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Brainwaves in Biometric Identification: A Theoretical Framework and Novel Methodology

Agyhullámok a biometrikus azonosításban: elméleti keretrendszer és új módszertan

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Abstract — **This paper provides a thorough overview of biometric identification methods, including fingerprints, facial recognition, iris scans, voice patterns, and brainwaves. The unique features are examined of each type and their success rates, False Acceptance Rates (FAR), and False Rejection Rates (FRR) are compared to highlight their strengths and weaknesses. A novel method utilizing frontal beta brainwaves is also introduced for biometric identification with electroencephalography (EEG). This approach offers better security and reliability, potentially setting a new standard in biometric systems. Although not described in detail, its benefits are outlined, and future advancements are anticipated in brainwave-based biometrics. Our goal is to help the understanding and application of biometric systems, offering new insights and possibilities for secure and reliable identification methods. This work aims to push the boundaries of biometric research and pave the way for future innovations in secure identification.**

Keywords: brainwaves, biometric identification, beta brainwaves, EEG, FRR, FAR

Összefoglalás — **Ez a tudományos tanulmány átfogó áttekintést nyújt a biometrikus azonosítás különböző módszereiről, beleértve az ujjlenyomatot, arcfelismerést, íriszszkennert, hangmintázatokat és az agyhullámokat. Vizsgáljuk minden egyes típus egyedi jellemzőit, és összehasonlítjuk sikerességi arányukat, a téves elfogadási rátát (False Acceptance Rate, FAR) és a téves elutasítási rátát (False Rejection Rate, FRR), hogy kiemeljük erősségeiket és gyengeségeiket. Ezen felül bemutatunk egy új, elektroenkefalográfián (EEG) alapuló módszert, amely a frontális béta agyhullámokat használja biometrikus azonosításra. Ez a megközelítés nagyobb biztonságot és megbízhatóságot ígér, és potenciálisan új mércét állíthat fel a biometrikus rendszerek terén. Bár a módszer részletes technikai leírását ebben a cikkben nem fejlesztjük ki teljes részletességgel, vázoljuk előnyeit, és bizakodással tekintünk a jövőbeni fejlesztések felé az agyhullám-alapú biometria terén. Célunk a biometrikus rendszerek jobb megértésének és alkalmazásának elősegítése, új betekintéseket és lehetőségeket kínálva a biztonságos és megbízható azonosítási módszerek területén. Munkánk arra törekszik, hogy kitágítsa a biometriai kutatások határait, és megalapozza a jövőbeni innovációkat a biztonságos azonosításban.**

Kulcsszavak: agyhullámok, biometrikus azonosítás, béta agyhullámok, EEG, FRR, FAR

1 INTRODUCTION

The science of biometrics dates back several centuries but was accepted first as a scientific system used by the police to identify criminals in the 19th century, when Alphonse Bertillon developed a method for identifying criminals based on body measurements. This field advanced significantly in the 20th century with the introduction of fingerprint recognition, and has continued to evolve with technological advancements. Currently, biometric identification is a crucial component of security systems, providing a reliable and efficient means of verifying identity in various applications, ranging from law enforcement to personal device security. This paper investigates the theoretical foundations of biometric identification, comparing different types of biometric data and their effectiveness.

Biometric identification is a method of recognizing individuals based on unique physical and behavioural characteristics. Such biometric data includes fingerprints, facial features, iris patterns, voice characteristics, and even brainwave patterns. Biometric identification is defined as the utilization of these unique traits to authenticate or identify individuals.

2 BIOMETRIC IDENTIFICATION TYPES

Biometric identification methods are essential tools for verifying individual identities by analysing unique physical and behavioural traits.

2.1 Fingerprint Recognition

Fingerprint recognition involves analysing the unique ridge and valley patterns found on an individual's fingertip. Each person's fingerprint is unique, making this method highly reliable for identity verification. The technology operates by capturing an image of the fingerprint, then processing, and comparing it to a stored template to verify identity. Despite its widespread use, fingerprint recognition may be influenced by dermatological conditions or injuries. [1]

2.2 *Iris Recognition*

Iris recognition analyses the unique patterns in the coloured ring (iris) surrounding the pupil of the eye. The process involves capturing a detailed image of the iris, which is then converted into a digital template for comparison. Iris patterns are stable throughout a person's life, making this method highly reliable. However, it requires the subject to be relatively close to the camera, which can be a limitation in some scenarios. [2]

2.3 *Facial Recognition*

Facial recognition identifies individuals based on distinctive features of their faces, such as the distance between the eyes, nose shape, and jawline. Advanced algorithms analyse a captured image or video of a face and compare it to stored templates. While facial recognition is convenient and not intrusive, it can be affected by changes in appearance due to aging, makeup, or facial hair, and even varying lighting conditions. [3]

2.4 *Voice Recognition*

Voice recognition uses vocal traits for identity verification. Each person's voice has unique characteristics, such as pitch, tone, and cadence, which can be analysed and used for secure access to devices and services. The technology records a voice sample, extracts features, and matches them against a stored voiceprint. However, it can be influenced by background noise, or vocal changes caused by illness. [4]

2.5 *Retina Scanning*

Retina scanning examines the unique pattern of blood vessels at the back of the eye. This method requires close proximity to the scanning device, ensuring high accuracy. The process involves shining low-intensity light into the eye and capturing the reflection from the retina. While it is highly secure, retina scanning can be uncomfortable for users and requires heavily specialized equipment. [5]

2.6 *Hand Geometry Recognition*

Hand geometry recognition studies the shape and structure of an individual's hand, including the length and width of fingers and the contours of the palm. Hand geometry scanners capture an image of the hand and compare it to a stored template. [6]

2.7 *Vein Recognition*

Vein recognition maps the unique pattern of veins in a person's palm or finger. This method provides high security because vein patterns are difficult to replicate and are located beneath the skin's surface, making them less susceptible to external damage or alteration. The technology uses near-infrared light to capture an image of the veins, which is then processed and compared to stored templates. [7]

2.8 *Gait Recognition*

Gait recognition analyses an individual's walking pattern, which is unique and can be used for continuous identification and surveillance. This method captures and analyses the motion dynamics and rhythm of a person's gait through video footage or wearable sensors. However, it can be influenced by changes in walking conditions, such as injuries. [8]

2.9 *Ear Recognition*

Ear recognition focuses on the unique morphological features of an individual's ear. This method holds potential in various environments due to the distinctiveness of ear features and their stability over time. Ear recognition systems capture an image of the ear and compare it to stored templates. [9]

2.10 *DNA Matching*

DNA matching involves comparing genetic codes to verify identity, making it vital in forensic analysis and paternity tests. Each person's DNA is unique, except for identical twins, providing a definitive means of identification. DNA samples can be collected from biological samples containing blood, hair, skin cells, or other biological materials. While highly accurate, DNA matching is time-consuming and requires specialized laboratory equipment, making it unsuitable for real-time identification. [10]

3 FAR AND FRR BASED ANALYSIS

3.1 *FAR*

The False Acceptance Rate (FAR) is the probability that a biometric security system will incorrectly accept an unauthorized person as an authenticated user. It quantifies the likelihood of the system misidentifying an individual, allowing access to someone who should be denied. [11]Calculation of the FAR is presented in equation (1).

$$FAR = \frac{Nfp}{Nfp + Ntn} 100\% \quad (1),$$

where *Nfp* denotes the number of false positives, and *Ntn* represents the

number of true negatives.

3.2 *FRR*

The False Rejection Rate (FRR) is the probability that a biometric security system incorrectly rejects an authorized person. It measures the likelihood of the system failing to recognize a legitimate user, denying them access. Calculation of the FRR is determined as shown in equation (2) [11]:

$$FRR = \frac{Nfn}{Nfn + Ntp} 100\%, \quad (2)$$

where *Nfn* denotes the number of false negatives, and *Ntp* corresponds tonumber of true positives.

3.3 *Overall Error*

By summing the FAR and FRR values upand dividing the resultant value by the total number of accesses, one may calculate the overall error rate (3). [11]

$$Error = FAR + FRR. \quad (3)$$

3.4 TAR and TRR

3.4.1 True Acceptance Rate (TAR): The probability that a biometric system correctly accepts an authorized user. [12]

$$TAR = 1 - FRR \quad (4)$$

3.4.2 True Rejection Rate (TRR): The probability that a biometric system correctly rejects an unauthorized user. [12]

$$TRR = 1 - FAR \quad (5)$$

4 FAR AND FRR RATES OF MOST USED BIOMETRIC IDENTIFICATION METHODS

4.1 The False Rejection Rate (FRR) and False Acceptance Rate (FAR) for Fingerprint Recognition Systems

Fingerprint recognition systems have been extensively studied due to their widespread use in security applications. Numerous studies have highlighted the performance of these systems under different conditions.

4.1.1 Robust Partial Fingerprint Recognition:

Baseline models show an FRR ranging from 14.67% to 17.57% at an FAR of 0.1% under challenging conditions such as a 10% occlusion ratio. Improved models have reduced the FRR to 9.99% under the same conditions. [13]

4.1.2 US-VISIT System:

The US-VISIT study demonstrated a True Acceptance Rate (TAR) of approximately 96%, corresponding to an FRR of approximately 4%, with an FAR of 0.09% for a large database of 6 million fingerprints. Using high-quality fingerprint images, the TAR increased to 98% (FRR of 2%) at an FAR of 0.01%. [14]

4.1.3 Optical Spatial-Frequency Correlation System (OSC):

This system achieved an FRR and FAR balance point (Equal Error Rate or EER) at around 0.527. Under real-world conditions, the performance of this system was found to be very high, with significant accuracy improvements compared to commercial systems. [15]

4.1.4 General Findings from Multiple Studies:

The performance of fingerprint systems can vary widely. For example, the TAR ranged from 56.10% to 99.01% when the FAR was held constant at 0.01% in various tests. State-of-the-art systems achieved TARs greater than 98%, indicating an FRR of less than 2% at this FAR threshold. [16]

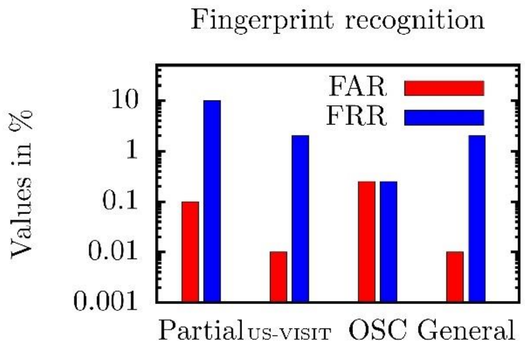

Figure 1: Statistical representation of the different FAR and FRR rates in fingerprint recognition

4.2 FRR and FAR for Iris Recognition Systems

Iris recognition is highly regarded for its precision and reliability. Multiple studies have examined the performance of these systems.

4.2.1 Study on Combined Feature Extraction Methods:

This study utilized databases such as CASIA V1.0 and MNU V.2. The reported results for the CASIA V1.0 database showed an FAR of approximately 0.02% and an FRR of around 0.19%. [12]

4.2.2 Review of Different Iris Recognition Techniques:

In a comprehensive review of various techniques, including the use of Gabor filters and wavelet transforms, the FRR and FAR were found to be highly dependent on the feature extraction and matching algorithms used. Typical values from reviewed studies showed FAR values ranging from 0.1% to 0.5% and FRR values from 0.5% to 1.5%. [18]

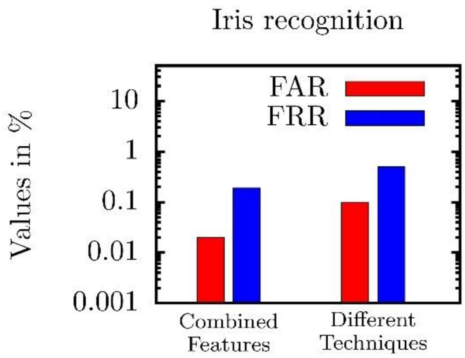

Figure 2: Statistical representation of the different FAR and FRR rates in iris recognition

4.3 Facial Recognition FRR and FAR Study Results

4.3.1 NIST Study on Face Recognition Algorithms:

The National Institute of Standards and Technology (NIST) has conducted extensive evaluations of facial recognition algorithms through its Face Recognition Vendor Test (FRVT) program. Their studies revealed significant variation in accuracy among different algorithms. In their 2019 evaluation, NIST found that the most accurate algorithms could achieve very low error rates: False Acceptance Rates (FAR) of approximately

0.25% and similarly low False Rejection Rates (FRR) for specific demographic groups. However, the performance varied considerably across demographics, with error rates sometimes differing by factors ranging from 10 to 100 times depending on the algorithm and the demographic group in question. [19]

4.3.2 Multimodal Biometric System Study:

A study published in the International Journal of Intelligent Unmanned Systems examined a multimodal biometric system combining facial and voice recognition using K-Nearest Neighbours (KNN) classifier. This system reported a FAR of 0.5% and an FRR of 0.75%, showcasing the improved accuracy when integrating multiple biometric modalities. [20]

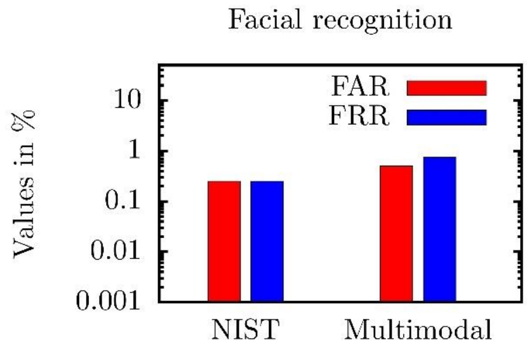

Figure 3: Statistical representation of the different FAR and FRR rates in facial recognition

4.4 FRR and FAR for Voice Recognition Systems

4.4.1 Multimodal Biometric System Using KNN Classifier:

In a study that incorporated both facial and voice recognition, the system achieved a FAR of 0.5% and an FRR of 0.75%. This study utilized algorithms such as the Viola-Jones method for face detection and Mel-frequency cepstral coefficients for processing voice data, which were integrated using a KNN classifier. [21]

4.5 FRR and FAR for Retina Scanning

4.5.1 FRR and FAR Values:

A study reported that retina scanning has a False Rejection Rate (FRR) of 1.8%, which underscores its high accuracy in identifying individuals correctly. The False Acceptance Rate (FAR) for retina scanning has been reported to be extremely low, with some findings suggesting an error rate as low as 1 in 10 million. [22]

4.5.2 Effect of Distance from the Sensor:

Retina scanning requires close proximity to the scanning device, similar to looking through a microscope. This necessity for closeness means that any deviation from the optimal distance may negatively impact the accuracy and effectiveness of the scan. This requirement necessitates user compliance and comfort with the scanning procedure, as maintaining the correct position is crucial for accurate readings. This need for precise positioning and the potential discomfort it causes may contribute to higher FRR if the user moves or fails to position their eye correctly. [22]

4.6 Hand Geometry Recognition: FRR and FAR Metrics

4.6.1 Hand Geometry and Vascular Patterns Study:

This study combined hand geometry and vascular patterns for biometric recognition, achieving high recognition accuracy. The reported Equal Error Rate (EER), representing the point at which FAR and FRR are equal, was 0.06%. While the study focuses on EER, this low value suggests that both FAR and FRR are minimal. [23]

4.6.2 General Hand Geometry Recognition:

Hand geometry systems typically exhibit FARs and FRRs ranging from 0.1% to 0.2%. These figures indicate high reliability in distinguishing between authorized and unauthorized users. [23]

4.6.3 Neural Network-Based Hand Geometry Recognition:

A research project employing neural networks for hand geometry recognition reported an FAR of 0.13% and an FRR of 0.14%. These values reflect the robustness of neural network classifiers in improving the accuracy of biometric systems. [24]

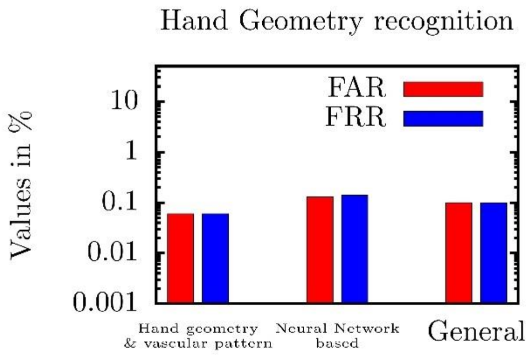

Figure 4: Statistical representation of the different FAR and FRR rates in hand geometry recognition

4.7 FRR and FAR of Vein Recognition

FRR and FAR results from recent studies on vein recognition, particularly finger vein and hand vein recognition.

4.7.1 Finger Vein Recognition:

A systematic review on finger vein recognition techniques reported that modern algorithms have improved significantly. The study indicated that some advanced methods achieve FRRs as low as 0.15% and FARs of around 0.1% [25]

Another study utilizing a convolutional neural network (CNN) for finger vein recognition reported an FRR of 0.11% and an FAR of 0.07%, highlighting the high accuracy and reliability of CNN-based methods. [26]

4.7.2 Hand Vein Recognition:

A study focusing on dorsal hand vein recognition using CNNs found that FRR and FAR could be reduced to 1.2% and 1.5%, respectively, when using a feature learning and transfer learning approach [27]

Another research highlighted that using a combination of texture and shape clues in hand vein recognition resulted in an FRR of 1.34% and an FAR of 1.05%, demonstrating the effectiveness of multimodal feature integration. [27]

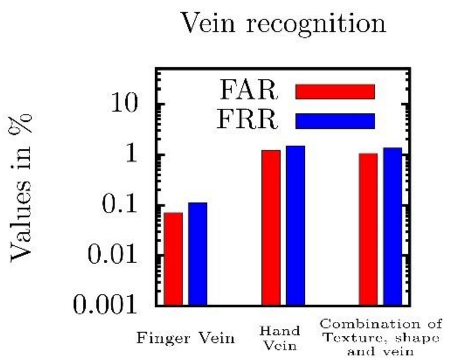

Figure 5: Statistical representation of the different FAR and FRR rates in vein recognition

4.8 False Rejection Rate (FRR) and False Acceptance Rate (FAR) of Gait Recognition

4.8.1 Security and Privacy Enhanced Gait Authentication:

This study reported an FRR of 4.17% and an FAR of 0% using gait data from specific datasets, including OU-ISIR. [28]

4.8.2 OpenGait Benchmark Study:

An in-depth analysis in the OpenGait study highlighted the practical challenges and performance variations across different environmental conditions. It reported that certain advanced models could achieve an FRR of 5.44% and FAR of 0.05% under optimized, controlled settings. [29]

4.8.3 *Gait Recognition using CNNs:*

A study focusing on convolutional neural network (CNN) models for gait recognition achieved an FRR of 3.2% and an FAR of 2.1%, demonstrating the potential of deep learning techniques in improving gait recognition accuracy. [30]

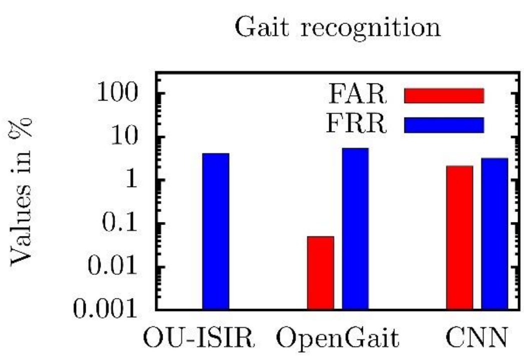

Figure 6: Statistical representation of the different FAR and FRR rates in gait recognition

4.9 An overview of the FAR and FRR rates

Table 1: Comparative summary of FAR and FRR rates

	4.1	4.2	4.3	4.4	4.5	4.6	4.7	4.8
FAR	0.01%	0.02%	0.5 %	0.5 %	-*	0.1 %	0.07%	2.1 %
FRR	2%	0.19%	0.75%	0.75%	1.8 %	0.1 %	0.11%	3.2 %

The values presentedin the table represent the most favourable for each type of biometric identification method.

* No conclusive FAR value was reported for retina scanning. For further details, see section (4.5), as the number from 4.1 to 4.8 corresponds to the subsection numbers.

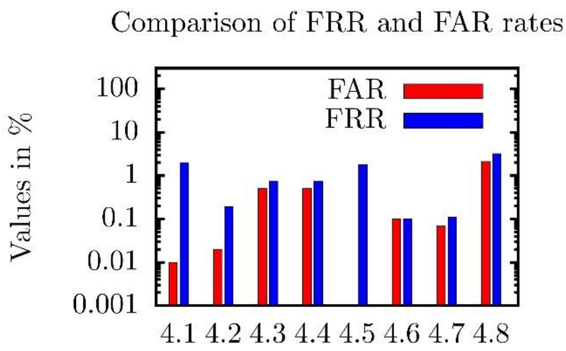

Figure 7: Statistical representation of the different FAR and FRR rates across different biometric identification methods

As observed, FAR and FRR rates are impressively small throughout every method of biometric identification type, however, these statistical numbers represent measurements taken in ideal laboratory conditions, where no attempts at impersonation were present. There are multiple weak points to each of the methods (as mentioned above in the definitions of the methods), some of which are easier to exploit than others.

Accordingly, the pursuit for a safer biometric identification method still continues. One possible solution to such an impossible task might be brainwave-based identification.

5 Brainwave Biometric Identification - Theoretical Background

5.1 Overview

Brainwaves are electrical patterns generated by the synchronized firing of neurons in the brain. There are several types of brainwaves, each associated with different states of consciousness and mental activities. . These electrical signals generate electromagnetic waves, and their measurement through electroencephalography (EEG) unveils the dynamic landscape of neural activity. Neurons, the fundamental units of the brain, communicate through electrical impulses.

5.2 Types of brainwaves

When large groups of neurons fire in a coordinated manner, they produce distinct and measurable wave patterns. These patterns are categorized based on their frequency, measured in Hertz (Hz), and are related to distinct mental states.

5.2.1 Alpha brainwaves (8 – 13 Hz)

Alpha waves are associated with a relaxed and alert state of consciousness. They are typically observed when the mind is calm, such as during meditation or light relaxation. Alpha waves are also observed when the eyes are closed but the individual is not asleep. Increased alpha activity may enhance learning, concentration, and mental coordination. [33]

5.2.2 Beta brainwaves (13 – 30 Hz)

Beta waves are associated with active, analytical thought and concentration. They predominate during wakefulness, especially when engaged in problem-solving, decision-making, or focused mental tasks. Higher beta frequencies are associated with stress and anxiety, while lower beta frequencies are linked to heightened alertness and cognitive engagement.

Different categorization methods: Categorizing beta brainwaves involves various methods aimed at discerning distinct aspects of their activity, contributing to a nuanced understanding of cognitive states. This enables researchers and clinicians to interpret neural dynamics comprehensively. Several categorization methods for beta brainwaves encompass frequency bands, task-related changes, and spatial distribution.

Spatial Distribution:

Rolandic beta brainwaves: Rolandic beta waves originate in the sensorimotor cortex, playing a crucial role in motor planning and execution. These waves are implicated in motor functions and are often observed during movement preparation. [31], [34]

Frontal beta brainwaves: Frontal beta waves emanate from the frontal lobe, contributing to higher cognitive functions, decision-making, and executive control. Frontal beta activity is linked to active mental engagement, attentional control, and complex cognitive processes. [31], [34]

5.2.3 Gamma brainwaves (30 – 100 Hz)

Gamma waves are the fastest brainwaves and are associated with high-level cognitive functions, such as memory recall and problem-solving. They are further linked to peak states of concentration and heightened perception. Gamma waves are thought to play a role in integrating information across different brain regions and are associated with moments of insight and learning.[33]

5.2.4 Theta brainwaves (4 - 8 Hz)

Theta waves are commonly present during light sleep, deep relaxation, and meditation. They are also associated with creativity, intuition, and a dream-like state. Theta waves play a role in memory consolidation and are often observed during the early stages of sleep or when engaged in activities requiring a focused, yet relaxed, state of mind. [38]

5.2.5 Delta brainwaves (0.4 – 4 Hz)

Delta waves are the slowest brainwaves and are most prominent during deep sleep. They are associated with the restorative and healing functions of sleep, including physical rejuvenation and immune system maintenance. Delta waves are crucial for overall well-being and are indicative of the deepest stages of non-REM sleep. [33]

5.3 Types of identification brainwave methods

Brainwave identification, a subtype of biometrics, uses the brain's unique electrical patterns as a distinguishing characteristic. Several methods have been used to extract these different patterns.

5.3.1 Power Spectral Density – PSD

PSD is a fundamental signal processing technique that decomposes a signal into its constituent frequency components. In the context of brainwaves, PSD provides a spectral representation of brain activity. By quantifying the power distribution across different frequency bands (delta, theta, alpha, beta, gamma), PSD offers insights into the overall brain state and cognitive processes. For identification, variations in the spectral power distribution across individuals can serve as discriminating features. [35]

5.3.2 Geometrical Approach

Geometrical features focus on the shape and form of brainwave signals. Fractal dimension metrics quantify the complexity and self-similarity of the EEG signal and serve as discriminative features. Additionally, techniques like principal component analysis (PCA) and independent component analysis (ICA) are applied to reduce dimensionality and extract underlying components. [36]

5.3.3 Machine Learning

Machine learning algorithms excel at finding patterns in complex datasets. Support Vector Machines (SVMs), Random Forests, and Artificial Neural Networks (ANNs) are commonly used for brainwave classification. These algorithms can learn to differentiate individuals based on extracted features. [32,37]

5.3.4 Time-Frequency Analysis with Wavelet Transform

The wavelet transform offers a powerful tool for analysing the time-frequency characteristics of brainwaves. By decomposing the signal into different frequency components at different time scales, it reveals how brain activity evolves over time. Wavelet coefficients can be used as features for classification, capturing both the spectral and temporal aspects of brainwave patterns. [38]

5.3.5 Dynamic Time Warping – DTW

DTW is a versatile algorithm for comparing time series data, making it suitable for beta wave analysis. It allows for non-linear alignment of two time series, accommodating variations in speed and rhythm. By calculating the distance between two beta wave sequences using DTW, it's possible to assess their similarity and determine if they originate from the same individual. [39]

5.3.6 Hidden Markov Models

HMMs are probabilistic models that are well-suited for capturing the temporal dynamics of brain signals. By modelling brainwave sequences as a hidden Markov process, it's possible to represent the underlying states and transitions between them. HMMs can be used for both classification and generation of synthetic brainwave patterns. [40]

5.3.7 *Entropy Measures for Complexity Analysis*

Entropy quantifies the degree of disorder or randomness in a system. Applied to brainwaves, it can quantify the complexity and variability of brain activity. Individuals might exhibit distinct entropy levels in their brainwave patterns, providing another feature for identification. [41,42]

5.4 *Measuring brainwaves*

Brainwave measurement technologies record and analyse the electrical activity produced by neurons in the brain. These techniques are critical for studying brain function and detecting neurological disorders. Various approaches have distinct advantages in terms of temporal and spatial resolution, invasiveness, and practical use.

5.4.1 *EEG – Electroencephalography*

Electroencephalography (EEG) is one of the most used brainwave measurement methods. It involves placing electrodes on the scalp to detect and record the electrical activity generated by neurons. EEG captures brainwaves in real-time, offering high temporal resolution, which makes it particularly useful for studying dynamic brain activities such as sleep, cognition, and epileptic seizures. The process begins with strategically placing electrodes on the scalp, usually following the International 10-20 system. The electrodes pick up electrical signals produced by neuronal activity, which are then amplified and recorded for further analysis. EEG is widely used in clinical diagnosis for conditions like epilepsy, sleep disorders, and brain injuries, as well as in research settings to study cognitive processes and brain functions. Despite its advantages, EEG has limited spatial resolution and is prone to artifacts from muscle movements and external electrical sources. [43]

5.4.2 *MEG – Magnetoencephalography*

Magnetoencephalography (MEG) measures the magnetic fields produced by neural activity, providing high temporal resolution comparable to EEG but with better spatial accuracy. MEG sensors detect the magnetic fields generated by neuronal activity, which are then recorded and mapped to localize the source of the brain activity. This technique is highly valuable for clinical applications, such as mapping brain function prior to surgery, especially for epilepsy patients. It is also used extensively in research to study brain dynamics and functional connectivity. While MEG offers improved spatial resolution over EEG, it is more expensive and requires specialized facilities. Additionally, MEG is sensitive to head movements, which can affect the quality of the data. [44]

5.4.3 *fMRI - Functional Magnetic Resonance Imaging*

Functional Magnetic Resonance Imaging (fMRI) indirectly measures brain activity by detecting changes in blood flow and oxygenation levels, offering excellent spatial resolution. The fMRI process involves placing the subject in an MRI scanner, where a strong magnetic field is applied. The scanner detects changes in blood flow and oxygenation associated with neural activity, collecting data over time to map brain activity. This method is particularly useful for identifying brain regions affected by stroke, tumours, or neurological disorders, and for investigating brain function and cognitive processes. However, fMRI has slower temporal resolution compared to EEG and MEG, is expensive, and may cause discomfort due to the confined space of the MRI scanner. [45]

5.4.4 *NIRS - Near-Infrared Spectroscopy*

Near-Infrared Spectroscopy (NIRS) uses light to monitor changes in blood oxygen levels in the brain, providing a portable and non-invasive method for measuring brain activity. NIRS devices emit near-infrared light into the scalp, which penetrates the brain and is absorbed differently by oxygenated and deoxygenated blood. Detectors measure the reflected light, offering information about blood oxygen levels and, consequently, brain activity. NIRS is used in clinical monitoring, cognitive research, and portable applications such as field studies. Its advantages include portability, non-invasiveness, and real-time monitoring capabilities. [46]

5.4.5 *fNIRS - Functional Near-Infrared Spectroscopy*

Functional Near-Infrared Spectroscopy (fNIRS) is a variation of NIRS that measures brain activity by detecting changes in blood oxygenation levels during cognitive tasks. The process involves emitting near-infrared light into the scalp, which is absorbed differently by oxygenated and deoxygenated blood. Detectors measure the reflected light, providing information on blood oxygen levels. fNIRS is applied in cognitive research, clinical applications, and portable applications such as field studies. [47]

5.4.6 *PET - Positron Emission Tomography*

Positron Emission Tomography (PET) involves injecting radioactive tracers to visualize brain activity, providing insights into metabolic processes and neurotransmitter functions. The process starts with injecting a radioactive tracer into the bloodstream, which accumulates in areas of high activity. The PET scanner detects the gamma rays emitted by the tracer, and the data are reconstructed into images showing tracer concentration. PET is used for clinical diagnosis, research, and drug development, offering unique insights into brain metabolism and chemistry. However, PET requires the injection of radioactive tracers, is expensive, and has slower temporal resolution compared to EEG and MEG. [48]

5.4.7 *SPECT - Single Photon Emission Computed Tomography*

Single Photon Emission Computed Tomography (SPECT) is analogous to PET but uses different tracers and detection methods. After injecting a radioactive tracer into the bloodstream, the SPECT scanner detects gamma rays emitted by the tracer, and the data are reconstructed into 3D images showing tracer distribution. SPECT is used in clinical diagnosis, neuroscience research to assess brain perfusion, detect seizures, and diagnose dementia. While SPECT provides functional imaging and can image deep brain structures, it requires radioactive tracers, has lower spatial and temporal resolution compared to PET and fMRI, and involves exposure to small amounts of radiation. [49]

6 INTRODUCING A NEW METHOD

6.1 Motivation

In the field of biometric identification, a new frontier is emerging that uses the unique electrical signals of the brain to validate individuals. This cutting-edge technique, known as brainwave-based biometric identification, takes advantage of the distinct properties of brainwaves. In this study, we focus on beta brainwaves, which range from 13 to 30 Hz, and are mostly connected with active, analytical cognition and high levels of cognitive engagement. These waves, with their complicated and individualized patterns that reflect a person's unique cerebral activity during cognitive tasks, offer a viable option for biometric identification.

While most brainwave-based biometric identification systems have generally centred on alpha brainwaves, which are associated with relaxation and alertness, focusing on beta brainwaves introduces a novel dimension to biometric identification research. Beta waves vary significantly between persons during tasks that require concentration and problem-solving, providing a rich source of data for creating robust identification algorithms.

Electroencephalography (EEG) is the most straightforward and accessible method for measuring brainwave activity, making it particularly suitable for practical biometric applications. EEG involves placing electrodes on the scalp to detect and record the electrical activity generated by neurons, offering real-time brainwave capture with high temporal resolution. This ease of use and non-invasive nature make EEG a preferable choice over other measurement techniques like MEG, fMRI, and PET, which can be more complex, expensive, and less accessible.

Implementing brainwave-based identification methods such as power spectral density, geometrical approaches, machine learning, time-frequency analysis with wavelet transform, dynamic time warping, hidden Markov models, and entropy measures for complexity analysis involves considerable computational load and time. These techniques require sophisticated processing to effectively extract, decode, and classify the unique brainwave patterns, ensuring reliable and secure biometric identification.

6.2 Our Novel Method

To enhance the investigation of brainwave-based biometric identification, we launched a comprehensive research program centred on the distinct patterns of frontal beta brainwaves. Our goal is to create a robust and reliable biometric identification system that makes use of the complexities of these brainwave patterns. To support this aim, we developed a simpler EEG circuit designed exclusively for this study. Our circuit is inspired by the following design [50], that is specifically built for alpha and beta brainwaves combined data acquisition.

Our custom-built simplified EEG circuit is designed to be both efficient and user-friendly, powered by two 9V batteries to ensure portability and ease of use. This circuit can capture the delicate electrical signals produced by neuronal activity in the frontal lobe, which are crucial for analysing beta brainwaves. We hope to take advantage of the distinct cognitive engagement patterns that occur during concentration and problem-solving tasks by focusing on the frontal lobe.

The captured brainwave data is transmitted to a computer via a dedicated connection. We have developed a specialized software program that receives these signals in the form of audio files. This program is a critical component of our research setup, designed to handle the complex processing requirements of brainwave data. Upon receiving the audio files, the program converts them into the appropriate digital format for further analysis.

One of the key functionalities of our software is its ability to plot the measured brainwave data points, providing a visual representation of the neural activity. This visual output is essential for initial inspections and real-time monitoring during data acquisition sessions. Beyond plotting, the program also employs Fourier transform techniques to convert the time-domain signals into their frequency-domain counterparts. This transformation is necessary for isolating and analysing the specific beta wave frequencies, allowing us to delve deeper into the unique patterns associated with individual cognitive engagement.

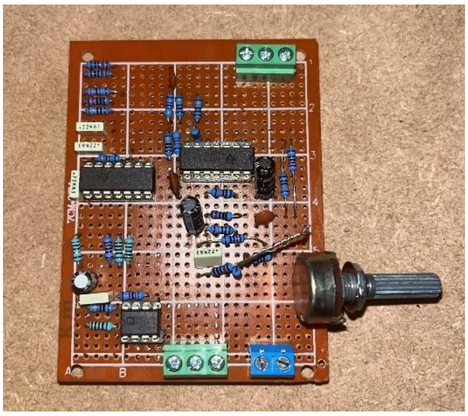

Figure 8: Our simplified EEG circuit in real life

Fig. 8 shows our simplified EEG circuit specifically to measure frontal beta brainwaves and convert them to a usable file format to computers.

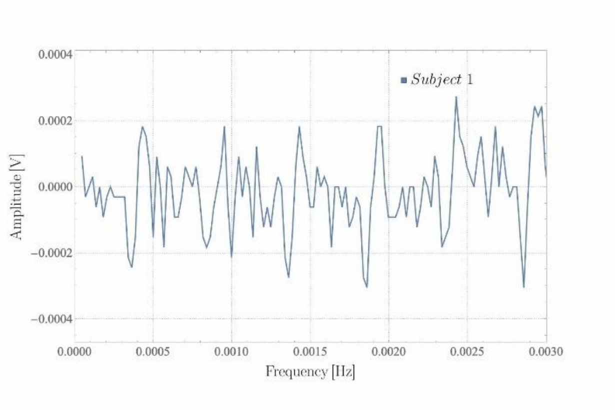

Figure 9: The representation of subject 1's measured frontal beta brainwave

Fig. 9 illustrates an example of the graphical representationof the, frontal beta brainwave in Fourier space, measured from Subject 1 using our custom device.

Currently our program can only measure for a short duration, due to data size constraints (approximately 44,100 samples per second).

7 Future plans

As discussed before, the device currently can only measure for about half a second because of computational problems regarding the data size. In the future we aim to extend the recording duration to at least 10 minutes.

Also, we wish to compare the different measurement types, and identify differences and similarities between alpha, beta, and frontal beta brainwaves, to discover the brainwave-based identification method with the lowest FAR and FRR rate.

We also plan to take measurements from a bigger data pool and public to include a more diverse and statistically representative sample.

8 Conclusion

This study presents a theoretical exploration of brainwave applications in biometric identification, covering multiple frequency bands and introducing a novel method focusing on frontal beta brainwaves. Leveraging electroencephalography (EEG), this method expands the scope of biometric systems. Brainwaves, generated by synchronized neuronal activity, offer insights into various states of consciousness. Beta brainwaves, associated with analytical thought, are categorized based on frequency and subjected to different identification methods. EEG, a key measurement technique, captures and analyses brainwave patterns, contributing to advancements in biometric identification. Ongoing research focuses on beta brainwaves, employing a novel approach that diverges from existing methodologies. The paper concludes by presenting measurements of frontal beta brainwaves and Fourier transform analysis, highlighting our efforts to reduce signal noise and enhance salient featuresfor improved identification accuracy.

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