جامعة بيرزيت
BIRZEIT UNIVERSITY

Faculty of Engineering and Technology

Department of Computer Science

Brain Waves as a Biometric Property

Laith Marzouka	ID: 1160827
Khaled Awashreh	ID: 1150393

Supervisor: Dr.Hafez Barghouth

Spring Semester 2019

Date: May 21, 2019

Abstract:

In the world of privacy and security, the search for better ways to ensure the safety of both data and our lives is everlasting, with every generation rising on the shoulder of its predecessors. In this paper, we explore the possibility of using brain waves as a biometric. We learn about the nature of the brain, how it works and how to understand it, how to use what we learnt to utilize it. We find that when it comes to permanence, the inconsistency of identification performance requires us to search for improvements, leading us to study an experiment led by *S´ebastien Marcel* and *Jos´e del R. Mill´an* and concluding that one of the best methods to do so is incremental learning which this paper will discuss in depth.

Table of Content:

1.1 Introduction	**4**
1.2 Overview of the Report	**5**
2.1 Main brainwaves types	**7**
2.2 ERPs	**9**
3.1 EEG	**10**
3.2 Identification	**11**
3.3 Authentication	**15**
3.4 Environment	**16**
4.1 Experiment Overview and environment	**17**
4.2 DATA collection and identification	**17**
4.3 Identification/Authentication	**18**
4.4 Protocols	**19**
4.5 Results	**20**
4.6 Discussion	**21**
5.1.1 Universality	**21**
5.1.2 Distinctiveness	**22**
5.1.3 Permanence	**23**
5.1.4 Collectability	**25**
5.1.5 Performance	**26**
5.1.6 Acceptability	**26**
5.1.7 Circumvention	**27**
6.1 Future Work	**30**
6.2 Conclusion	**32**

Chapter 1: Enlightenment

1.1 Introduction

As the waves of digital growth, internet of things, internet intertwining with our lives, and the dependency on technology in every aspect of life continues to rise the need to identify unique users, develop more secure ways to realize the true identity of an outside attempting to breach or access the systems, to provide the maximum abstraction as well as comfort and ease of use for such users becomes an expectation. The field of biometric studies has become so advanced that there are many ways for implementation for security systems, one of the more novel ones are EEG based-biometric. An electroencephalogram (**EEG**) is a test that detects electrical activity in your brain using small, metal discs (electrodes) attached to your scalp.

EEG based biometrics are based on the idea that brain waves are unique enough that they can be used as a biometric to identify individuals accurately, a review of the literature confirms that EEG-based biometrics cannot be lost by users and are difficult to steal or forge. Thus, EEG has considerable potential for use in person recognition systems.

1.2 Overview of the Report

In our report, we divided the material into chapters based on content. In **chapter 2**, we study how the brain works and its components in order to understand how do we understand things and how is information processed, What is unique and what isn't, is the brain random or systematic in its functionality.

In **chapter 3**, we discuss systems that make use of this newly acquired knowledge to identify, analyze, and recognize the very core of the brain's functionality. Brain waves.

In **chapter 4**, we discuss a system in which those ideas were implemented and how were they conducted, as well as discussing how successful they were based on the results and standard calculations.

In **chapter 5**, we criticize the developed system and see how do they stand in regard of the biometric standards.

In **chapter 6**, we discuss the properties and characteristics that could be improved and what aspects require further work in order for brain waves to be used openly for authentication and what methods that can be used in order to do so.

Ch..apter 2: Brainwaves

The brain is composed of several components, cerebrum, cerebellum, and brain stem. Each serves a purpose in the overall function of the brain in synch. Brain tissue is divided into two types, Gray Matter and White Matter. Each of their names is simply derived from their appearance to the naked eyes. Grey matter is made up of the cell bodies of nerve cells. White matter is made up of the long filaments that extend from the cell bodies.

Here we are interested in Gray matter, the nerves inside Gray matter consist of neurons. Neurons are the basic building block of the nervous system and their job is to transfer information from a neuron to another for processing. This process of information transportation actually occurs in constant patterns, which have their frequency and in turn create what we call brain waves. Brain waves affect what we are feeling and thinking, and while they differ from a person to another they can be categorized into three major bands based on frequency, which is measured in Hertz. Each band is observed to have a unique effect across its frequencies.

2.1 Main brainwaves types

1. **GAMMA WAVES (38 TO 42 HZ)**

Gamma brain waves are the fastest measurable EEG brainwaves, they are believed to be related to “higher perception” and peak mental state. They are more commonly found in consistently meditating individuals such as monks. Gamma waves are associated with many things between the researchers, some debate that Gamma waves reflect the brain’s ability to concentrate it's focused on a single target for a long period of time (attentive focusing), others debate that gamma waves are related to rapid eye movements, so-called micro-saccades, which are considered integral parts for sensory processing and information intake.

2. BETA WAVES (13 TO 32 HZ)

Beta waves are most easily measurable when we are actively thinking, calculating, learning, or solving a problem.

Over motor regions in the brain, beta frequencies become stronger as we plan or execute a movement in the body, thinking about moving your arm then doing so.. Etc. Odd enough the increase in the beta waves also occurs when we observe the movements of others. It seems that our brain trying to mimic their movement.

3. ALPHA WAVES (8 TO 13 HZ)

Alpha waves are considered to be generally one of the easiest to be detected and were one of the earliest ones to be discovered. They are detectable when the body and the mind are in a state of relaxation. Sleeping, yoga, listening to music, creativity related activities, art., Etc. It’s notable to keep in mind they are different than Gamma waves.

4. **THETA WAVES (4 TO 8 HZ)**

Theta waves usually occur when we’re doing a task that doesn’t require too much mental activity and is somewhat automatic, meaning you are relaxed but still active. Example of this is sleeping, washing teeth, daydreaming, and so on. Theta waves are related to memory, creativity and psychological well-being.

5. **DELTA WAVES (0.5 TO 4 HZ)**

Delta waves are the slowest with the lowest frequency, they occur during complete rest and healing periods such as sleep. In this state healing and rejuvenation are stimulated.

2.2 ERPs

ERPs stand for Event-related potentials, they are small voltages generated in the brain structure in response to specific events or stimuli. Such as seeing the picture of someone you like, type of food, a nice object, or anything that is rather **uniquely identified.** EPR comes in different waveforms dependent on wave latency and amplitude, for example: P200, P300, and N200, and can be identified into two major categories: sensory waves and cognitive waves based on the response time to the stimuli.

Chapter 3: Authentication

3.1 EEG

An electroencephalogram (**EEG**) is a test that detects electrical activity in your brain using small, metal discs (electrodes) attached to your scalp. The electrodes detect the brain waves and the EEG machine amplifies the signals and records them in a wave pattern on graph paper or a computer screen.

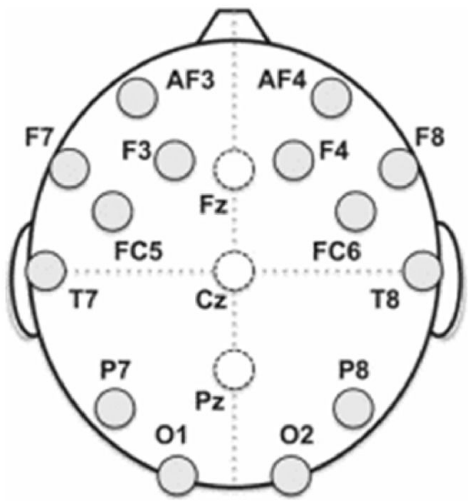


Figure: EEG electrodes placement[1]

[1] (Damaševičius, 2018)

3.2 Identification

The subjects are exposed to cognitive stimuli (images, video, math problems, ...etc), while wearing the EEG machine (such as EPOC+). Brain electric activity is then detected by the machine. Several attempts are acquired to maximize precision.

The data goes through three parts in order. The first step is collecting the EEG signals. After that, the data goes through a process of denoising. Then based on the major frequency sub-bands, the features of EEG signals are extracted.

3.2.1 Signal Acquisition:

EEG signals are often recorded with the Emotiv EPOC headset which uses integrated sensors located at standard positions. The total time of each recording is about 10 seconds. The dataset from subjects is recorded for some active cognitive tasks during each recording session.

Some of these cognitive tasks:

1- Meditation activity: The subject is asked to meditate for a fixed period of time while his brain waves are recorded.

2- Math activity: The subject is given non-trivial multiplication problems, and is asked to solve them without vocalizing or making any other physical movements. The problems were designed so that they could not be solved in the time allowed.

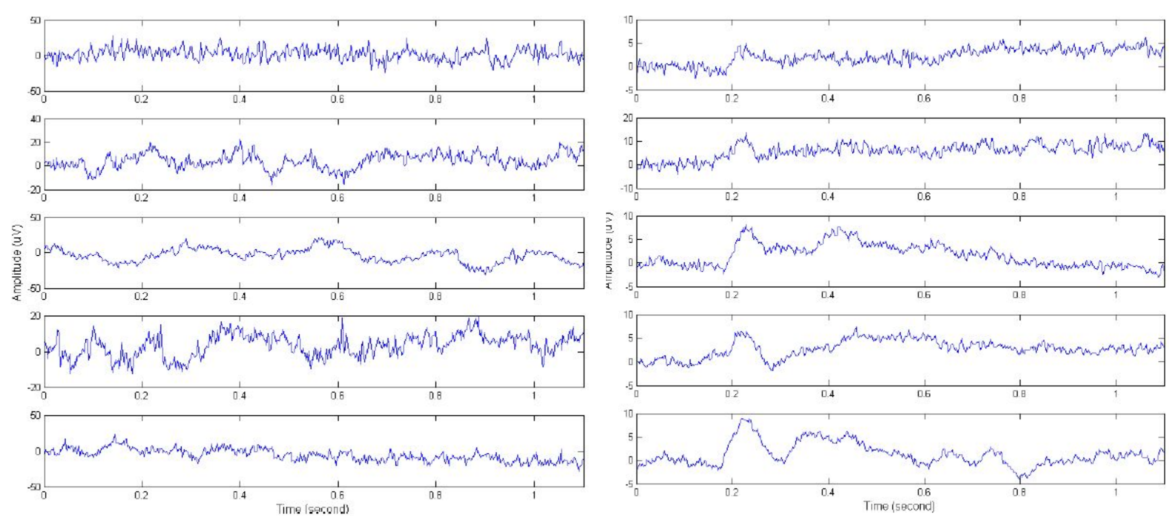
3- A video: The subject is shown a video that motivates certain areas in the brain.

4- Images: The subject is exposed to a set of images, and the brain of the subject reacts to these images based on their experience and background, which is different among individuals.

Also, other activities that can motivate certain frequency bands may be used.

3.2.2 Pre-processing:

Pre-processing is applied to improve the resolution of brain signals since the raw EEG signals are noisy. Ensemble averaging is a technique by averaging multiple measurements. Although it is a simple signal processing, it is very effective and efficient in reducing noise because the standard deviation of noise after average is reduced by the square root of the number of measurements *(Figures below show data obtained before pre-processing and after[2]).*



[2] (Qiong, 2014)

3.2.3 The feature extracting:

The brain patterns used are characterized by certain features. Describing the signals by a few relevant values. The statistical features, such as mean, median, and variance, belong to the time domain. The frequency domain features use Fourier Transform to analyze the frequency distribution of the EEG signals.

The EEG data is segmented. Channel spectral power for three spectral bands Alpha, Beta and Gamma are computed. 14 x 3 = 42 features are extracted for each segment of the data. The power spectral density (PSD) reflects the 'frequency content' of the signal or the distribution of signal power (amplitude) over frequency. PSD is a positive real function of a frequency variable associated with a stationary stochastic process. It is the measure of the power strength at each frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak. The unit of PSD is energy per frequency (width). Computation of PSD can be done directly by the method of Fourier analysis or computing autocorrelation function and then transforming it.

The Discrete Fourier transform is given by:

$$X(f) = \sum_{i=1}^{N} x(i) w_N(i-1), \text{ Where } w_N = e^{2\pi i}/N$$

is the Nth root of unity. Power spectral density is given by:

$$S_x(f) = (1/N) \sum_{i=1}^{N} |X(f)|^2$$

The channel spectral power is the measure of the total power between two frequencies and is given by:

$P_{f_1,f_2} = \int_{f_1}^{f_2} S_X(f)\, df$,where (f_1, f_2) is the frequency band and $S_x(f)$ is the power spectral density[3].

Finally, the enhanced data is stored in the database.

Figure: General Structure of the Authentication System[4]

[3] This work was done by Mohanchandra and his team (Mohanchandra, 2013)
[4] General Structure of the Authentication System

3.3 Authentication

The subject is exposed to the same stimuli. Then, the latter steps are applied in the same manner, but instead of storing the data in the database, it goes through a process of classification.

3.3.1 Classification:

The obtained feature vector is compared against a previously stored feature vector for that subject, using Euclidean Distance for template matching. The match is considered good if the result of the comparison is lower than the threshold value after repeated trials keeping in mind the need to satisfy low False Match RATE (FMR) and False Non-Match Rate (FNMR).

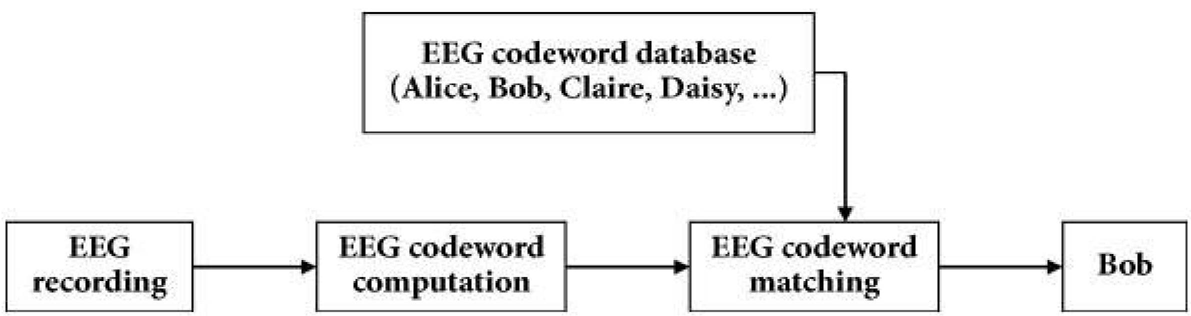


Figure: EEG-based user identification/authentication framework[5]

[5] (Damaševičius, 2018)

3.4 Environment

Brain prints can be captured by anyone. Although, good quality signals requires an expert's observation and guide to help to place the EEG and giving instructions on blinking or moving the body during the data collection to prevent the noise caused due to artefacts. So no artefact rejection or correction is employed. Artefacts due to eye blinks produce a high amplitude signal called Electrooculogram (EOG) that can be many times greater than the EEG signals required because any move may affect the experiment since EEG are most sensitive to any activity. Thus, due to its sensitivity, it is also more favourable to be done in a standard static environment where no sound (electromagnetic waves) or any other disturbance could occur and interfere with the desired signals.

Chapter 4: Experiment

This experiment was done by (***S´ebastien Marcel*** and ***Jos´e del R. Mill´an***) at the ***IDIAP Research Institute***, in Switzerland. And published by the name of ***Person Authentication using Brainwaves (EEG) and Maximum A Posteriori Model Adaptation***.

4.1 Experiment Overview and environment

EEG signals were recorded with a Biosemi system using a cap with 32 integrated electrodes located at standard positions of the International 10-20 system. The sampling rate was 512Hz. Signals were acquired at full DC. No artefact rejection or correction was employed.

This dataset contains data from 9 normal subjects during 12 non-feedback sessions over 3 days (4 sessions per day).

4.2 DATA collection and identification

The subject sat in a normal chair, relaxed arms resting on their legs. There are 3 tasks:

1) The imagination of repetitive self-paced left-hand movements, (left).

2) The imagination of repetitive self-paced right-hand movements, (right).

3) Generation of words beginning with the same random letter, (word).

For all sessions of a given subject acquired on the same day (each lasting 4 minutes with 5-10 minutes breaks in between them), the subject performed a given task for about 15 seconds and then switched randomly to another task at the operator's request. EEG data can then be split into segments corresponding to a given mental task. Each segment is considered as a record. There are 3 records per sessions.

4.3 Identification/Authentication

Data went through pre-processing and feature extracting to obtain the PSD features.

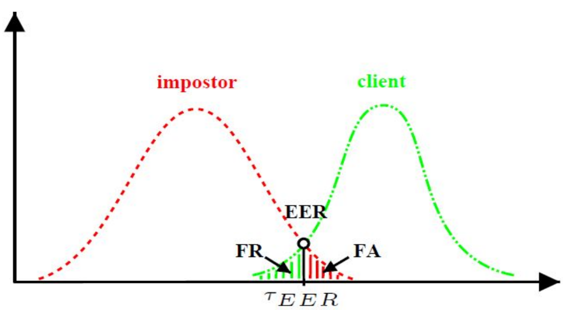
Authentication systems make two types of errors: a False Acceptance (FA), which occurs when the system accepts an impostor, or a False Rejection (FR), which occurs when the system refuses a true claimant. The performance is generally measured in terms of False Acceptance Rate (FAR) and False Rejection Rate (FRR) expressed in percentages. To aid the interpretation of performance, the two error measures are often combined using the Half Total Error Rate (HTER), defined as:

HTER = (FAR + FRR) /2

The verification decision is then reached as follows:

• the claim is accepted when $\Lambda(X) \geq \tau$,

• the claim is rejected when $\Lambda(X) < \tau$,



Since in real life the decision threshold τ has to be chosen a priori, this threshold is chosen to optimize a given criterion, such as the Equal Error Rate (EER), i.e when FAR = FRR, on the validation set. This threshold is then used on the evaluation set to obtain an HTER figure.

4.4 Protocols*:*

person	session	Kfold 1			Kfold 2			Kfold 3		
		T	V	E	T	V	E	T	V	E
1	1	C			C				I	
	2		C/I			C/I			I	
	3			C/I			C/I			I
	4			C/I			C/I			I
2	1	C				I		C		
	2		C/I			I			C/I	
	3			C/I			I			C/I
	4			C/I			I			C/I
3	1		I		C			C		
	2		I			C/I			C/I	
	3			I			C/I			C/I
	4			I			C/I			C/I

person	session	P2			P3			P4		
		T	V	E	T	V	E	T	V	E
clients (2, 3, 4, 5, 7, 8)	1	C			C			C		
	2	C			C			C		
	3		C/I			C/I			C/I	
	4			C/I		C/I				C/I
	5			C/I	C			C^{d+1}		
	6			C/I	C					C/I
	7			C/I		C/I				C/I
	8			C/I		C/I				C/I
	9			C/I			C/I	C^{d+2}		
	10			C/I			C/I			C/I
	11			C/I			C/I			C/I
	12			C/I			C/I			C/I
impostor 1	1		I			I			I	
	2		I			I			I	
impostors 6, 9	1			I			I			I
	2			I			I			I

4.5 Results:

Number of Gaussians	Protocol								
	P4-d1			P4-d2			P4-d3		
	FAR	FRR	HTER	FAR	FRR	HTER	FAR	FRR	HTER
4	15.1	17.2	16.1	20.0	50.5	**35.3**	24.7	46.8	**35.7**
32	5.7	8.5	**7.1**	7.3	82.7	45.0	8.3	96.0	52.1
	Protocol								
	$P4^{d+1}$-d2			$P4^{d+1}$-d3			$P4^{d+2}$-d3		
	FAR	FRR	HTER	FAR	FRR	HTER	FAR	FRR	HTER
4	24.9	2.7	13.8	29.4	10.6	20.0	29.3	1.2	15.25
32	16.0	0.2	**8.1**	17.8	28.3	**23.0**	24.5	0.02	**12.3**

4.6 Discussion:

The paper investigated the use of brain activity for person authentication, By using a statistical framework based on Gaussian Mixture Models and other advanced models. Intensive experimental simulations were performed using strict train/test protocols.

It was noticed that HTER increases as days go by, so *Maximum A Posteriori Model Adaptation*[6] was offered as an efficient solution

[6] Further explanation about his method is to be said later in this research.

Chapter 5: Biometrical Characteristics

Let us take a look at the quality of brain prints in consideration of the biometrical characteristics metric:

5.1.1 Universality:

Universality means that each person, object… etc of interest must have the biometric feature of interest.

Brain waves authentication is the most consistent method when we study this characteristic, it is superior to the other authentication methods due to the fact that each living human requires a functioning brain. Other cases in which individuals have problems possessing the biometric in consideration such as Speech-Impaired users cannot use voice recognition, those with damage to their finger ends could possibly not use fingerprints, War veterans could possibly have missing eyes. Etc. people could survive without eyes but not without a brain! Even mentally disorder people have emotions, thoughts, etc., which are transferred through neurons as electric charges and translated by the brain.

5.1.2 Distinctiveness:

Distinctiveness means that each person, object… etc of interest must have a unique value for the biometric system. Each person needs to have their own fingerprint, their own voice, their own dental records…. And their own brain waves.

Studies have demonstrated the high recognition accuracy of EEG biometrics within a small group of people. (La Rocca, 2014) proposed a person identification system using functional connectivity during eye-closed (EC) and eye-open (EO) conditions as features. They achieved 100% recognition accuracy among 108 subjects. The CEREBRE system proposed by (Ruiz-Blondet, 2016) integrates EEG features contributed by various functional brain systems. They achieved 100% recognition among 50 subjects. (Thomas, 2017) proposed a person authentication system using the power spectrum density (PSD) of resting-state EEG signals as features. They achieved an equal error rate (EER) of just 0.008 among 70 subjects. However, the distinctiveness of EEG characteristics among a large population has yet to be investigated. Research into this topic would require the collection of data from many subjects as well as collaboration between research groups. This, in turn, requires the means by which to share data efficiently(Hui-Ling, 2018). Nevertheless, previous studies (Smit, 2006) have shown that some EEG features are highly heritable including alpha frequency and P300 amplitude. Thereby undermining the distinctiveness of the system.

5.1.3 Permanence:

Permanence describes the quality of lasting or remaining to an object, attribute, ...etc. Here we are interested in the Permanence of brainwaves, meaning the consistency of an individual's brainwaves in similar situations and after some time.

In the study of *Marcel and Millán Jdel* (Marcel, 2007), the half total error rate (HTER) of EEG-based authentication system increased from 7.1 to 36.2 within just 3 days. This trend was also observed in the study of *Hu et al.* (Hu et al., 2011), where the performance of the identification system was evaluated over various time spans. The true positive rate (TAR) after a 1-day span was 94.60%; however, this dropped to 83.64% after a span of 1 week and to 78.20% after 6 months.

Aging (Dushanova, 2014) (Sleimen-Malkoun, 2015) (Kropotov, 2016) (Khawar, 2004), disease (Schulz, 2012), pain (Jeong, 2004), mental state (Al-Shargie,2016), and emotional state (Iacoviello, 2015); They all play a role in changing the brain prints, thus decreasing the stability of high recognition accuracy.

One of the studies (Khawar, 2004) showed how beta waves are replaced by alpha waves and alpha waves become dominant with ageing. However, theta waves gradually become prominent in the age of 61 - 70 years.

5.1.4 Collectability:

Collectability refers to the ease of collectability of the biometric of interest.

With the huge technological development, brain waves are easily collected using various EEG electrodes such as the EPOC headset, with affordable price. In addition, numerous mathematical ways exist for quantifying brain prints such as Fourier transform, PSD, P300 and other wave's properties/features.

Figure: BSI Wireless headset[7]

[7] http://cargocollective.com/futurehealth/wireless-bci-headset

5.1.5 Performance:

Performance refers to the achievable recognition accuracy and speed of the recognition. By relating to the studies from the distinctiveness part above, it is shown that an accuracy of 100% can be obtained. However, this topic is still controversial in the security field, since first of all there is no 100% accuracy system. Secondly, a larger dataset is needed in order to be capable of generalizing this statement. Lastly, the heritability of brain prints problem is still unsolved and must be taken into consideration.

As for the matter of speed, Identification may take from 5 to 10 minutes (including setting up the headset) in order to capture the brain waves properly for at least three external stimuli (photos, writings, sounds, problem-solving, etc.). Whenas, authentication may take less time (a maximum of 5 minutes).

5.1.6 Acceptability:

Acceptability refers to the social acceptance of the population of the usage of such biometric for the identification and authentication purposes. In other words, is it ok with them to use that biometric or not?

Technically speaking, brain prints must not be feared of, since no advanced technology is yet developed and that may be used against the user (reading thoughts, mental disorders, etc.). But yet, common people’s ignorance may lead them to run away even from hearing about it.

However, the idea of obtaining one’s brain prints may be enhanced in order to be a little bit more appealing to the user by using a small number of dry electrodes. A bunch of research was done concerning this matter, perhaps one of the best researches (Stevenson, 2017) suggests that 4 to 8 electrodes are enough for neonatal seizure detection.

Of course, this cannot be generalized, since it depends on the quality of the electrodes and their placement, in addition to the purpose behind detection so that the electrodes are focused in the regions where desired neurons exist.

5.1.7 Circumvention:

Circumventing refers to how easy it is you can give values to the system and have false desired results, such as a false match. In other words how easily can you trick the system

Circumventing brainwaves capturing system may be the hardest thing to do ever. This follows from the fact that recording the brainwaves of individuals requires their agreement and cooperation since it takes time and equipment. Even if an individual were to be coerced into allowing recording of their brainwaves, their subsequent negative emotions would produce brainwaves that differ from the templates in the database, leading to rejection by the system. On the other hand, other conventional biometrics are easily forged or collected without one’s consent. Fingerprints can be stolen from a cup that the user has held and voices and faces can be recorded in secret.

If we were to understand how much EEG-based biometric systems are secure and flexible, we ought to be familiar with the following two concepts:

5.2.1 Friendly Privacy:

We’ve discussed that capturing brainwaves is not that simple, a headset must be worn and a considerable amount of time would be consumed. However, this is not as bad as it seems, in contrast, it is a great advantage since it makes EEG data difficult to obtain. Unlike facial images and fingerprints which can often be obtained without the consent of subjects. Furthermore, tracing individuals based on facial images, voices, or other biometrics is not that hard. But brainwaves are almost untraceable because even if an EEG data storage system was compromised, it would be difficult to find the true identity of a person based on the features of his EEG data. This greatly enhances the security of enrolled clients.

5.2.2 Cancelability:

An important type of brain electrical signals in which we’ve deliberately mentioned in brain waves section along with the main bands is the event-related potential (ERP) brainwave which can be changed once different stimuli are presented. This special feature of brain response offers the potential to design truly cancelable biometrics. If an ERP brainwave is produced in response to a series of images, that ERP brainwave can be cancelled, and a new ERP brainwave can be generated in response to another series of image stimuli. Comparing with other biometrics, such as iris or fingerprint which if are once divulged, the authentication system is compromised and is no longer safe to use. Thus, ERP-based brain password is superior because the originally stored credential of brainwave can be cancelled if divulged or suffered an attack.

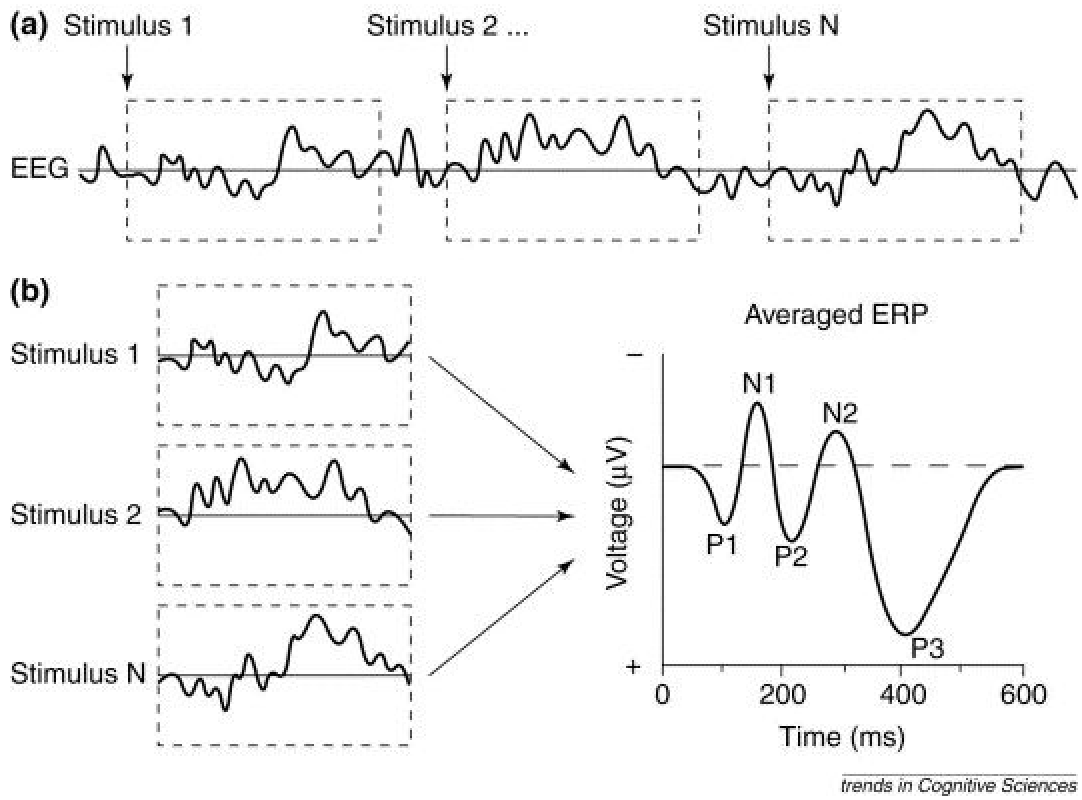


Figure: EPR signals in corresponding to different stimuli[8]

[8] (Luck, 2000)

Chapter 6: Putting Pieces Together

6.1 Future Work

For the brain waves authentication to be spread and used worldwide plenty of improvements must be implied and taken into consideration. We've already talked about reducing the number of electrodes to make using the EEG machine more accepted, but this may not solve the problem completely. For this reason, further studies are being made in order to capture the brainwaves in a different manner with the same efficiency. ***Ear-EEG Method*** (*was introduced by Mikkelsen KB. and his team in 2015*) suggests measuring EEG from the outer ear with electrodes placed on an earpiece. In spite of it being a decent method, it still needs lots of improvements to have good quality measurements and be used in public.

In Experiment part, we investigated ***Marcel's experiment*** which mainly focused on improving the permanence characteristic by applying ***Maximum A Posteriori Model Adaptation.*** This method is based on incremental learning in which users' brainwaves are updated continuously using a special algorithm. Still, this algorithm needs further improvements but due to the lack of deep understanding of brain waves and function, we are incapable of further improvement for the moment.

Variety of alternatives methods of improving accuracy and reliability were proposed. One of them used a ***novel method*** (***Armstrong 2015***, ***Palaniappan 2008***) which is based on **multi-tasking**, five tasks are combined (resting, math activity, geometric rotation, letter composing and visual counting). Multitask learning constructs a decision model by considering the main task separately from the extra tasks. In the experiment, participants were asked to return to the lab between a week and six months after their first session, classification accuracy for some participants remained as high as 100% even after 178 days. However, Acquiring EEG data from a variety of tasks can be time-consuming because the tasks must be performed sequentially. A second method to improve recognition accuracy is ***Multimodal biometrics*** (Shekhar, 2014) which proposes representing the test data by a sparse linear combination of training data at the same time without any time extended. Thus, taking into account correlations as well as coupling information among biometric modalities. Permanence and reliability are significantly enhanced by this method. Nevertheless, doing so will be at the expense of acceptability.

As technology is advancing quickly, I reckon we will see improvements we've never even thought of considering brain waves authentication methods.

6.2 Conclusion

We can confirm, there is not a single biometric system that can satisfy 100% security and reliability. Nevertheless, brainwaves biometric system is certainly superior to other biometrics regarding universality, distinctiveness, collectability, and circumvention.

Regarding universality apart from what has been said and that everyone has brainwaves; From a medical point of view, the lack of EEG is a clinical indicator of brain death. Distinctiveness was lengthily explained and asserted that everybody has a unique EEG pattern. Collectability is very efficient in EEG by virtue of our advanced mathematical and technological techniques. Circumvention is shown to be nearly impossible due to our current methods of obtaining EEG.

Referring to our argument and further discussion in future work, plenty of methods and ways can be applied in order to enhance performance and acceptability. Even though, achieving high acceptability still needs lots of work and research that is yet to be done.

In the experimental part, we focused on permanence which is the real struggle of EEG-based authentication, and we've seen the method of incremental learning used in the experiment. As well as, many other methods were discussed such as multitasking and multimodal.

Also, we've gone through the authentication of brainwaves process and took one method of the various divergent methods. The method we used is from the easiest ways concerning mathematical complications but also has adequate results. It is worth to mention that each method has its own advantages and uniqueness.

After this said, lots of questions arise in mind but the most important one is that can we really use brainwaves authentication in our real life on a daily basis? Or is it just another too good to be true biometric?

From a personal perspective, brainwaves authentication at the moment is appropriate to be utilized in only high-privacy organizations and money related authentication such as ATM or bank-safe. For personal daily usage, it is yet to be suitable due to the consumption of money and time. But who knows? Maybe one day, we will be able to log in to Facebook using our earbuds.

References:

1. Marcel, S´ebastien, and Jos´e del R. Mill´an. "Person Authentication Using Brainwaves (EEG) and Maximum A Posteriori Model Adaptation." Apr. 2007,doi:10.1109/TPAMI.2007.1012.

2. "What Are Brainwaves?" *What Are Brainwaves ? Types of Brain Waves | EEG Sensor and Brain Wave – UK*, brainworksneurotherapy.com/what-are-brainwaves?.

3. "A Deep Dive Into Brainwaves: Brainwave Frequencies Explained." *Muse*, 1 Apr. 2019, choosemuse.com/blog/a-deep-dive-into-brainwaves-brainwave-frequencies-explained-2/?fbclid=IwAR0cbvZgt_ulxaKnLNYWIFFUq6zixX0vDTu-vjGTlzpUUqnwX9LOsaIi0DQ

4. Mindvalley. "This Is How Brain Waves Contribute To The State of Mind." *Mindvalley Blog*, 2 May 2019, blog.mindvalley.com/brain-waves/?.

5. Damaševičius, Robertas, et al. "Combining Cryptography with EEG Biometrics." *Computational Intelligence and Neuroscience*, vol. 2018, 22 May 2018, pp. 1–11., doi:10.1155/2018/1867548.

6. Rocca, D. La, et al. "Human Brain Distinctiveness Based on EEG Spectral Coherence Connectivity." *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 9, Apr. 2014, pp. 2406–2412., doi:10.1109/tbme.2014.2317881.

7. Ruiz-Blondet, Maria V., et al. "CEREBRE: A Novel Method for Very High Accuracy Event-Related Potential Biometric Identification." *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 7, July 2016, pp. 1618–1629., doi:10.1109/tifs.2016.2543524.

8. Thomas, Kavitha P, and A. P. Vinod. "EEG-Based Biometric Authentication Using Gamma Band Power During Rest State." *Circuits, Systems, and Signal Processing*, vol. 37, no. 1, 11 Apr. 2017, pp. 277–289., doi:10.1007/s00034-017-0551-4.

9. Chan, Hui-Ling, et al. “Challenges and Future Perspectives on Electroencephalogram-Based Biometrics in Person Recognition.” *Frontiers in Neuroinformatics*, vol. 12, 9 Oct. 2018, doi:10.3389/fninf.2018.00066.

10. Smit, Christine M., et al. “Genetic Variation of Individual Alpha Frequency (IAF) and Alpha Power in a Large Adolescent Twin Sample.” *International Journal of Psychophysiology*, vol. 61, no. 2, Aug. 2006, pp. 235–243., doi:10.1016/j.ijpsycho.2005.10.004.

11. Gui, Qiong, et al. “Exploring EEG-Based Biometrics for User Identification and Authentication.” *2014 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, 13 Dec. 2014, doi:10.1109/spmb.2014.7002950.

12. Hu, Bin, et al. “A Real-Time Electroencephalogram (EEG) Based Individual Identification Interface for Mobile Security in Ubiquitous Environment.” 2011 IEEE Asia-Pacific Services Computing Conference, Dec. 2011, doi:10.1109/apscc.2011.87.

13. Dushanova, Juliana, and Mario Christov. “The Effect of Aging on EEG Brain Oscillations Related to Sensory and Sensorimotor Functions.” *Advances in Medical Sciences*, vol. 59, no. 1, Dec. 2014, pp. 61–67., doi:10.1016/j.advms.2013.08.002.

14. Sleimen-Malkoun, R., et al. “Brain Dynamics of Aging: Multiscale Variability of EEG Signals at Rest and during an Auditory Oddball Task.” *ENeuro*, vol. 2, no. 3, June 2015, doi:10.1523/eneuro.0067-14.2015.

15. Kropotov, Juri, et al. “Effect of Aging on ERP Components of Cognitive Control.” *Frontiers in Aging Neuroscience*, vol. 8, 6 Apr. 2016, doi:10.3389/fnagi.2016.00069.

16. Khawar, S., S. Rafique, A. Mehmood, and M. Hussain. “Electrical Changes in Brain With Aging”. *Annals of King Edward Medical University*, Vol. 10, no. 3, May 2004, https://annalskemu.org/journal/index.php/annals/article/view/2376.

17. Stevenson, Nathan J., et al. “The Effect of Reducing EEG Electrode Number on the Visual Interpretation of the Human Expert for Neonatal Seizure Detection.” *Clinical Neurophysiology*, vol. 129, no. 1, Nov. 2018, pp. 265–270., doi:10.1016/j.clinph.2017.10.031.

18. Lin, Feng, et al. “Brain Password.” *Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services - MobiSys 18*, June 2018, doi:10.1145/3210240.3210344.

19. Luck, Steven J., et al. “Event-Related Potential Studies of Attention.” *Trends in Cognitive Sciences*, vol. 4, no. 11, Nov. 2000, pp. 432–440., doi:10.1016/s1364-6613(00)01545-x.

20. Schulz, E., et al. “Decoding an Individual’s Sensitivity to Pain from the Multivariate Analysis of EEG Data.” *Cerebral Cortex*, vol. 22, no. 5, May. 2011, pp. 1118–1123., doi:10.1093/cercor/bhr186.

21. Jeong, Jaeseung. “EEG Dynamics in Patients with Alzheimer's Disease.” Clinical Neurophysiology, vol. 115, no. 7, July 2004, pp. 1490–1505., doi:10.1016/j.clinph.2004.01.001.

22. Al-Shargie, Fares, et al. “Mental Stress Assessment Using Simultaneous Measurement of EEG and FNIRS.” 1 Oct. 2016, doi:10.31224/osf.io/gdzcw.

23. Iacoviello, Daniela, et al. “A Real-Time Classification Algorithm for EEG-Based BCI Driven by Self-Induced Emotions.” *Computer Methods and Programs in Biomedicine*, vol. 122, no. 3, Dec. 2015, pp. 293–303., doi:10.1016/j.cmpb.2015.08.011.

24. Mohanchandra, Kusuma, et al. “Using Brain Waves as New Biometric Feature for Authenticating a Computer User in Real-Time.” *International Journal of Biometrics and Bioinformatics (IJBB)*, vol. 7, no. 1, 30 June 2013, pp. 49–57., www.cscjournals.org/library/manuscriptinfo.php?mc=IJBB-211.

25. Mikkelsen, Kaare B., et al. “EEG Recorded from the Ear: Characterizing the Ear-EEG Method.” *Frontiers in Neuroscience*, vol. 9, 18 Nov. 2015, doi:10.3389/fnins.2015.00438.

26. Armstrong, Blair C., et al. “Brainprint: Assessing the Uniqueness, Collectability, and Permanence of a Novel Method for ERP Biometrics.” *Neurocomputing*, vol. 166, May 2015, pp. 59–67., doi:10.1016/j.neucom.2015.04.025.

27. Palaniappan, Ramaswamy. “Two-Stage Biometric Authentication Method Using Thought Activity Brain Waves.” *International Journal of Neural Systems*, vol. 18, no. 01, Feb. 2008, pp. 59–66., doi:10.1142/s0129065708001373.

28. Shekhar, Sumit, et al. “Joint Sparse Representation for Robust Multimodal Biometrics Recognition.” *IEEE*, vol. 36, no. 1, 11 Jan. 2014, pp. 113–126., doi:10.1109/TPAMI.2013.109.