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A Review on Development of an EEG-based Biometric Authentication System

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ABSTRACT

The authentication system is the system that provides security and ensures confidentiality of information. Biometric systems provide the best security among other authentication systems. There are some classical approaches of biometric systems for authentication such as fingerprints, eyeballs and voices. However, the threat of fake fingerprints, eyeballs and recorded voices still compromise security walls. Electroencephalogram (EEG) signal is the electrical activity of the brain which may contain much useful information. It can possibly be used for building a robust biometric recognition because of its uniqueness. EEG signal is required to undergo advanced signal processing in order to get the useful information. There are three main stages included in advanced signal processing namely pre-processing, feature extraction and classification. The techniques of signal processing are categorized into two groups which are linear and non-linear. Although many different research activities have been reported, however, a systematic exploration of research findings yet to be done. Therefore, this paper aims to critically review significant findings in the field of signal processing and present the analysis in a simplistic manner for readers under findings.

Keywords: Authentication, Biometric, EEG, Processing, Recognition.

1. INTRODUCTION

A user has the privilege to access secured information which is verified by the authentication processes. In order to ensure confidentiality of information, authentication is the most critical feature to be taken into consideration. Classical password approach is user-friendly but it is easy to be stolen. Biometric systems have promised the privacy protection. There are some classical approaches of biometric systems for authentication like fingerprints, eyeballs and DNA. Those biometric traits are unique and user-friendly. Fingerprints biometric system can easily use by scanning the finger on the device. Eyeballs biometric system scans the user's iris for authentication. DNA not only used to recognise people but also can be used to identify the user's biological relatives which have blood relations with the user.

However, these biometric authentication systems still compromise security walls. With the advanced technologies, the threat of fake fingerprints, eyeballs, and DNA have happened. Moreover, those biometric traits can easily get by forcing the user [1]. People can easily obtain and duplicate the user's fingerprint when the user touches the things. Eyeballs can easily be captured and duplicated. Saliva contains everyone's DNA. Therefore, DNA can easily get when the user eats and drinks. Furthermore, it requires a few days to obtain the results of DNA.

Current biometric recognition for authentication is troublesome for people who face problems with their biometric traits especially fingerprint which is most widely used. Some people who

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have problems with their fingerprint because of losing fingers or dead skin keeps peeling off from the fingers have faced problems in daily life. The chips of identity card and driving license do not record their fingerprint. Some banks do not allow them to open a bank account. They cannot use their fingerprint to check in. They have to queue for manual counter instead of the auto gate when they travel. Those applications with fingerprint are not suitable for them.

EEG signals contain five frequency bands in total which are delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ). Brain activity has its own frequency band. Delta (1-4 Hz) is the primarily associated with deep sleep. Theta (4-8 Hz) appear as consciousness slips towards drowsiness. Alpha (8-13 Hz) usually found over the occipital region. It indicates the brain is relaxing. Beta (13-30 Hz) is often associated with active thinking and concentration. Gamma (30-100 Hz) represents the binding of different populations of neurons [1].

EEG signal is collected by using an EEG bio-amplifier. The cap of this bio-amplifier has a different number of channels, the minimum channel is 19-channel and the maximum channel is 128-channel cap [2]. The brain is divided into different lobes. Frontal lobe (F) is involved in problem solving, judgment and motor function. Temporal lobe (T) is responsible for memory and hearing. Parietal lobe (P) is about managing sensation, handwriting and body position. Occipital lobe (O) contains the brain's visual processing system [3]. Figure 1 shows the 32-channel cap with labelling. Left hemisphere shows an odd number and the right hemisphere shows even number. Figure 2 shows the parts of the brain with names.

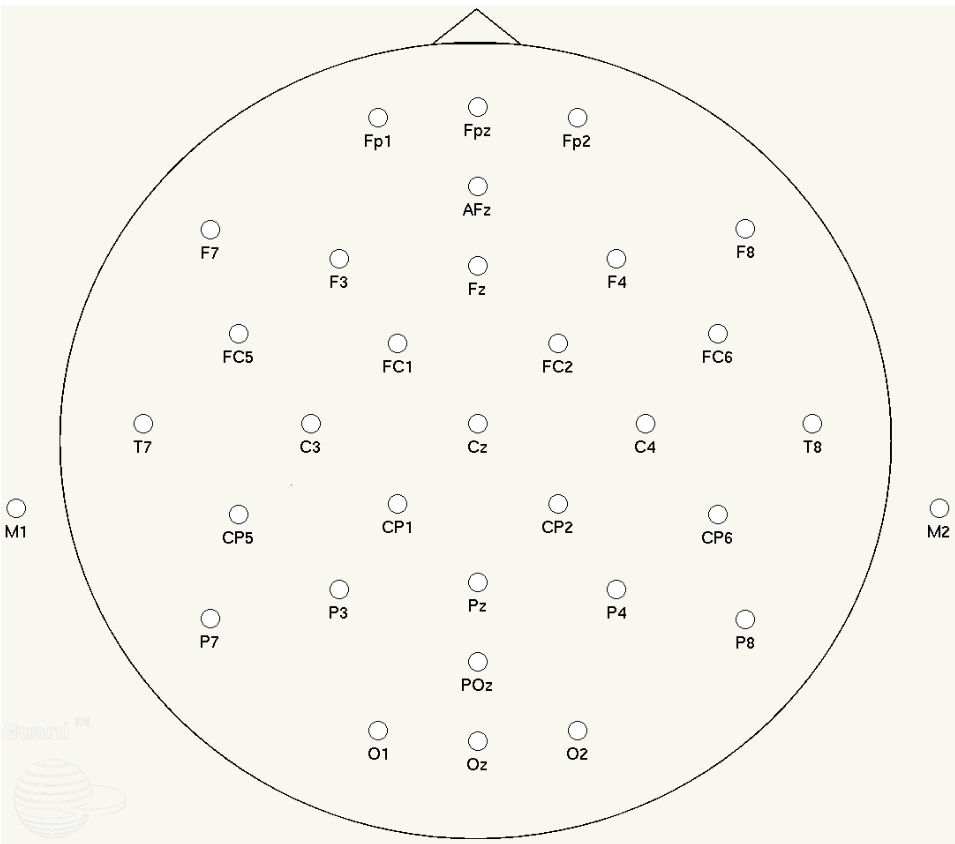

Figure 1. 32-channel cap [2].

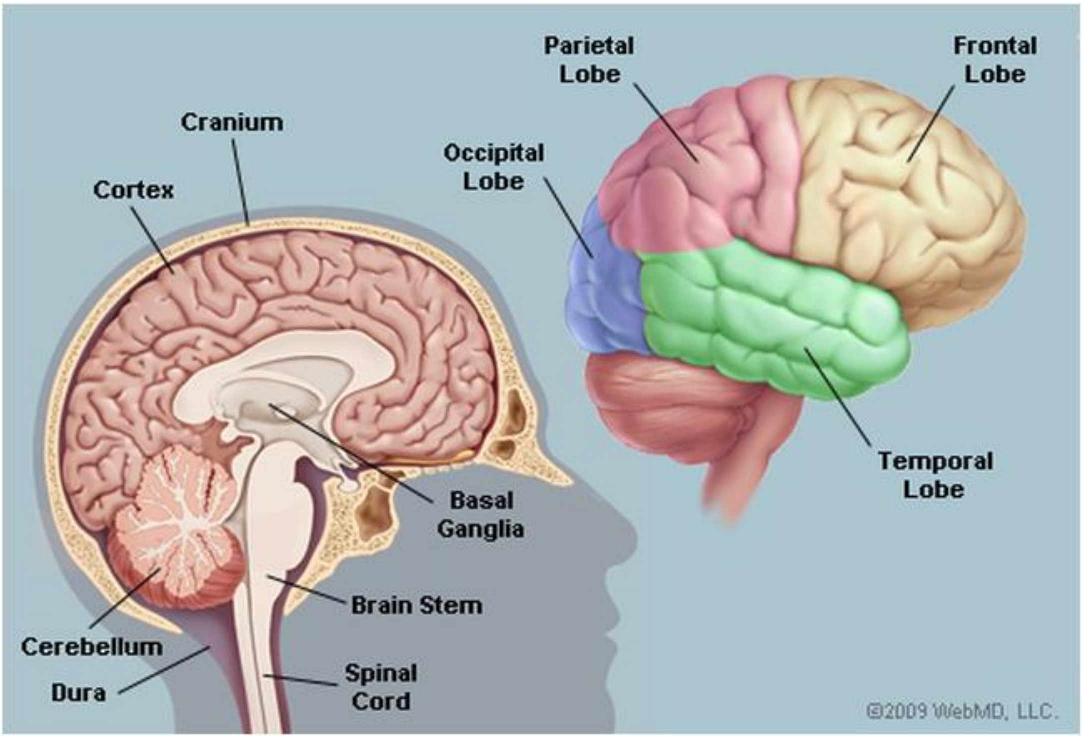

Figure 2. Picture of brain [3]

EEG signals can possibly be used for building a robust biometric recognition due to its uniqueness. In this paper, an authentication system by using EEG signals will be discussed. Advanced signal processing is used to extract most informative features which can be used for the authentication system. In EEG signal processing, there are three main stages involved namely pre-processing, feature extraction and classification. Pre-processing is the stage of removing unwanted signals and feature extraction is to extract most useful information features. Many types of filter such as band-pass filter [1], [4], anti-aliasing low-pass filter [5], notch filter [6], [7] and Butterworth band-pass filter [8] used in the stage of pre-processing. The method of feature extraction such as common spatial pattern (CSP) [1], power spectral density (PSD) [5], [9], [10], [11], and wavelet analysis, based on Morlet and "Mexican hat" wavelets [12] is used. Classification of EEG signals will be carried out after feature extraction.

2. BIOMETRIC AUTHENTICATION USING ELECTROENCEPHALOGRAM (EEG)

There are various researches with different experimental protocols and a different method of signal processing have been carried out. This paper gathers works conducted from the year 2002 to the year 2016. Table 1 shows the summary of biometric authentication using EEG.

Table 1 Summary of biometric authentication using electroencephalogram (EEG) signals

References and Year	Datasets	EEG Signal Processing			Observation
		Pre-processing	Feature Extraction	Classification	
[1], 2016	12 subjects	Band-pass filter	Common Spatial Pattern (CSP)	Linear Discriminant Analysis (LDA)	The most appropriate frequency band is Alpha and Beta combined frequency because its accuracy is the highest.
[4], 2012	Graz IIIa 2005 (3 subjects), Graz A 2008 (9 subjects), Graz B 2008 (9 subjects), Australian EEG (40 subjects), Alcoholism large (20 subjects), Alcoholism full (122 subjects)	0.5 Hz and 100 Hz band-pass filter for Graz A 2008 dataset	Open-source Emotion and Affect Recognition toolkit's feature extraction backed openSMILE		The accuracy was 99% on Graz IIIa 2005. A speech-based approach to EEG signal feature extraction was proposed for identification. The set of 8 channels showed good identification performance.
[5], 2014	108 subjects	Anti-aliasing low-pass filter	Non-parametric Fourier Transform-based spectral analysis, power spectral density (PSD)	Mahalanobis distance-based classifier	When integrating functional connectivity between the regions in the frontal lobe, the accuracy of 100% recognition was obtained.
[6], 2016	10 subjects	200 Hz low-pass, 0.05 Hz high-pass, 50 Hz notch filter, and Scan 4.3 software (Neuroscan)	Fisher distance method	Back-propagation (BP) neural network	The accuracy of classification is more than 87.3%.
[7], 2015	5 subjects	Band-pass filter of 0.2 Hz to 45 Hz and digital notch filter at 50 Hz	Short-time Fourier transform (STFT)	k-nearest neighbours (k-NN) algorithm	TAR 60% to 100% approximately revealing the potential for person classification and identification was achieved.
[8], 2013	A number of subjects	Butterworth bandpass filter, detrending and baseline removal, bandpass filter and independent component analysis	Zero-crossing rate values, power spectral density and wavelet analysis, based on Morlet and "Mexican hat" wavelets		The scenarios of an unexpected or sudden need to prove or authenticate an identity are suitable for the mobile-based system. EEG not easy to duplicate.
[9], 2013	A number of subjects	PCA	Power spectral density (PSD)	Euclidean Distance	The percentage of accuracy in classification showed good performance.
[13], 2015	10 subjects	Joint-optimized convolutional neural network (CNN), accomplishes the tasks of feature extraction and classification			The accuracy is above 80% for the full data set. The accuracy of REO is 88% which yielded the highest rate of accuracy among this three conditions.
[14], 2014	32 subjects	Ensemble averaging, and 60 Hz low-pass filter	Wavelet packet decomposition (WPD)	Feed-forward, back-propagation, multi-layer perception Neural Network (NN)	Around 90% of classification rates for differentiating one subject or a small group of individuals can be reached.

2.1 Brain ID: Development of an EEG-Based Biometric Authentication System

12 subjects were involved in this research project. The experimental protocol required the subjects to visualize a randomly selected four-digit number. Each experiment was repeated 15 times. The sampling rate was 128 Hz. The band-pass filter used for pre-processing. Common Spatial Pattern (CSP) was the feature extraction algorithm that had been used. The classification method was Linear Discriminant Analysis (LDA) which known as Fisher's linear discriminant. The accuracy is above 80% such as 81.81% accuracy for Alpha band (8-13 Hz) and 90.91% accuracy for Beta band (13-30 Hz). However, the most appropriate frequency band for EEG signals in Brain-computer Interfaces (BCI) was the Alpha and Bethe ta combined frequency (8-30 Hz). The accuracy for this combined frequency is 96.97%. [1].

2.2 Human Brain Distinctiveness Based on EEG Spectral Coherence Connectivity

108 healthy subjects participated in this research project. The experiment was conducted during the resting state. The EEG signals were collected during resting state conditions which was eyes-closed (EC) and eyes-opened (EO). In order to reduce signal noise, the ocular blinks had avoided. The sampling rate was 160 Hz. Anti-aliasing low-pass filter was used for pre-processing. Non-parametric Fourier Transform-based spectral analysis, power spectral density (PSD) was used during feature extraction. The classifier that had been used was Mahalanobis distance-based classifier. To assess the recognition performance, cross-validation framework was used. When integrating functional connectivity between the regions in the frontal lobe, the accuracy of 100% recognition was obtained. However, when fusing power spectrum information from centroparietal regions, the accuracy was lower. Only 97.41% accuracy was obtained in eyes-closed condition and 96.26% accuracy was obtained in eyes-opened condition. These results showed that brain connectivity leads to higher distinctiveness with respect to power-spectrum measurements for the eyes-closed and eyes-opened condition. In order to improve EEG-based biometric systems, the functional connectivity patterns can be used for effective features [5].

2.3 EEG-Based Person Authentication Using a Fuzzy Entropy-Related Approach with Two Electrodes

10 healthy Chinese subjects participated in this research paper. The visual stimulations for this experimental protocol were self-photo and non-self-photo. The sampling rate was 1000 Hz. 200 Hz low-pass filter, 0.05 Hz high-pass filter and 50 Hz notch filter were used for filter out the frequency below 0.05 Hz, above 200 Hz and power line noise. Scan 4.3 software (Neuroscan) was used for pre-processing. In the stage of feature extraction, a non-linear analysis method was used to extract fuzzy entropy. The fisher distance method was used to analyse the features of EEG signals of different electrodes. Back-propagation (BP) neural network is the algorithm that had been used for classification. The accuracy of classification is more than 87.3%. This showed that the combination of the feature and feature selection method can get higher classification rates. This proposed method just made use of two electrodes. This two electrodes located in the frontal regions (FP1 and FP2) [6].

2.4 Resting State EEG-Based for Individual Identification Using Convolutional Neural Networks

10 subjects recruited for this research project. The EEG signal was captured during resting state with open eyes (REO) and resting state with closed eyes (REC). There were divided into three conditions (REO, REC and REO+REC) in this research. The sampling rate was 160 Hz. Joint-optimized convolutional neural network (CNN) was carried out[15]. CNN models topology accomplishes the tasks of feature extraction and classification. The accuracy of this joint-optimized convolutional neural network (CNN) method is above 80% for the full data set. The

accuracy of REO is 88% which yielded the highest rate of accuracy among this three conditions. The results showed that this method used for EEG-based biometric system yields a high degree of accuracy of human identification [13].

2.5 A Proposed Feature Extraction Method for EEG-Based Person Identification

Three subjects involved in Graz IIIa 2005 dataset [16], each subject was asked to perform cued four motor imagery task which included left hand, right hand, foot and tongue. Nine subjects took part in Graz A 2008 dataset [17], they used same cue-based BCI paradigm as the Graz IIIa 2005. The 0.5 Hz and 100 Hz band-pass filter was used. Nine subjects involve in Graz B 2008 dataset [18]. This dataset consisted of motor imagery of left hand and right hand. The sampling frequency for this three datasets was 250 Hz. 40 patients participated in Australian EEG Database [19]. The sampling frequency for this dataset was 167 Hz. 10 alcoholic and 10 control subjects took part in Alcoholism large dataset [19]. 122 subjects involved in Alcoholism full dataset [19]. The sampling frequency was 256 Hz. Open-source Emotion and Affect Recognition toolkit's feature extraction backed open SMILE [20] was used for feature extraction. The features such as jitter and shimmer, the probability of voicing, zero crossing rate, pitch (F0), energy, spectral features, MFCCs, and statistics functionals[21] were extracted individually and were merged together. The accuracy was 99% on Graz IIIa 2005, 80.8% on Grz B 2008, 46.24% on Graz A 2008, 92.8% on Alcoholism large and 61.7% on Alcoholism full datasets. A speech-based approach to EEG signal feature extraction was proposed for identification. The set of 8 channels showed good identification performance. [4].

2.6 An Investigation of Using SSVEP for EEG-Based User Authentication System

Five healthy subjects participated in this research project. The experimental protocol was to fixate stimuli displaying on RGB LED light source. The associated SSVEP waveform was recorded. This task was to demonstrate high usability, flexibility and adaptability of the visual stimulator. It also determined the optimal parameters for the comfortably of subjects. Only two channels namely occipital lobe from left (O1) and right (O2) cerebral hemispheres were be considered in this research. The sampling rate was 128 Hz. Band-pass filter of 0.2 Hz to 45 Hz and digital notch filter at 50 Hz were fixed in a wireless Emotiv™ headset. Short-time Fourier transform (STFT) was used in feature extraction technique. The spatial-temporal content was determined by using STFT. In order to calculate the distance between the input EEG data and the enrolled features, k-nearest neighbours (k-NN) algorithm was used. The true acceptance rate (TAR) 60% to 100% approximately revealing the potential for person classification and identification was achieved by this proposed system [7].

2.7 Exploring EEG-Based Biometrics for User Identification and Authentication

32 subjects took part in this research project. This research used an "EASY CAP" device which included six midline electrode sites. The midline electrode sites were Cz, Pz, Fpz, O1, O2 and Oz. The experimental protocol was using visual stimuli. An unconnected list of texts which consisted 75 acronyms, 75 pseudowords, 75 words, 75 illegal strings and 150 instances of their own names were read silently by the subjects[22]. The best channel that suggested for brain activity was the single channel of Oz. It was analysed for acronyms stimuli. Averaging multiple measurements which known as ensemble averaging was used to reduce noise. Then, the noise which out of the major range of the EEG signals was removed by using a 60 Hz low-pass filter. In order to analyse the time-frequency information, wavelet packet decomposition (WPD) was used. It is a process which known as the downsampling process. This process is in which the signal is passed through multi-level filters. During classification, feed-forward, back-propagation, multi-layer perception Neural Network (NN) was used. Around 90% of classification rates for differentiating one subject from a small group of individuals can be reached. However, less than 11% of the classification rate was achieved by identifying each

individual subject from a large pool. It was the worst performance. Around 40% of the classification rate was obtained by the side-by-side method. It showed an improvement in recognizing all subjects. The classification rate was 5 times the accuracies in identifying the subjects. Figure 3 shows the general structure of the side-by-side method. Several smaller size training datasets based on different combinations of different subjects were made. After training these small size datasets, sub-models were built. Based on all outputs of the sub-models, a decision was made [14].

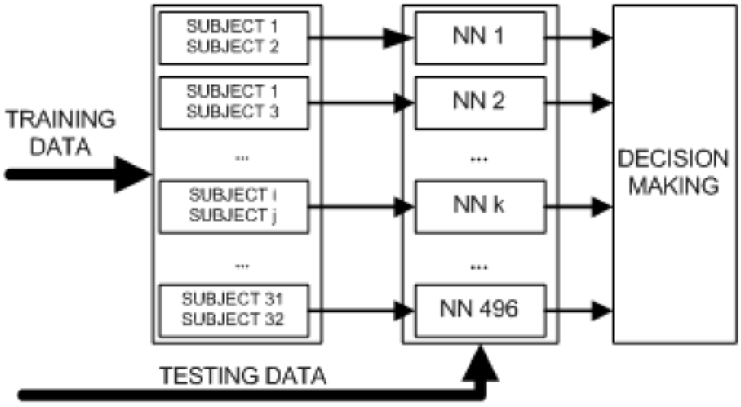

Figure 3. The general structure of the side-by-side method [14].

2.8 Using Brain Waves as a New Biometric Feature for Authenticating a Computer User in Real-Time

The sampling rate was 128 Hz for data collection [23]. There are two active cognition tasks for this research. The brain waves were recorded while the subject was asked to meditate for a fixed period of time. Math activity was solving non-trivial multiplication problems without vocalizing or making any other physical movements. In order to decrease the feature size, PCA was applied. The power spectral density (PSD) was also applied for feature extraction. During classification, Euclidean Distance was used for template matching. False Acceptance Error (FAE) and False Rejection Error (FRE) should be low. A good match was shown when the proximity value of 0.78 and above. In this research, all works were performed in real time [9].

2.9 ID Proof on the Go: Development of a Mobile EEG-Based Biometric Authentication System

In combination with technologies that had been proven, a mobile biometric authentication system was developed using EEG. There are two major parts of this prototype, the front-end part and back-end part. Processing EEG data and handling the authentication algorithms is the work of a remote server which is the location of the back-end part. An Android smartphone is responsible for interaction of user which is the location of front-end part. The Emotiv EPOC EEG neuroheadset was chosen for the prototype solution. The headset was used for EEG signal transmission. When recording EEG data by using a headset, the person required to sit with a relaxed and comfortable position, stay relatively still, and concentrate on a photograph of a person. The user was redirected to a new page when the face was detected. The process authentication process continues with motion detection. While recording brain waves, the user's visual cortex was stimulated by a back-end server which provided a photograph of a person. The system vibrated the smartphone for a short period of time before showing the photo. This was to alert the user to be concentrated. The user was ready, the alpha waves will be lowered. The image shown for five seconds.

There are two main modules for the back-end part which are the signal acquisition and pre-processing module and the feature extraction and classification module. By adjusting the signal acquisition and pre-processing module, the system can adapt to any EEG hardware. The data obtained from four EEG sensors located at P7, P8, O1, O2. In order to obtain the frequencies between or equal to 0.5Hz and 40Hz, Butterworth bandpass filter was used. The CSV Package File Writer was used. The baseline of the raw EEG data set for each electrode measurements was removing individually by using detrending and baseline removal. Bandpass filter and independent component analysis were applied to reduce the configuration space. Zero-crossing rate values were used but it must use together with other techniques. This is because it was not efficient enough to base the entire authentication decision-making process when it alone. Several techniques were applied to improve the system reliability. There were power spectral density and wavelet analysis, based on Morlet and "Mexican hat" wavelets. Multidimensional coefficient matrices were the form of feature output. Similarities in the histogram of the spectrogram image were be found by using power spectral density. At the occipital lobe area, the wavelet analysis was beneficial to measure latencies of visual-evoked potentials. Figure 4 shows the two main modules for EEG signal handling steps.

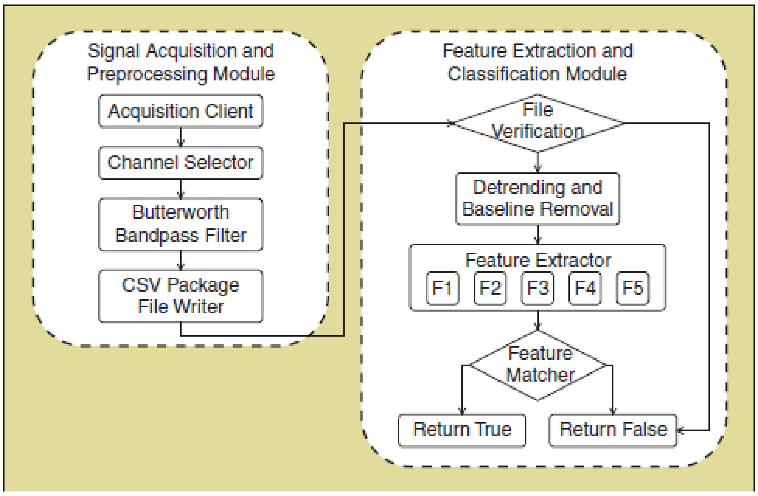

Figure 4. Flow chart of the two main modules for EEG signal handling steps [8].

The scenarios of an unexpected or sudden need to prove or authenticate an identity are suitable for the mobile-based system. EEG is not easy to duplicate. An intruder is impossible to directly force a user for this authentication system. A result in a denial of access occurred if stress signals presented when collecting the brain signals. This is because the result of basing the system on brain-wave was recordings from relaxed persons[8].

3. DISCUSSION

In this review paper, development of an EEG-based biometric authentication system was discussed. A growing interest in EEG-based biometric systems in the past few years. From those proposed methods, there are many appropriate techniques for the development of an EEG-based biometric authentication system. Most of the accuracy for the biometric authentication is above 80% from the previous researchers. This proves that EEG-based biometric provides the high possibility that can be used for recognition. Brain signal has its own useful feature such as uniqueness, robustness and continuous identification. These features are very useful for biometric traits to enhance diverse security levels and more reliable than other biometric authentication systems. Some new techniques in lie detection, crime detection and the record of specific terrorist act detection used brain signals to develop. However, there are some challenging issues. Human has different emotion such as happy, sad, angry, scare and disappointed. That emotion will produce different EEG signal. The EEG cap has many channels of the electrode. In addition, a conductive gel is required to apply on the scalp to reduce electrode-scalp impedance. This is not convenient for the EEG-based biometric authentication system to be widely used. Furthermore, the acquisition protocol is important which can generate informative signals. In most of the studies, only one protocol is considered. The comparison analysis between the different of acquisition protocol yet to be done. EEG signals is a continuous-time, non-stationary, and non-linear signal. It changes over time. Most of the researches only extracted features in the time domain.

4. CONCLUSION

EEG for biometric recognition has received increasing attention in recent years. EEG activity has two main advantages compared to other biometric traits such as fingerprints, eyeballs and voice. EEG signal is hard to steal and it is a dynamic measure that allows for constant recognition and mental state monitoring. With the EEG-based biometric authentication system, the problems that happened when using other common biometric authentication systems can be solved. This EEG-based biometric authentication system can enhance the security walls. Currently, the EEG-based authentication system is not so perfect, it is still in the process of development. In the future, the researchers should design various acquisition protocols for comparison in the research works. Fusion features is a more effective method to be used for EEG signals. The EEG bio-amplifier should design in a more convenient and effective way to record EEG signals. Although it is still not fully develop yet, EEG-based authentication systems probably will turn out to be a robust biometric recognition due to its uniqueness and widely use in the world.

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REFERENCES

[1] I. Jayarathne, M. Cohen & S. Amarakeerthi, "BrainID: Development of an EEG-based biometric authentication system," in 7th IEEE Annual Information Technology, Electronics and Mobile Communication Conference, IEEE IEMCON 2016, (2016).

[2] Waveguard™, "EEG Cap & Accessories," Ant Neuro Inspiring Technology. [Online]. Available: *https://www.ant-neuro.com/products/waveguard/electrode-layouts*. [Accessed: 18-Sep-2017].

[3] M. Matthew Hoffman, "Picture of the Brain," WebMD, 2014. [Online]. Available: *https://www.webmd.com/brain/picture-of-the-brain#1*. [Accessed: 10-Nov-2017].

[4] P. Nguyen, D. Tran, X. Huang & D. Sharma, "A Proposed Feature Extraction Method for EEG-based Person Identification," in The International Conference on Artificial Intelligence, (2012).

[5] D. La Rocca, P. Campisi, B. Vegso, P. Cserti, G. Kozmann, F. Babiloni & F. De Vico Fallani, "Human brain distinctiveness based on EEG spectral coherence connectivity," IEEE Trans. Biomed. Eng. **61**, 9 (2014) 2406–2412.

[6] Z. Mu, J. Hu & J. Min, "EEG-Based Person Authentication Using a Fuzzy Entropy-Related Approach with Two Electrodes," Entropy, **18**, 12 (2016).

[7] M. Phothisonothai, "An investigation of using SSVEP for EEG-based user authentication system," in 2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA ASC 2015, December (2015) 923–926.

[8] J. Klonovs, C. Petersen, H. Olesen & A. Hammershoj, “ID proof on the go: Development of a mobile EEG-based biometric authentication system,” IEEE Veh. Technol. Mag. **8**, 1 (2013) 81–89.
[9] K. Mohanchandra, L. GM, P. Kambli & V. Krishnamurthy, “Using Brain Waves as New Biometric Feature for Authenticating a Computer User in Real-Time,” Int. J. Biometric Bioinforma. **7**, 1 (2013) 49–57.
[10] F. Cona, M. Zavaglia, L. Astolfi, F. Babiloni & M. Ursino, “Changes in EEG power spectral density and cortical connectivity in healthy and tetraplegic patients during a motor imagery task,” Comput. Intell. Neurosci. 2009 (2009) 1–12.
[11] M. Zavaglia, L. Astolfi, F. Babiloni & M. Ursino, “The effect of connectivity on EEG rhythms, power spectral density and coherence among coupled neural populations: Analysis with a neural mass model,” IEEE Trans. Biomed. Eng. **55**, 1 (2008) 69–77.
[12] C. S. Herrmann, M. Grigutsch & N. A. Busch, EEG oscillations and wavelet analysis, January 2004 (2004).
[13] L. Ma, J. W. Minett, T. Blu & W. S. Wang, “Resting State EEG-Based Biometrics for Individual Identification Using Convolutional Neural Networks,” in 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society **57**, 1 (2015) 2848–2851.
[14] Q. Gui, Z. Jin & W. Xu, “Exploring EEG-based biometrics for user identification and authentication,” in 2014 IEEE Signal Processing in Medicine and Biology Symposium, IEEE SPMB 2014 - Proceedings, (2014).
[15] D. C. Cireșan, U. Meier, J. Masci, L. M. Gambardella & J. Schmidhuber, “Flexible, high performance convolutional neural networks for image classification,” in IJCAI International Joint Conference on Artificial Intelligence, (2011) 1237–1242.
[16] G. Pfurtscheller & A. SchlÃ˝ugl, “Dataset IIIa: 4-class EEG data.” [Online]. Available: *http://www.bbci.de/competition/iii/*.
[17] C. Brunner, R. Leeb, G. R. MÃijller-Putz, A. SchlÃ˝ugl & G. Pfurtscheller, “BCI Competition 2008 - Graz dataset A.” [Online]. Available: *http://www.bbci.de/competition/iv/*.
[18] R. Leeb, C. Brunner, G. MÃijller-Putz, A. SchlÃ˝ugl and G. Pfurtscheller, “BCI Competition 2008 - Graz dataset B.” [Online]. Available: *http://www.bbci.de/competition/iv/*.
[19] M. Hunter, R. L. L. Smith, W. Hyslop, O. A. Rosso, R. Gerlach, J. A. P. Rostas, D. B. Williams and F. Henskens, “The Australian EEG Database,” Clin. EEG Neuroscience **36**, 2 (2005).
[20] F. Eyben, M. Wöllmer & B. Schuller, “OpenEAR - Introducing the Munich open-source emotion and affect recognition toolkit,” in Proceedings - 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, ACII 2009, (2009).
[21] B. Schuller, S. Steidl, A. Batliner, F. Schiel & J. Krajewski, “The INTERSPEECH 2011 speaker state challenge,” in Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH, (2011) 3201–3204.
[22] M. Ruiz-blonde, N. Khalifian, B. C. Armstrong, Z. Jin, K. J. Kurtz & S. Laszlo, “Brainprint : Identifying Unique Features of Neural Activity with Machine Learning,” in Proc. 36th Annual Conf. of the Cognitive Science Society, (2014) 827–832.
[23] J. D. R. Millán, J. Mouriño, M. Franzé, F. Cincotti, M. Varsta, J. Heikkonen & F. Babiloni, “A local neural classifier for the recognition of EEG patterns associated to mental tasks,” IEEE Trans. Neural Networks **13**, 3 (2002) 678–686.