions should be considered. Moreover, the work which has been done regarding the performance variation when an individual is in different emotional states shows that accuracy is high in a situation of stressed emotion while it decreases when the individual is in an excited emotional state.

Heger *et al*. (2013) focused on Functional Near Infrared Spectroscopy (FNRIS), which has become a good alternative to EEG; it uses frontal FNRIS signals for people's recognition and it consist of subject-specific information. Independent sessions were recorded for the purpose of training and testing using 8 channels of frontal FNIRS. Achieving 80% identification accuracy, they have used Logarithmic Power Spectral Densities as features to test a Naïve Bayes classifier using five subjects.

Methodology

In this section of the study, methodologies of the state of the art studies and research will be discussed. As in most authentication systems, there are two processes in brain activity-based biometric authentication systems: The enrolment process and the authentication process. In the enrollment process brain activities are recorded in order then to be further examined for unique features used for authentication. The second part is an authentication process that compares the features of newly acquired brain activities with the already recorded features of those activities. Steps of both processes are explained below in details and are shown in Fig. 1.

Human Brain

The brain is an active organ with high complexity that acquires and processes the signals from the human body and environment, generates the responses accordingly and remembers the information when needed. It is a phenomenon that the brain presents behavioral and physiological information at the same time. Accordingly, it has huge significance for biometric purposes. Different kinds of brain signals are produced by brain activity, such as electrical, magnetic and metabolic. There are different ways of recording the above activity; Electroencephalogram EEG recording is not only the fastest, but its characteristic are also unique for each individual (Klonovs *et al*., 2012). Furthermore, Functional Near-Infrared Spectroscopy (FNIRS) can be a good alternative to EEG (Serwadda *et al*., 2015).

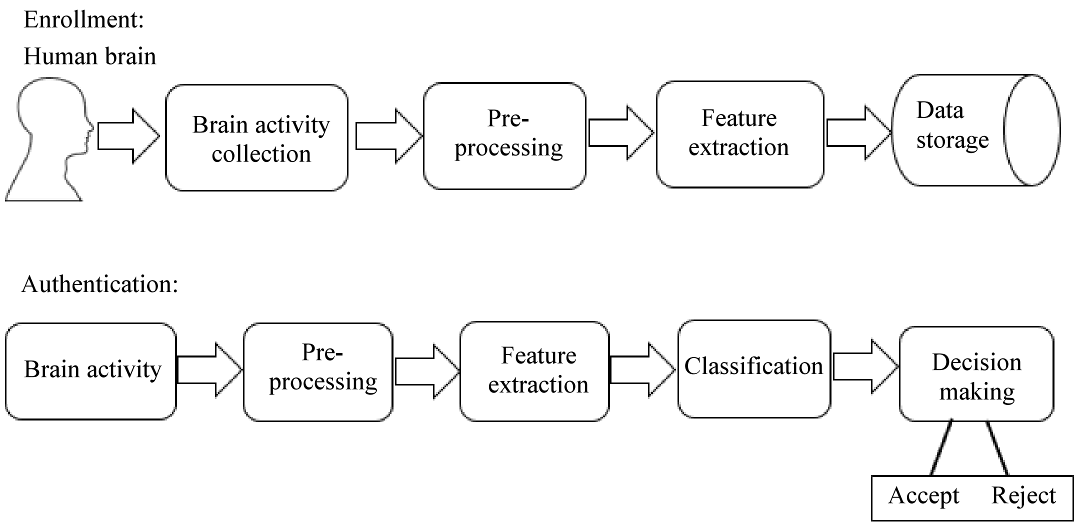

Fig. 1: Brain activity-based biometrics method

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EEG/FNIRS Signals Acquisition/Collection

Acquisition in biometrics is the process of collecting or obtaining features of human characteristics for a biometric authentication system. In brain activity-based biometrics, raw signals are acquired or collected by using this process. The point of this process is to have a data collection that can be analyzed in order to find unique features for the authentication purposes (Klonovs *et al*., 2012). EEG records the brain's electrical activity through voltage fluctuation measurement on the scalp surface with the placement of electrodes on the skin. These signals show the brain activities as determined by the individual's neural pathways; therefore, it is difficult to copy. Moreover, these signals are unique to an individual's mood, stress and mental state, which makes it difficult to be obtained by force and threat. In addition, the genetic information associated with each individual can also be unique for each person and remain stable over time (Bashar *et al*., 2016). Furthermore, FNIRS, which can be used as a good alternative to EEG, measures light absorbed by blood. Using the FNIRS device, changes in light absorbed by the blood during mental tasks are recorded (Serwadda *et al*., 2015).

Pre-Processing

The EEG and FNIRS raw signals are noisy, thus it is necessary to decrease the noise before feature extraction. There are many techniques that can be used to decrease the noise for EEG, such as ensemble averaging and correlation. The ensemble averaging uses multiple measurements and is effective and efficient in reducing the noise from the collected signals (Gui *et al*., 2014). Finally, there is correlation, which is a mathematical operator where the signals serve as the inputs of the operator that produces a third signal named cross-correlation coefficient of the two input signals. Correlation is frequently used to find signals in a noisy environment.

Blondet *et al*. (2015) furthermore, to reduce signal drifts for FNIRS, linear detrending and moving average filter are applied (Heger *et al*., 2013).

Feature Extraction

Feature extraction is the process by which key features of a method or classification algorithms are selected and extracted for future authentication. Among people, either during specific mental tasks or resting state, it is shown that specific features of the brain activity have different degrees of distinctiveness when dealing with EEG signals. Time and frequency are the two domains used mostly in which EEG features are extracted; most features of these domains rely on the resting state during the extraction process (Campisi and La Rocca, 2014). In addition, changes in blood cells such as oxyhemoglobin, deoxyhemoglobin and total hemoglobin are extracted as features for FNRIS (Serwadda *et al*., 2015).

Table 1 shows state of the art studies and their usage of the time and frequency based features for both FNIRS and EEG. 1 means the feature has been used by the study and 0 means the feature has not been used in the study.

Similarly, Fig. 2 shows features for the brain activity-based biometrics; the X axis represents feature types used by the recent studies, while the Y axis is the number of times the most updated studies use these features. As can be seen, time and frequency based features together have the highest usage rate; they have been used in studies by (Pham *et al*., 2015; Hasan *et al*., 2016; Kang *et al*., 2016; Bashar *et al*., 2016).

Table 1: Features of EEG/FNIRS

Brain activity biometrics can be recorded by these methods with have their sub methods					
Features		Blood flow biometrics Functional Near-Infrared Spectroscopy (fNIRS)		Neuron's electrical activity Electro-Encephalography (EEG)	
Study	Author	Time	Frequency	Time	Frequency
S1	Gui *et al*. (2015)	0	0	1	0
S2	Ruiz-Blondet *et al*. (2016)	0	0	1	0
S3	Bashar *et al*. (2016)	0	0	1	1
S4	Fraschini *et al*. (2015)	0	0	0	1
S5	Blondet *et al*. (2015)	0	0	0	1
S6	Pham *et al*. (2015)	0	0	1	1
S7	Hasan *et al*. (2016)	0	0	1	1
S8	Kang *et al*. (2016)	0	0	1	1
S9	Serwadda *et al*. (2015)	0	0	0	0

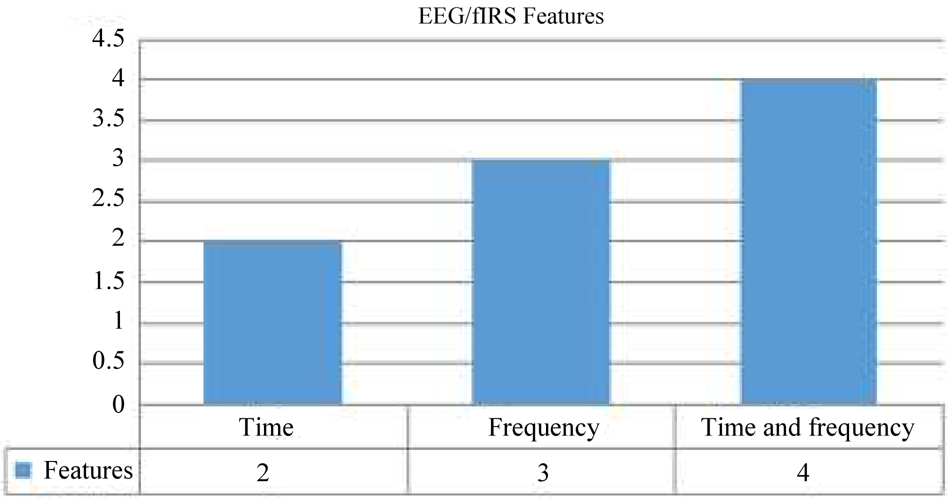

Fig. 2: Features of EEG/fIRS

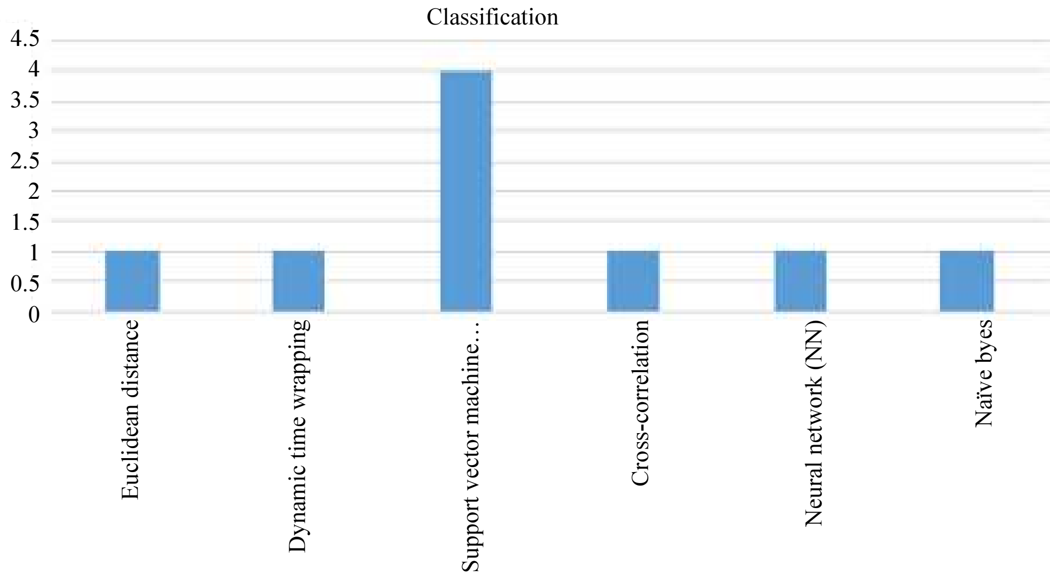

Fig. 3: Classification of EEG/fNIRS

Furthermore, Fig. 3 shows the classification for the brain activity-based biometrics; the X-axis is classification types and the Y-axis is the number of times they have been used in the most recent studies. We have found that Support Vector Machine (SVM) classifier has the highest usage rate. SVM is used in (Ruiz-Blondet *et al*., 2016; Pham *et al*., 2015; Kang *et al*., 2016) and (Bashar *et al*., 2016) with 100% maximum accuracy rate. Some of the other classifiers mentioned in the related work section of this review paper also have high accuracy rate but their usage in the studies is low compared to SVM.

Data Storage

As in most authentication systems, extracted features of brain biometrics are stored in the storage component of the biometric system for future comparison during the authentication process.

Classification

In this process the level of matching score is generated based on the comparison of the acquired features with the features already saved in the database or storage component. In order to see if the two biometric measurements come from the same person, a higher matching score should be created. Based on our research, most of the recent studies use Euclidean Distance, Dynamic Time Wrapping, Support Vector Machine (SVM), Cross Correlation and Neural Network (NN) classification types for EEG and Naïve Bayes for FNIRS.

Figure 4 shows the classification for the brain activity-based biometrics. The X axis is classification types and the Y axis is the number of times they have been used in the most recent studies. We have found that Support Vector Machine (SVM) classifier has the highest usage rate. SVM is used in (Blondet *et al*., 2015; Pham *et al*., 2015; Kang *et al*., 2016; Bashar *et al*., 2016) with 100% maximum accuracy rate. Some of the other classifiers mentioned in the related work section of this review paper also have high accuracy rates, but their usage in the studies is low compared to SVM.

Decision Process

The last process or component of a biometric system is decision making. Based on the matching score generated from the classification process, this component is responsible for making decisions either accepted or denied. After collecting a new pattern of brain activities, it is analyzed in order to identify the potential owner. A comparison between the newly acquired pattern is compared with the already known and saved one and the distance between the two patterns is calculated, with the final decision of a brain biometric system being made based on the smallest distance reached between the two patterns (Gui *et al*., 2015).

Performance Measurement

For a particular biometric system to be evaluated, four important error rates need to be taken into consideration; namely, False Rejection Rate (FRR), False Acceptance Rate (FAR), Equal Error Rate (EER) and accuracy. Pattern classifier output is sensitive to many factors, including algorithm choice, amount of training data and the chosen features in the feature vector. These factors will have an effect on the performance metrics computed for each classifier (Crawford, 2012).

The Confusion Matrix below (Table 2) is used to compute the performance measure of any classifier. It shows all of the possible results in a two-class problem, with the class decisions made by the classifier in the columns and the true, known classes in the rows. The diagonal from top left to bottom right shows the number of correctly classified patterns. True accept and true reject are seen when the classifier produces the same result as the known classification for the pattern. False accept and false reject are when the classifier produces the opposite result to the known classification. According to (Crawford, 2012) several different types of error rates are commonly reported in biometrics which are listed below.

False Rejection Rate (FRR)

FRR is a statistic that represents the number of times the system results in a false rejection (in terms of percentage). A false rejection occurs when an authorized user sample of a biometric is not matched with the stored template and is then rejected by the system. Let False Reject (FR) represent the number of false rejects from the classifier output and NA be the number of authorized user patterns. Then FRR is calculated using Equation 1:

$$FRR = \frac{Number\ of\ genuine\ rejects}{Number\ of\ genuine\ attempts} = \frac{FR}{NA} \tag{1}$$

False Acceptance Rate (FAR)

FAR is a statistic that represents the number of times (percentage) the system results in a false accept. This result occurs when an imposter sample biometric is matched with a stored template biometric and is accepted by the system. Let FA be the number of false accepts and NI be the number of impostor patterns. FAR is calculated as in Equation 2:

$$FAR = \frac{Number\ of\ imposter\ accepts}{Number\ of\ imposter\ patterns} = \frac{FA}{NI} \tag{2}$$

Equal Error Rate (EER)

EER is the point at which the plotted curves of TAR (1-FRR) and FAR meet. As shown in Fig. 4, EER can also be determined by plotting the ROC curve for the classifier, as detailed below and determining its abscissa by plotting a diagonal line from the upper left to the lower right corners and observing where the two lines cross (Clarke *et al*., 2002).

Accuracy

In as much as a confusion matrix gives all the information required, to evaluate the performance of a classification model, it can be easier to compare different models' performance. The confusion matrix provides the results to calculate the accuracy. It is specified as follows (Saevanee, 2014):

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{3}$$

In most cases classification algorithms look for models that can give the highest accuracy or give the lowest error rate when applied to a training set.

Table 2: Confusion Matrix for Two-class Problem; source: (Crawford, 2012)

		Predicted class	
		Positive	Negative
True class	Positive	True accept	False reject
	Negative	False accept	True reject

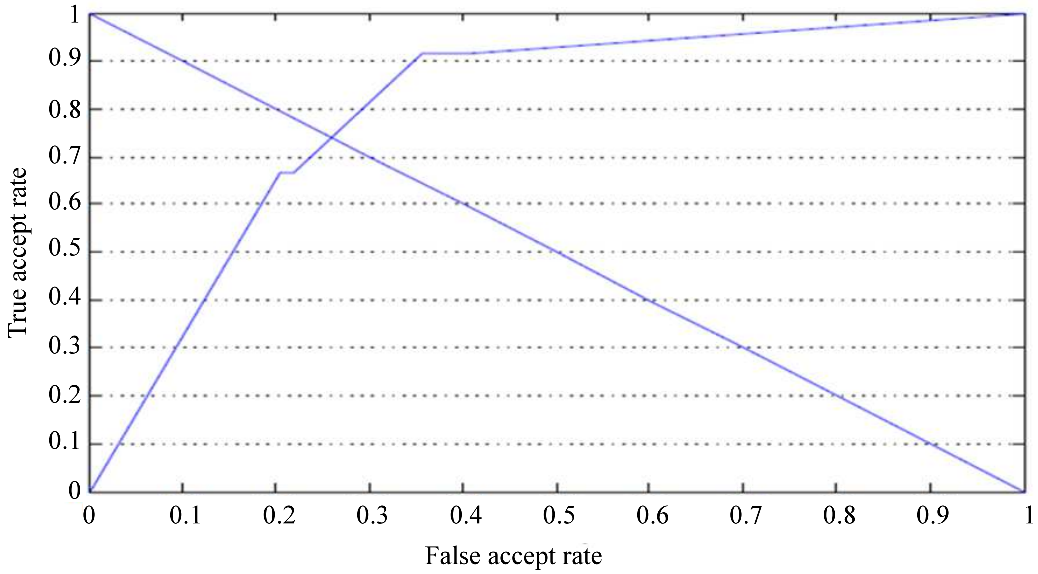

Fig. 4: The EER (25.99%) point; source: (Crawford, 2012)

Table 3: Comparison of related work

No.	Author	Features	Classification	No. users	Device	Performance
1	Gui *et al*. (2016)	(Time based)	Euclidean distance, Dynamic time warping.	30	EEG headset	Accuracy rate for ED 80% and 68% for DTW
2	Ruiz-Blondet *et al*. (2016)	Event-Related Potential (ERP). (Time based)	Support Vector Machine (SVM)	50	EEG headset	Accuracy rate of 100%
3	Bashar *et al*. (2016)	WPS/WPES, MSD and Alpha-Beta) features (Time and frequency based)	Support Vector Machine (SVM)	9	EEG headset	Accuracy rate of 94.44%
4	Fraschini *et al*. (2015)	Nodal centrality (Frequency based)	Euclidean distance	109	EEG headset	EER = 0.044
5	Blondet *et al*. (2015)	Non-volitional activities (Frequency Based)	Cross-correlation	15	EEG headset	Average accuracy rate of 84%
6	Pham *et al*. (2015)	Autoregressive (AR) features, Power Spectral Density (PSD) features (Time and frequency based)	Support Vector Machine (SVM)	32	EEG headset	N/A
7	Hasan *et al*. (2016)	Intra-individual features Vs. trials, Inter-individual features Vs. trials (Time and frequency based)	Neural network (NN)	3	EEG headset	Time domain: overall regression was 99.427% Frequency domain: Square error is 0.10095%
8	Kang *et al*. (2016)	Power Spectral Density, Lyapunov exponents (Time and frequency based)	Support Vector Machine (SVM)	7	EEG headset	Accuracy rate of 94.9%
9	Heger *et al*. (2013)	(Frequency based)	Naïve Bayes	5	EEG headset	Accuracy rate of 80%

Related Work Comparison

In Table 3 below state of the art studies and research have been thoroughly compared. They are compared based on their features, classifications, number of users, devices and their performances.

Conclusion and Future Work

Brain activity-based biometrics is the best replacement for other types of biometrics. Reviewing the most recent sources, we have found that the new EEG and FNIRS based biometrics which represents human

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brain's activities have a promising future. The properties of EEG and FNIRS biometrics have proven that it is almost impossible to mimic this kind of biometrics. Furthermore, we have found that using time and frequency based features together has high efficiency rate and that the Support Vector Machine (SVM) classifier is the best classification option for features extraction in brain-activity based biometrics with higher accuracy and can be applied on a high number of users.

In the future, we plan to study and investigate the combination of both Electroencephalogram (EEG) and Functional Near-Infrared Spectroscopy (fNIRS). We believe that using EEG and FNIRS together will achieve the best efficiency, effectiveness and performance ever achieved in the history of biometrics.

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Author's Contributions

Ala Abdulhakim Alariki: Offered all the necessary support needed to succeed in writing this paper.

Abdul Wasi Ibrahimi: Doing related work, methodology and conclusion section.

Mohammad Wardak: Doing the abstract, introduction, performance measurement section.

John Wall: English check and proof reading.

Ethics

This review study is original and it is not considered for publication elsewhere. It is confirmed by the corresponding author that all others have read and approved the manuscript and thus there is no ethical issues involved.

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