Brain Waves and Evoked Potentials as Biometric User Identification Strategy: An Affordable Low-cost Approach

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Abstract: The relatively recent introduction on the market of low-cost devices able to perform an Electroencephalography (EEG) has opened a stimulating research scenario that involves a large number of researchers previously excluded due to the high costs of such hardware. In this regard, one of the most stimulating research fields is focused on the use of such devices in the context of biometric systems, where the EEG data are exploited for user identification purposes. Based on the current literature, which reports that many of these systems are designed by combining the EEG data with a series of external stimuli (Evoked Potentials) to improve the reliability and stability over time of the EEG patterns, this work is aimed to formalize a biometric identification system based on low-cost EEG devices and simple stimulation instruments, such as images and sounds generated by a computer. In other words, our objective is to design a low-cost EEG-based biometric approach exploitable on a large number of real-world scenarios.

1 INTRODUCTION

The introduction on the market of low-cost devices capable of detecting brain waves with relative accuracy has opened numerous research paths ranging from canonical domains (Xavier et al., 2021; Prathibha et al., 2017) to completely new ones, such as those oriented to the definition of biometric systems (Nakanishi and Maruoka, 2019). The growing number of such devices is accompanied by an equally increasing availability of applications and libraries to support the development of new applications: a representative example is that of the *Muse* (https://choosemuse.com) device, marketed together with an application aimed at supporting meditation activities, and widely used in literature for numerous experiments, also thanks to a large number of programming libraries available.

More formally, these devices perform an *Electroencephalogram* (EEG) (Thakor and Sherman, 2013) by measuring the electrical activity of the brain using a series of electrodes positioned on the scalp. In this regard, it should be added that the number of these electrodes is greater in professional devices, where even the positioning requires more attention, requiring also the use of a conductive paste, differently from the low-cost devices that use a smaller number of electrodes, which can usually do not require any conductive paste. However, in both cases the positioning of the electrodes follows the *10-20 System of Electrode Placement* (Homan et al., 1987) formalization shown in Figure 1.

Such a system indicates the relationship between each electrode location and the underlying cerebral cortex area. In order to guide in the correct positioning of the electrodes, each position reports the lobe and the hemisphere indication, i.e., the *C*, *F*, *P*, *O*, and *T* letters indicate, respectively, the *Central*, *Frontal*, *Parietal*, *Occipital*, and *Temporal* lobe (the *Central* lobe is used only for identification purposes, as it does not actually exist). Similarly, the even numbers 2, 4, 6, 8, and 10 denote the right hemisphere, and the odd numbers 1, 3, 5, 7, and 9 the left one; the *z* letter indicates a median-line electrode (the smaller is a number, the closer it is to the median line); the *Nasion* label denotes the area between the forehead and nose and *Inion* label denotes the area at the back of the skull. At the time of writing, the most popular low/medium cost EEG signal acquisition devices are those reported in Table 1, which also provides information about the data resolution in bits and the number of electrodes.

Based on the cost and features, as well as the availability of development tools, among the aforementioned devices we have chosen for this work the *InteraXon Muse-2*, a device marketed as a tool that helps in reaching a deep relaxed state, assisting the

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people during a meditation session, exploiting an aural feedback related to the detected brain activity. It uses five electrodes placed on a headband that, on the basis of the placements of Figure 1, are: a reference electrode (*NZ*) and four acquisition electrodes (*TP9*, *AF7*, *AF8*, and *TP10*). All the *Muse-2* functions can be managed through an application released for the *iOS* 12.2 and *Android* 8 or higher operating systems but a huge number of applications and libraries are also available on the Internet aimed to extend its features, allowing the researchers to create customized applications using libraries designed for several programming languages. Some representative examples are: *Brainflow* (https://brainflow.org), a *Python* library that offers API able to filter, parse, and analyze the EEG data; *Brains@play*(https://brainsatplay.com), an open-source framework that allows the developers to create brain-responsive applications based on the web technologies; *Muse LSL* (https://github.com/alexandrebarachant/muse-lsl), a *Python* package that provides functions for streaming, visualizing, and recording the EEG data. Among those available, in this work we have chosen to use *Muse LSL*, which operates under the *Linux* operating system, allowing us to perform a *Bluetooth Low Energy* (BLE) communication between the computer and the *Muse* device (compatible with *Muse 1*, *Muse 2*, and *Muse S*), providing functions for managing and testing the device connection, as well as a *Python* library (working with both *Python* versions 2.7 and 3.x) for developing the code. It should be added that the *Lab Streaming Layer* (LSL) adopted by *Muse LSL* is a mechanism widely used for the unified collection of time-series measurements in the scientific field since it allows us the synchronization of the streaming data for real-time analysis or recording. Based on the results of other studies in this regard, the idea behind this work is related to the exploitation of external stimuli to induce reliable/stable EEG patterns, with the aim to exploit them as a biometric approach for user authentication. Differently from the solutions in the literature, which are usually unsuitable for large-scale use in the real-world scenarios due to a series of limitations mainly related to the need for expensive and/or complex EEG data acquisition and stimulation techniques, the proposed system is designed to use simple and low-cost hardware (i.e., one of those in Table 1) and stimulation techniques (i.e., computer sounds and images).

Table 1: Low-cost EEG Devices.

Brand name	Product name	Resolution bits	Electrodes number	Reference site
Emotiv	Insight	14	05	https://www.emotiv.com
Emotiv	Epoch X	14/16	14	https://www.emotiv.com
Emotiv	Epoch Flex	14	32	https://www.emotiv.com
InteraXon	Muse-2	12	04	https://choosemuse.com
InteraXon	Muse S	12	04	https://choosemuse.com
Neurowsky	MindWave Mobile 2	12	01	http://neurosky.com
OpenBCI	Cyton Biosensing Board	24	08	https://openbci.com

2 BACKGROUND AND RELATED WORK

The human brain is made up of billions of neurons, each of which can potentially connect with thousands of other neurons in order to establish communication channels through low intensity electric voltages (in the order of microvolts). This type of electrical activity of neurons generates brain waves, which on the basis of their frequency (in the range from 4 to 100 Hz) are classified into five categories, each of them denoted by a Greek letter: the *Delta* wave less than 4 Hz, the *Theta* wave from 4 to 8 Hz, the *Alpha* wave from 8 to 12 Hz, the *Beta* wave from 13 to 30 Hz, and the *Gamma* wave greater than 30 Hz. Each brain area is then characterized by different wave frequencies, which can be generated simultaneously. Several studies demonstrated the existence of a strong correlation between brain wave rhythms and brain state such as, for instance, between the fastest rhythms and the brain processing of information, and between the slowest rhythms and the inactive brain state (Sterman, 1996).

Nowadays, a growing number of literature works are focused on the exploitation of EEG signals as a biometric approach for the users identification (Yang and Deravi, 2017), proposing approaches/strategies able of producing unique and stable patterns over time. In this context, it is possible to find works aimed at formalizing these identification systems in a practical way (Thomas and Vinod, 2018), along with works that instead deal with issues and aspects connected to this research area (Fraschini et al., 2019). It should be noted that to improve the stability and reliability of the EEG patterns, an increasing number of works adopt external stimuli of different types, although in many cases these works do not propose a practical formalization of these systems usable in real-world contexts. This usually depends on a series of limitations such as, for example, the long data EEG acquisition times (Jayarathne et al., 2017).

A significant example of the above scenario is this work (Campisi and La Rocca, 2014), where the authors analyzed the brain activity for the automatic user recognition purpose, as well as in this work (Soni et al., 2016), where the authors instead propose a system that allows users to set a pattern of brain waves to perform the same task, combining eye blink, attention, and the *Alpha*, *Beta*, *Theta*, and *Delta* brain rhythms. Another significant work (Nakanishi and Hattori, 2017) exploits the EEG activity evoked by

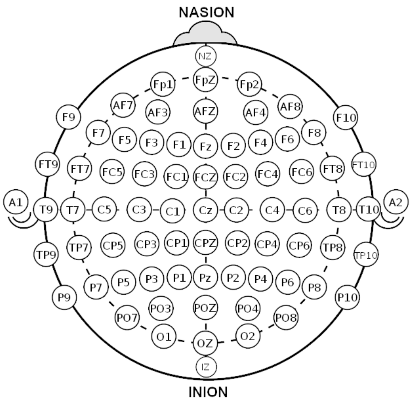

Figure 1: 10-20 System of Electrode Placement.

invisible visual stimulation as biometric approach, whereas this work (Reshmi et al., 2016) proposes an approach to brain biometric user recognition, and in this one (Abed and Abed, 2020) the authors formalize an authentication system based on the features of two brain waves, *Gamma* and *Beta*.

Evoked Potentials: An *Evoked Potential* (EP) (Walsh et al., 2005) is an electrical potential that is measured in an area of the nervous system, such as the brain, as a result of an external stimulus. These stimuli can be of different types, the most commonly used are the *Auditory Evoked Potentials* (AEPs) (Seha and Hatzinakos, 2018) (acoustical stimuli such as a short sound) and the *Visual Evoked Potentials* (VEPs) (Zhao et al., 2021) (visual stimuli such as a light flash). The EPs are widely used to evaluate the electrical activity related to specific areas of the brain or the spinal cord, this in order to diagnose neurological problems, and in the case of the brain that magnitude is in the order of a few microvolts at most.

An example of these approaches is the *Intermittent Photic Stimulation* (IPS) (Coull and Pedley, 1978), where a pair of glasses capable of emitting intermittent light are used, or devices capable of generate sound stimuli with different frequencies, such as in this study (Di et al., 2018), where the authors experimented the effect of intermittent pure tones at 50 and 6 phon (i.e., a logarithmic unit of loudness level for tones and complex sounds), using as frequency 125, 250, 500, 1000, and 4000 Hertz, and a duration of 10 seconds, demonstrating the relationships between the acoustic properties of stimuli and the EEG activity.

Other studies in the literature instead experimented the effect of the so-called binaural sounds (Colburn and Durlach, 1978), which are based on the brain perception of interaural differences during binaural stimulus (Blauert, 2013). In more detail, this technique inducts the brain to interpret as a single tone two different tones applied on the left and right ears (formally defined *carrier-tone* and *offset-tone*), where the detected single tone is given by the difference between the frequencies of these two ones. An interesting literature work (Rajan et al., 2018) evaluates the impact of binaural sounds in terms of their positive and negative impact in areas such as healthcare, security, education, and entertainment.

A recent work in literature (Zhao et al., 2021) compares the performance of three different VEP signals in the context of a VEP-based biometric user identification system, whereas another work (Rosli et al., 2021) takes into account the use of EEG data with visual stimuli for the same purpose, using the *Wavelet Packet Decomposition* (WPD) technique in the feature extraction process. With regard to the biometric user identification systems based on EEG data and auditory stimuli, in this work (Mukai and Nakanishi, 2020), the authors use ultrasound stimuli for the EEG stimulation, with the aim to avoid that the users can be distracted from their current activity during the identification process. For the sake of completeness, it should be added that although visual and auditory stimuli are the most commonly used in literature, some works use other type of stimuli such as, for instance, those based on vibrations (Nakashima et al., 2021).

However, it should be added that all the aforementioned approaches, as well as most of the others in the literature, do not have characteristics of performance, simplicity, and cost that make them suitable for widespread use as a biometric system.

Open Problems: Regardless of the technique/strategy used to define a biometric system based on EEG data, there are some well-known problems that reduce its practical feasibility, such as: the *Data Complexity*, which is given by the fact that the EEG data are complex, non-linear, and non-stationary (Mahato and Paul, 2019); the *Data Heterogeneity*, which depends on the fact that considerable differences exist in the EEG data related to different users (Jausovec, 1997); the *Data Calibration*, which is related to the need of a system calibration before the EEG data acquisition (Jayarathne et al., 2017); the *Data Diversity*, which depends on the difficulty of obtaining the same EEG patterns over time, due to multiple factors that influence users (Kaur et al., 2017).

Evaluation Metrics: The evaluation metrics largely adopted in the literature to evaluate the performance of the biometric systems based on the EEG data are mainly based on two rates, the *False Acceptance Rate* (FAR) and the *False Rejection Rate* (FRR) (Dahel and Xiao, 2003), which express, respectively, how many times a user is erroneously allowed access, and how many times a legitimate user is erroneously denied access. Another widely used metric based on the aforementioned two ones is the *Half Total Error Rate* (HTER), which is calculated as $HTER = \frac{(FAR+FRR)}{2}$, whereas the point at which we have the intersection of the FAR and FRR values is named *Equal Error Rate* (EER). The percentage of users correctly identified over their total number is the *Correct Recognition Rate* (CRR) metric is calculated as *TAR=1-FRR*.

Research Motivation: This work stems from the observation that, unlike other biometric user identification approaches (e.g., facial recognition, fingerprint recognition, retinal recognition, etc.), those based on EEG data are characterized in literature by a more theoretical than practical formalization, due to some intrinsic limitations. The most important of these are certainly the difficulty of obtaining EEG patterns that well characterize the user and that are stable over time, as well as a series of problems related to the preliminary configuration of the biometric system and the related acquisition time. In light of this observation, this work is aimed at formalizing a low-cost biometric identification system based on EEG data detected during an external stimulation of the users, which is practically usable in the real-world scenarios, although with some limitations, in order to provide a starting point for subsequent improvements.

Table 2: Experimental Environment.

Type	Version	Details	Reference
Experimental Workstation	Intel i7-6700	CPUs 3.40 GHz×8 RAM 16 GB	
EEG device	Muse Headband	Version 2	https://choosemuse.com
Operating system	Linux Debian 11	64 bit Kernel 5.10.0-9	https://www.debian.org https://www.kernel.org
Programming language/IDE	Python Eclipse PyDev	Version 3.9.2 Version 9.2.0	https://www.python.org https://www.pydev.org
Python libraries for EEG and external stimuli	AccelBrainBeat Scikit-learn eeglib Muse LSL	Version 1.0.5 Version 1.0.1 Version 0.4.1 Version 2.1.0	pypi.org/project/AccelBrainBeat https://scikit-learn.org https://github.com/Xiul109/eeglib https://github.com/alexandrebarachant/muse-lsl

3 APPROACH FORMALIZATION

The idea behind the proposed approach is mainly based on the differential analysis of EEG data recorded before and after the application on the subject of a series of stimuli: practically, we capture the brain waves activity in a defined time-frame, operating without the external stimuli for the half of time, and with them in the remaining time. We take into consideration all the brain waves types, read data from the *Muse LSL* stream, compute the average power of a signal in each specific frequency range in order to reduce the noise, according to the most widely used approach for the EEG data analysis, where the sensors data is decomposed into distinct frequency bands, i.e., $\delta = [0.5, 4]$ Hz, $\theta = [4, 8]$ Hz, $\alpha = [8, 12]$ Hz, $\beta = [12, 30]$ Hz, and $\gamma = [30, 100]$ Hz. The band power is calculated computing the one-dimensional *Discrete Fourier Transform* (DFT) using the *Fast Fourier Transform* (FFT) algorithm, which returns, for each frequency, a complex number that allows us to extract amplitude and phase of the signal at the desired frequency. The experimental environment in terms of the software and hardware will be composed by the elements reported in Table 2.

The steps that compose the proposed approach, whose high-level architecture is shown in Figure 2, are reported in the following:

- *Acquisition System Calibration:* verification of the correct positioning of the *Muse-2* device after the user wore the headband; this is performed by measuring the signal activity on each headband electrode using the *Muse LSL* library functionalities;
- *Unstimulated EEG Data Collection:* collection of the EEG data for half of a experimentally defined time-frame, without applying any external stimulus during the data acquisition; in this phase the signals relating to all the brain waves will be acquired, the most characterized of which will be selected later;
- *Stimulated EEG Data Collection:* collection of the EEG data for the remaining period of the time-frame, applying a series of external stimuli; the nature and type of stimuli will be defined experimentally using both visual (VEP) and auditory (AEP) stimuli at different intensities and frequencies;
- *Data Transform and Analysis:* elaboration of the collected data through the FFT algorithm, preprocessing techniques, and differential analysis of the EEG patterns; the EEG data collected with and without the external stimuli are compared in order to extract information that characterizes the way in which the user responds to external stimuli;
- *Data Comparing and Classification:* the obtained patterns are compared to the database of existing ones with the aim to identify the users; a tolerance margin is experimentally defined in this phase.

Future Direction: According to the experimental steps previously mentioned, we want to investigate the influence on the EEG signal of simple stimuli generated through flashing of the computer screen and environmental sounds. In other words, differently from the work in the literature we want to explore the feasibility of a system realized using only low-cost EEG device and simple stimuli that do not require additional hardware.

In this regard, although this work proposes only a theoretical formalization, a series of preliminary experiments was carried out on a small number of users, the results of which indicate the feasibility of the idea

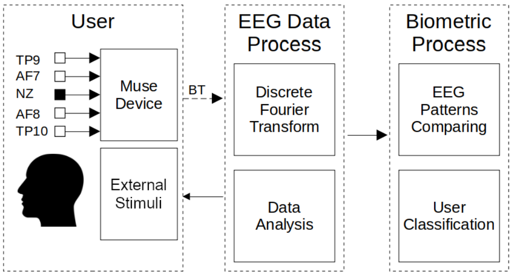

Figure 2: High-level Approach Architecture.

behind the proposed system, showing a greater characterization of the user and a better stability over time of the EEG patterns obtained through a comparative analysis of the EEG data collected before and after the application of an external stimulus (flashing of the computer screen), then without using dedicated hardware for its generation. These results must subsequently be verified and validated in depth using a significant number of users, as well as concerning different stimul and data analysis and classification techniques. Besides defining a low-cost affordable EEG-based biometric approach to user identification, our work will be facing the open issues previously described by experimenting with techniques already used in some previous works, such as, the *feature engineering* (Carta et al., 2020; Heaton, 2016), the *feature space transformation* (Saia et al., 2020), the *training data decomposition* (Saia et al., 2021), and the *data enrichment/discretization* (Saia et al., 2019a; Saia et al., 2019b). An automatic data calibration algorithm will be also developed to reduce the time of the initial process of data recognition, in the context of the *Muse-2* device functionalities will be exploited. The data diversity will be instead faced by the adoption of differential data patterns given by the comparison of the data collected before and after the application of external stimuli.

4 CONCLUSIONS

This work aimed to verify the existence of conditions that justified subsequent experimentation for practically formalizing a biometric user identification system based on EEG data acquired under the effect of external visual stimulation, to face some well-known problems related to the difficulty to obtain stable characterizing EEG patterns. The performed study of the current literature and the results obtained in our preliminary experimentation indicate the existence of such conditions, albeit with limitations whose impact will be quantified through future experiments.

Unlike most of the works in the literature, this work proposes an affordable biometric system based on low-cost hardware for the detection of EEG signals, and on an approach of generating external stimuli based on existing devices (i.e., the computer screen), therefore without the need to use dedicated devices for this purpose (e.g., flash-emitting glasses). This combination was designed to allow us a wide use of the system that will be used in many real-world contexts, perhaps combined with other different widespread biometric approaches in order to face the EEG limitations, improving the reliability of the biometric system.

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REFERENCES

Abed, S. S. and Abed, Z. F. (2020). User authentication system based specified brain waves. *Journal of Discrete Mathematical Sciences and Cryptography*, 23(5):1021–1024.

Blauert, J. (2013). *The technology of binaural listening*. Springer.

Campisi, P. and La Rocca, D. (2014). Brain waves for automatic biometric-based user recognition. *IEEE transactions on information forensics and security*, 9(5):782–800.

Carta, S., Podda, A. S., Recupero, D. R., and Saia, R. (2020). A local feature engineering strategy to improve network anomaly detection. *Future Internet*, 12(10):177.

Colburn, H. S. and Durlach, N. I. (1978). Models of binaural interaction. *Handbook of perception*, 4:467–518.

Coull, B. M. and Pedley, T. A. (1978). Intermittent photic stimulation. clinical usefulness of non-convulsive responses. *Electroencephalography and Clinical Neurophysiology*, 44(3):353–363.

Dahel, S. and Xiao, Q. (2003). Accuracy performance analysis of multimodal biometrics. In *IEEE Systems, Man and Cybernetics SocietyInformation Assurance Workshop, 2003.*, pages 170–173. IEEE.

Di, G.-Q., Fan, M.-C., and Lin, Q.-H. (2018). An experimental study on eeg characteristics induced by intermittent pure tone stimuli at different frequencies. *Applied Acoustics*, 141:46–53.

Fraschini, M., Pani, S. M., Didaci, L., and Marcialis, G. L. (2019). Robustness of functional connectivity metrics for eeg-based personal identification over task-induced intra-class and inter-class variations. *Pattern Recognition Letters*, 125:49–54.

Heaton, J. (2016). An empirical analysis of feature engineering for predictive modeling. In *SoutheastCon 2016*, pages 1–6. IEEE.

Homan, R. W., Herman, J., and Purdy, P. (1987). Cerebral location of international 10–20 system electrode placement. *Electroencephalography and clinical neurophysiology*, 66(4):376–382.

Jausovec, N. (1997). Differences in eeg activity during the solution of closed and open problems. *Creativity Research Journal*, 10(4):317–324.

Jayarathne, I., Cohen, M., and Amarakeerthi, S. (2017). Survey of eeg-based biometric authentication. In *2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST)*, pages 324–329. IEEE.

Kaur, B., Kumar, P., Roy, P. P., and Singh, D. (2017). Impact of ageing on eeg based biometric systems. In *2017 4th IAPR Asian Conference on Pattern Recognition (ACPR)*, pages 459–464. IEEE.

Mahato, S. and Paul, S. (2019). Detection of major depressive disorder using linear and non-linear features from eeg signals. *Microsystem Technologies*, 25(3):1065–1076.

Mukai, K. and Nakanishi, I. (2020). Introduction of fractal dimension feature and reduction of calculation amount in person authentication using evoked eeg by ultrasound. In *2020 IEEE REGION 10 CONFERENCE (TENCON)*, pages 567–572. IEEE.

Nakanishi, I. and Hattori, M. (2017). Biometric potential of brain waves evoked by invisible visual stimulation. In *2017 International Conference on Biometrics and Kansei Engineering (ICBAKE)*, pages 94–99. IEEE.

Nakanishi, I. and Maruoka, T. (2019). Biometric authentication using evoked potentials stimulated by personal ultrasound. In *2019 42nd International Conference on Telecommunications and Signal Processing (TSP)*, pages 365–368. IEEE.

Nakashima, H., Shindo, Y., and Nakanishi, I. (2021). Performance improvement in user verification using evoked electroencephalogram by imperceptible vibration stimuli. In *2021 20th International Symposium on Communications and Information Technologies (ISCIT)*, pages 109–113. IEEE.

Prathibha, R., Swetha, L., and Shobha, K. (2017). Brain computer interface: Design and development of a smart robotic gripper for a prosthesis environment. In *2017 International conference on networks & advances in computational technologies (NetACT)*, pages 278–283. IEEE.

Rajan, A., Hashim, A., Akre, V., Walid, H., Nassiri, N., and Ahmed, M. (2018). The impacts of binaural beats. In *2018 Fifth HCT Information Technology Trends (ITT)*, pages 353–357. IEEE.

Reshmi, K., Muhammed, P. I., Priya, V., and Akhila, V. (2016). A novel approach to brain biometric user recognition. *Procedia Technology*, 25:240–247.

Rosli, F. A., Saidatul, A., Abdullah, A. A., and Navea, R. F. (2021). The wavelet packet decomposition features applied in eeg based authentication system. In *Journal of Physics: Conference Series*, volume 1997, page 012035. IOP Publishing.

Saia, R., Carta, S., Recupero, D. R., and Fenu, G. (2020). A feature space transformation to intrusion detection systems. In *KDIR*, pages 137–144.

Saia, R., Carta, S., Recupero, D. R., Fenu, G., and Saia, M. (2019a). A discretized enriched technique to enhance machine learning performance in credit scoring. In *KDIR*, pages 202–213.

Saia, R., Carta, S., Recupero, D. R., Fenu, G., and Stanciu, M. (2019b). A discretized extended feature space (defs) model to improve the anomaly detection performance in network intrusion detection systems. In *KDIR*, pages 322–329.

Saia, R., Podda, A. S., Fenu, G., and Balia, R. (2021). Decomposing training data to improve network intrusion detection performance. In *KDIR*, pages 241–248. SCITEPRESS.

Seha, S. N. A. and Hatzinakos, D. (2018). Human recognition using transient auditory evoked potentials: a preliminary study. *IET Biometrics*, 7(3):242–250.

Soni, Y. S., Somani, S., and Shete, V. (2016). Biometric user authentication using brain waves. In *2016 International Conference on Inventive Computation Technologies (ICICT)*, volume 2, pages 1–6. IEEE.

Sterman, M. B. (1996). Physiological origins and functional correlates of eeg rhythmic activities: implications for self-regulation. *Biofeedback and Self-regulation*, 21(1):3–33.

Thakor, N. V. and Sherman, D. L. (2013). Eeg signal processing: Theory and applications. In *Neural Engineering*, pages 259–303. Springer.

Thomas, K. P. and Vinod, A. P. (2018). Eeg-based biometric authentication using gamma band power during rest state. *Circuits, Systems, and Signal Processing*, 37(1):277–289.

Walsh, P., Kane, N., and Butler, S. (2005). The clinical role of evoked potentials. *Journal of neurology, neurosurgery & psychiatry*, 76(suppl 2):ii16–ii22.

Xavier, G., Ting, A. S., and Fauzan, N. (2021). P-eg002. an exploratory study of brain waves and corresponding brain regions of fatigue post-call doctors using quantitative electroencephalogram. *Clinical Neurophysiology*, 132(8):e78.

Yang, S. and Deravi, F. (2017). On the usability of electroencephalographic signals for biometric recognition: A survey. *IEEE Transactions on Human-Machine Systems*, 47(6):958–969.

Zhao, H., Chen, Y., Pei, W., Chen, H., and Wang, Y. (2021). Towards online applications of eeg biometrics using visual evoked potentials. *Expert Systems with Applications*, 177:114961.