Neural Computing and Applications (2023) 35:11625–11651
https://doi.org/10.1007/s00521-023-08539-4

REVIEW

Influencing brain waves by evoked potentials as biometric approach: taking stock of the last six years of research

Roberto Saia[1] · Salvatore Carta[1] · Gianni Fenu[1] · Livio Pompianu[1]

Received: 16 December 2022 / Accepted: 24 March 2023 / Published online: 14 April 2023

Abstract
The scientific advances of recent years have made available to anyone affordable hardware devices capable of doing something unthinkable until a few years ago, the reading of brain waves. It means that through small wearable devices it is possible to perform an electroencephalography (EEG), albeit with less potential than those offered by high-cost professional devices. Such devices make it possible for researchers a huge number of experiments that were once impossible in many areas due to the high costs of the necessary hardware. Many studies in the literature explore the use of EEG data as a biometric approach for people identification, but, unfortunately, it presents problems mainly related to the difficulty of extracting unique and stable patterns from users, despite the adoption of sophisticated techniques. An approach to face this problem is based on the evoked potentials (EPs), external stimuli applied during the EEG reading, a noninvasive technique used for many years in clinical routine, in combination with other diagnostic tests, to evaluate the electrical activity related to some areas of the brain and spinal cord to diagnose neurological disorders. In consideration of the growing number of works in the literature that combine the EEG and EP approaches for biometric purposes, this work aims to evaluate the practical feasibility of such approaches as reliable biometric instruments for user identification by surveying the state of the art of the last 6 years, also providing an overview of the elements and concepts related to this research area.

Keywords Security · biometric · Brain waves · Electroencephalography · EEG · Evoked potential · EP

1 Introduction

The possibility of detecting brain activity by easy-to-use, small-sized, and low-cost sensors has opened up new perspectives in many fields of scientific research, from the canonical ones relating to health [96], to applications related to the control of robotic prostheses [59], or the most recent ones related to biometric applications [52], in addition to a huge number of applications related to meditation [39] and concentration [61], and these are just some of the many possible examples. The brain waves detection activity carried out by these sensors, which is formally defined *electroencephalogram* (EEG) [83], is performed by measuring the brain electrical activity through a series of electrodes placed on the scalp. This represents a quite complex operation in the context of canonical professional instruments since it requires the application of numerous electrodes, typically applied using a conductive paste, whereas it is a very simple task in the context of almost all the low-cost devices because it requires only to wear a light headband/headset. It should be observed that the aforementioned placement modality is afferent to the *extracranial* techniques, as there is another technique defined *intracranial* that requires the application of the sensors inside the skull; then, it is aimed to particular applications that require greater detection sensitivity, under medical

Salvatore Carta, Gianni Fenu and Livio Pompianu contributed equally to this work.

✉ Roberto Saia
roberto.saia@unica.it

Salvatore Carta
salvatore@unica.it

Gianni Fenu
fenu@unica.it

Livio Pompianu
livio.pompianu@unica.it

[1] Department of Mathematics and Computer Science, University of Cagliari, Via Ospedale 72, 09124 Cagliari, CA, Italy

supervision: It is formally defined *intracranial electroencephalography* (iEEG) [6].

The largest area of our brain is the cortex, composed of the *frontal*, *temporal*, *parietal*, and *occipital* lobes. The *frontal* one is related to the conscious thought (executive functions); the *temporal* one is related to the memory, understanding, and language, processing complex stimuli such as face and scene recognition; the *parietal* one is related to sensory information integration from different senses and the manipulation of objects (perception); and the *occipital* one is related to the vision. In addition, the *cerebellum*, which is located at the back of the brain, underlying the *occipital* and *temporal* lobes, manages the coordination and movement related to motor skills. The above information is summarized in Fig. 1.

The EEG is a technique able to read the scalp electrical activity that is generated by the brain structures, measuring the voltage variations (i.e., typically from 10 to 100 millivolt in an adult subject) related to the ionic current flows of the brain's neurons [2]. The placement of the electrodes on the scalp follows the *International 10–20 System* shown in Fig. 3, a formalization that takes into account the relationship between the location of the electrodes and the underlying cerebral cortex area, offering a guide for the possible placement of the electrodes: Each position is denoted by a letter that refers to the lobe and a number/letter that refers to the hemisphere location. In more detail, the letters *C*, *F*, *P*, *O*, and *T* indicate the *central*, *frontal*, *parietal*, *occipital*, and *temporal* lobes, and it should be noted that the *Central* lobe is used only for identification reasons (i.e., it does not exist). Analogously, the even numbers indicate the right hemisphere, and the odd numbers indicate the left hemisphere. In addition, the letter *z* indicates an electrode placed on the median line, and the smaller it is a number, the closer it is to the median line. Lastly, *Nasion* indicates the point between the forehead and nose and *Inion* the point at the back of the skull. About the relation between the electrodes during an EEG session, the measurements take into account the electrodes according to different combinations of them that are named *montages*. Concluding, we also formalize the *driven right leg* (DRL) and the *common mode sense* (CMS). They represent the electrical reference of the EEG system: The CMS represents the reference channel, in relation to which all EEG signals are measured, whereas the DRL task is to maintain the potential of the user as close as possible to the electrical zero value.

The brain is composed of billions of neurons, where each of one is mean connected to thousands of other ones, giving rise a communication based on small electrical voltages (microvolts) that involve a huge network of brain circuits. When a neuron is activated, it generates electrical pulses and these activities are defined as brain waves. The brainwaves activity formally refers to five areas, identified by a Greek letter, where each area is characterized by a frequency range, and each activity identifies a specific brain status.

Such signals, an example of which is shown in Fig. 2, indicate that each brain region is characterized by different wave frequencies, and they are emitted simultaneously. For this reason, an EEG signal is composed of several waves with different characteristics and this leads toward a hard task when it is necessary to interpret them, as the data patterns are unique for every person. The frequency range of these waves, measured on the scalp through some sensors, is from 4 to 100 Hz. An EEG output is typically divided into frequency bands, where we have (in descending order of frequency): the *Gamma* wave greater than 30 Hz, the *Beta* wave from 12 to 30 Hz, the *Alpha*

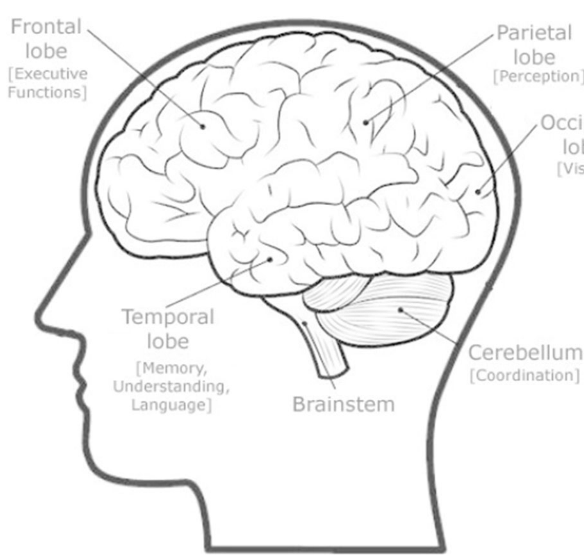


Fig. 1 Brain lobes' functions

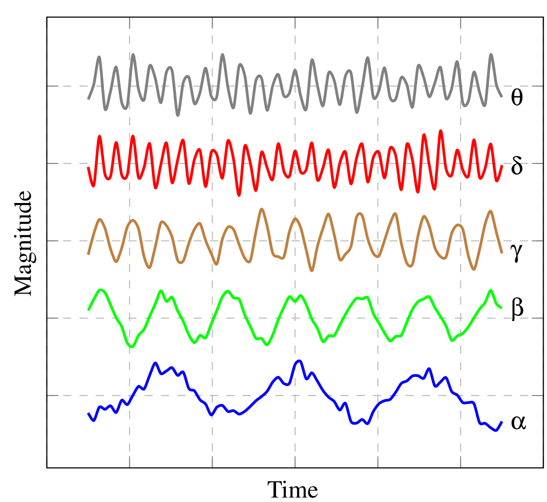


Fig. 2 Brain wave samples

wave from 8 to 12 Hz, the *Theta* wave from 4 to 8 Hz, and the *Delta* wave less than 4 Hz. In some cases, these frequency ranges are further divided into several parts (e.g., low, mid, and high), to better define the associated brain states. Generally, the performed studies demonstrate a strong correlation between the slowest rhythms and the inactive brain state, and between the fastest rhythms and the brain processing of information. In such a context, it should be observed that deep sleep is characterized by high-amplitude and low-frequency oscillations, whereas wakefulness is characterized by low-amplitude and high-frequency oscillations.

The literature shows how the ratios between two frequency bands can lead toward interesting metrics such as the *Delta/Beta* ratio, which provides an index of slow-wave sleep quality. This approach needs that both bands use the same window length of the periodogram because using different window lengths generates meaningless metrics [87]. The most used of them are discussed in several works [24].

1.1 Motivations and contributions

Unlike other biometric approaches (e.g., fingerprint recognition, facial recognition, retinal recognition, etc.), the study of which in the literature has led to scientifically valuable results after a certain period, we have observed a different trend regarding the EEG-based approaches. The reason is probably to be attributed to their not easy applicability, due to the intrinsic limitations of the EEG data, and a series of some collateral aspects such a the lack of stability over time of the EEG patterns, the time required for the detection respect to the other approaches, and so on. For this reason, this study aims to analyze the literature works of the last 6 years according to a metric of concreteness related to the feasibility of such approaches in the biometric field. More specifically, our main contributions are the following:

(1) We investigate the electroencephalography and evoked potentials feasibility as a biometric user recognition approach, taking into account techniques, strategies, and detection devices.
(2) We survey the literature on biometric recognition approaches based on visual, auditory, and vibration evoked potentials, collecting 26 works amenable to investigation, analyzing several aspects of them, such as hardware devices, data collection protocols, and experimental results.
(3) Based on the evaluated literature, we discuss the involved hardware and models, the data collection protocols, as well as the trends, challenges, and future research directions, both in general terms (brain–computer interface) and in the specifics of the approaches taken into consideration (EEG data under external stimuli).

1.2 Acronyms and organization

In order to simplify the reading of this paper, avoiding the reader to search from time to time the meaning of the acronyms already defined, their definition is repeated in most cases again. In addition, Table 1 reports the most important acronyms used in this work, alphabetically sorted.

The rest of the paper is organized as follows: Sect. 2 offers an overview of the research domain taken into account in this work, providing information about EEG acquisition devices, biometric approaches, evoked potential techniques, and evaluation metrics used in this field; Sect. 3 reports the methodology used to select the literature works of the last 6 years that are focused on the approach taken into consideration (EEG and EP), which are here analyzed and discussed; Sect. 4 compares and discusses all the considered literature works in terms of several common and most relevant characteristics, also discussing trends, models, architectures, challenges, and research directions related to this domain; and Sect. 5 concludes this work with some remarks and future research directions.

2 Domain overview

This section provides an overview of the research domain taken into account in this work and it is organized as follows: Sect. 2.1 provides information about the most popular low-cost EEG devices; Sect. 2.2 discusses the biometric approaches designed for user identification tasks; Sect. 2.3 presents the evoked potentials techniques; and Sect. 2.4 introduces the evaluation metrics largely used in this field to evaluate the performance of the biometric systems.

2.1 Detection devices

The main characteristics of the most popular low-cost EEG devices are summarized in Table 2. All these devices are easy to use since they are implemented as a kind of headband or headset, and they use dry electrodes that do not require any preparation (e.g., the application of a conductive paste), allowing a wireless use, which is usually implemented through the Bluetooth Low Energy (BLE) protocol. It should be observed that many of these devices make available other sensors in addition to those related to EEG analysis, such as the *InteraXon Muse* devices, which

Table 1 Used acronyms

Acronym	Meaning	Acronym	Meaning
ADC	Analog-to-digital converter	FRR	False rejection rates
AR	Auto-regressive	FVEP	Flash visually evoked potentials
ANN	Artificial neural network	GA	Genetic algorithm
BCI	Brain–computer interface	HDCA	Hierarchical discriminant component analysis
BNN	Backpropagation neural network	HTER	Half total error rate
CCC	Cross-correlation coefficient	IP	Induced potential
CMS	Common mode sense	IPS	Intermittent photic stimulation
CNN	Convolutional neural network	KNN	K-nearest neighbor
CVEP	Code-modulated visually evoked potentials	LSB	Least significant bit
CRR	Correct recognition rate	LSTM	Long short-term memory
DL	Deep learning	MFC	Mel-frequency cepstrum
DRL	Driven right leg	MFCC	Mel-frequency cepstral coefficient
EC	Eyes closed	PCA	Principal component analysis
EER	Equal error rate	RF	Random forests
EP	Evoked potential	RSVP	Rapid serial visual presentation
ERP	Event-related potential	SSA	Stationary subspace analysis
FAR	False acceptance rates	SSVEP	Steady-state visually evoked potential
FLC	Fisher linear classifier	SVM	Support vector machine
FMRI	Functional magnetic resonance imaging	TAR	True acceptance rate
FNIRS	Functional near-infrared spectroscopy	WPD	Wavelet packet decomposition

Table 2 Most popular low-/medium-cost EEG devices

Brand name	Product name	Data resolution (bits)	Bandwidth range (Hz)	Number of electrodes
Emotiv	Insight	14	0.50–43	05
Emotiv	Epoch X	14/16	0.16–43	14
Emotiv	Epoch +	14/16	0.16–43	14
Emotiv	Epoch Flex	14	0.20–45	32
InteraXon	Muse 2	12	0.20–45	04
InteraXon	Muse S	12	0.20–45	04
Neurowsky	MindWave mobile 2	12	3.00–100	01
OpenBCI	Cyton biosensing board	24	1.00–50	08

provide further sensors able to measure, in real time, the heart rate (PPG) by combining a *Photoplethysmogram* (i.e., an optically approach able to detect blood volume changes in the microvascular bed of tissue) and a *Pulse Oximetry* (i.e., a noninvasive approach able to monitor the oxygen saturation), the breathing combining the PPG and a *Gyroscope* data, and the body movements using an *Accelerometer*. The combined use of EEG data with that of other sensors can improve the discrimination of certain types of information, such as in this work [28], where the tracking of the body motion combined with the measurement of the neural activity is used to improve the recognition of the actual activity of a user. In this work, we will not take these additional sensors into account.

All devices are also powered by rechargeable Li-ion batteries and they communicate through wireless connections, typically based on the *Bluetooth Low Energy* (BLE) protocol. But the most interesting aspect in this research field is the great availability of applications and libraries for the most popular operating systems and programming languages, among which some significant 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 developers to create brain-responsive applications based on the web technologies; and *Muse LSL* (https://github.com/alexandrebarachant/muse-lsl), a *Python* package that provides functions for streaming, visualizing, and recording the EEG data.

The most popular low-/medium-cost devices available on the market at the time of writing this paper are summarized in Table 2 and subsequently described in detail. Some manufacturers, such as *OpenBCI*, also market higher-price-range products, which are not discussed here. In addition, in Table 2 we do not take into consideration the high-cost devices, which are unsuitable for widespread usage in the context of biometric identification systems since in addition to their high cost, they are usually characterized by larger size and numerous electrodes.

Emotiv (https://www.emotiv.com) The *Emotiv Insight* device provides 5 EEG channels, which are related to the *AF3*, *AF4*, *T7*, *T8*, and *Pz* placements of Fig. 3, plus the *common mode sense* (CMS) and the *driven right leg* (DRL) references. The data acquisition is performed through a single *analog-to-digital converter* (ADC) with a sampling rate of 128 Hz. The data resolution in terms of *least significant bit* (LSB) is 0.51 μV (14-bit mode). The bandwidth is in the frequency range from 0.5 to 43 Hz, with a digital notch filter applied at 50 and 60 Hz. The ratio between the largest and smallest values in the input data (*dynamic range*) is 8400 μVpp (peak-to-peak voltage). Its cost at the time of writing this work was 260 euros approximately.

The *Emotiv Epoch X* device provides 14 EEG channels, which are related to the *AF3*, *F7*, *F3*, *FC5*, *T7*, *P7*, *O1*, *O2*, *P8*, *T8*, *FC6*, *F4*, *F8*, and *AF4* placements of Fig. 3, plus 2 references at *P3* and *P4* (CMS and DRL). The data acquisition is performed through a single ADC with a sampling rate of 128 or 256 Hz (configurable). The data resolution in terms of LSB is 0.51 μV or 0.1275 μV, respectively, for the 14- and 16-bit mode. The bandwidth is in the frequency range from 0.16 to 43 Hz, with a digital notch filter applied at 50 and 60 Hz. The ratio between the largest and smallest values in the input data (*dynamic range*) is 8400 μVpp (peak-to-peak voltage). Its cost at the time of writing this work was 750 euros approximately.

The *Emotiv Epoch* + device has the same characteristics as the *Emotiv Epoch X* model, differing from this only for the battery life (6 instead of 9 h) and for the absence of the Bluetooth 5 (BT5) protocol support. This product is now discontinued and replaced with the *Emotiv Epoch X* model;

The *Emotiv Epoch Flex* device provides 32 EEG channels, which are configurable on standard 72 channel international 10–20 locations shown in of Fig. 3, plus the CMS and DRL references. The data acquisition is performed through a single ADC with a sampling rate of 128

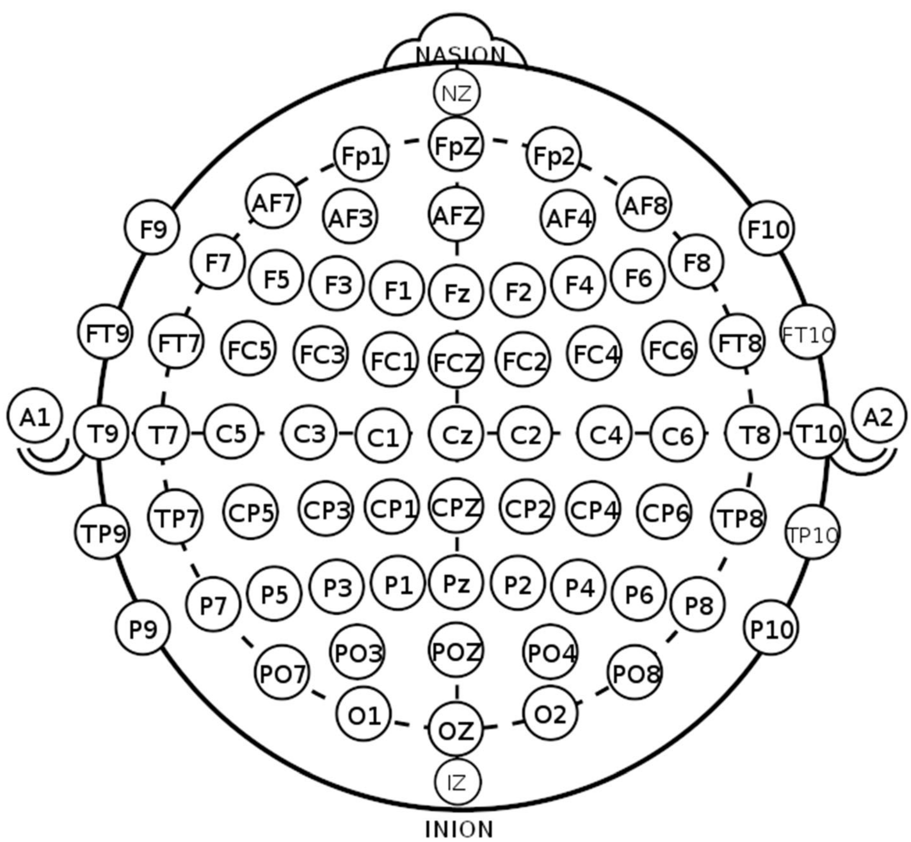


Fig. 3 International 10–20 system

Hz (1024 Hz internal). The data resolution in terms of LSB is 0.51 μV or 0.1275 μV, 14-bit mode (2-bit instrumental noise floor discarded). The bandwidth is in the frequency range from 0.2 to 45 Hz, with a digital notch filter applied at 50 and 60 Hz. The ratio between the largest and smallest values in the input data (*dynamic range*) is $\pm$ 4.12 *mVpp* (peak-to-peak voltage). Its cost at the time of writing this work was 1500 euros approximately.

InteraXon (https://choosemuse.com) The *InteraXon Muse 2* device provides 4 EEG channels, which are related to the *TP9*, *AF7*, *AF8*, and *TP10* placements of Fig. 3, plus the CMS and the DRL references. The bandwidth is in the frequency range from 0.2 to 45 Hz, and the data acquisition is performed through a single ADC with a sampling rate of 256 Hz. The data resolution is 12 bit, and its cost at the time of writing this work was 270 euros approximately.

The *InteraXon Muse S* (Gen 2) device provides 4 EEG channels, which are related to the *TP9*, *AF7*, *AF8*, and *TP10* placements of Fig. 3, plus the CMS and the DRL references. The bandwidth is in the frequency range from 0.2 to 45 Hz, and the data acquisition is performed through a single ADC with a sampling rate of 256 Hz. The data resolution is 12 bit, and its cost at the time of writing this work was 380 euros approximately.

Neurosky (http://neurosky.com) The *Neurosky MindWave Mobile 2* device provides 1 EEG channel, which are related to the *FP1* placement of Fig. 3, plus the CMS and the DRL references. The data acquisition is performed through a single ADC with a sampling rate of 512 Hz. The bandwidth is in the frequency range from 3 to 100 Hz, the data resolution is 12 bit, and its cost at the time of writing this work was 390 euros approximately.

OpenBCI (https://openbci.com) The *OpenBCI Cyton Biosensing Board* is a development board Arduino-compatible based on a 32-bit PIC32MX250F128B microcontroller; it provides 8 EEG channels, but the kit does not include electrodes (it is compatible with both active and passive electrodes). The data acquisition is performed through a single ADC (Texas Instruments ADS1299) with a sampling rate of 250 Hz. The data resolution is 24 bit, and its cost at the time of writing this work was 660 euros approximately.

It should be noted that the devices discussed here, even if they respect the placements formalized in Fig. 3, use a reduced number of electrodes. By way of example, the *InteraXon Muse 2* uses five dry electrodes placed on a headband, one of which used as a reference (*NZ*) and the remaining four for detection of brain activity (i.e., *TP9*, *AF7*, *AF8*, and *TP10*), as shown in Fig. 4.

2.2 Biometric approaches

The biometric authentication is a process aimed to identify a user based on some unique characteristics and it usually works by comparing the acquired biometric data of the user to identify with those stored in a database. For this reason, such a process involves approaches and strategies able to uniquely recognizing humans based on some characteristics, from the exploitation of physical attributes for recognition (e.g., fingerprint, iris, face, etc.), where the user cooperation is required (physical biometrics), to other indirect approaches/strategies (behavioral biometrics), where instead it is not necessary. The advantages and disadvantages of the biometrics techniques are discussed in several literature works [74].

A growing number of works in the literature are aimed at the exploitation of EEG signals in the biometric field [98], to identify unique patterns capable of identifying users, such as Campisi and La Rocca [11], where the authors analyzed the brain activity for the automatic user recognition purpose. Some works [20, 84, 85] faced this task by presenting practical approaches, as well as parallel studies focused on the involved aspects [26], such as the evaluation metrics, whereas another work [81] proposes 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.

Other approaches induce external stimuli of different types to improve the uniqueness of the brain waves patterns and, consequently, the reliability in identifying users, although it should be observed that the adopted stimulation tools often do not allow a practical use as a mechanism for authentication, due to the need of long time of detection and/or expensive tools [32]. In this work [51], the authors exploit the EEG activity evoked by invisible visual stimulation as a biometric approach, whereas another one [64] proposes an approach to brain biometric user recognition, such as this work [1], where the authors propose an authentication system based on the features of two brain waves: *Gamma* and *Beta*. This interesting survey [29] on the brain biometric systems literature provides a valuable overview on this specific research scenario.

Another interesting work [44] offers a deep and systematic biometric characterization of the frequency following response (FFR), an evoked potential generated by periodic or nearly periodic auditory stimuli, with the aim of providing the basis for biometric identification systems that use this neural signal. The experiments were performed using a hidden Markov model (HMM) to decode the identity of the users through FFR spectro-temporal patterns across multiple frequency bands, adopting a dataset related to 10 English native speakers and 10 Mandarin Chinese

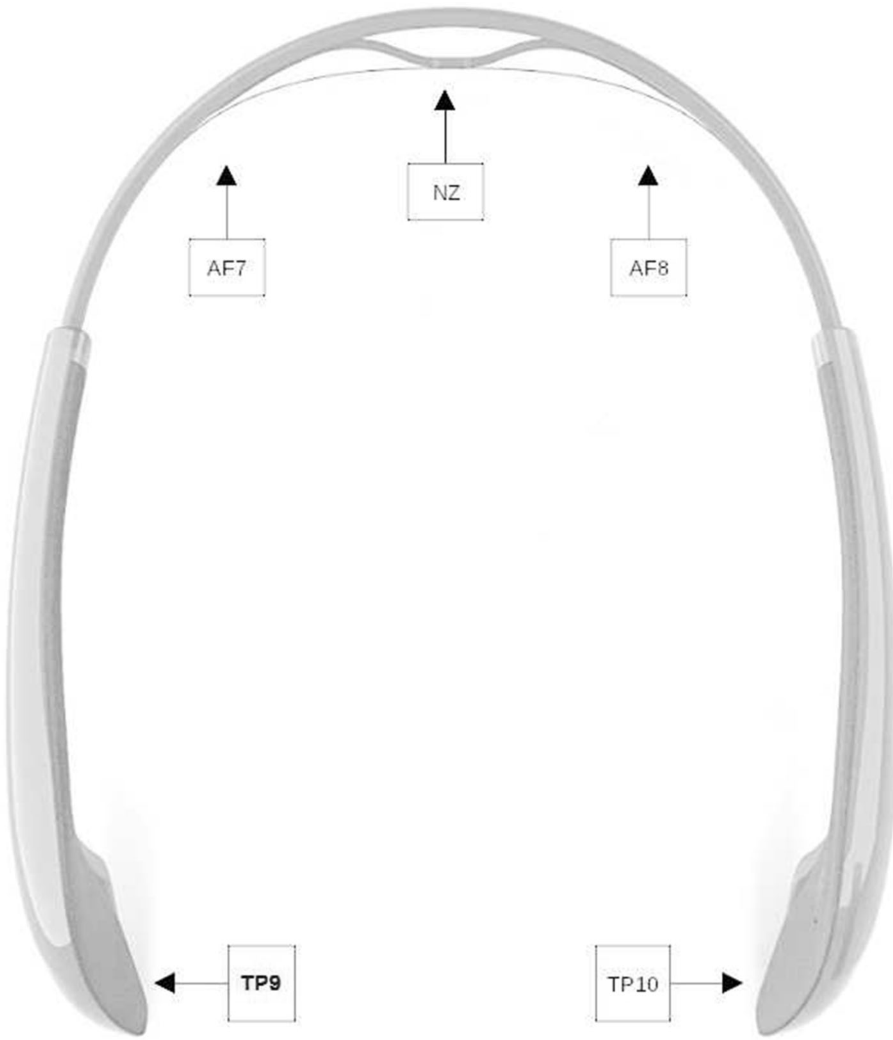


Fig. 4 *Muse 2* electrode placement

native speakers, recognizing the user identity in the same auditory context (same tone and session) and across different stimuli and recording sessions.

Usually, an EEG signal analysis is performed by following three main steps: (1) the EEG signal features are extracted; (2) the features related to the task to be performed are selected; and (3) an evaluation model is trained with these data to classify them.

2.3 Evoked potentials

The *evoked potentials* (EPs) or *induced potentials* (IPs) [92] are electrical potentials measured in a part of the nervous system, mainly in the brain, as the effect of a stimulus. Some examples related to the research area taken into account in this work are the *auditory evoked potentials* (AEPs), which refers to acoustical stimuli (e.g., a tone), or the *visually evoked potentials* (VEPs), which are instead related to visual stimuli (e.g., a light flash), and the *vibratory evoked potentials* [79], such as the imperceptible vibratory ones [73].

They are largely exploited in clinical routine, in order to evaluate the electrical activity related to some areas of the brain and spinal cord, where in combination with other diagnostic tests are exploited to diagnose neurological disorders (e.g., drug-related sensory dysfunctions). With regard to the brain area, the amplitude of this potential is very low, typically from less than a microvolt to several microvolts.

Some examples of used devices in this field are the *Intermittent Photic Stimulation* (IPS) [17], which is usually implemented through glasses able to generate intermittent light emission. Similarly to the IPS, it is possible to use sound stimuli with different frequencies. For instance, in Di et al [22] the authors investigated the effect of 50 and 6 phon (a logarithmic unit of loudness level for tones and complex sounds), intermittent pure tones, using the frequency of 125 Hz, 250 Hz, 500 Hz, 1000 Hz, and 4000 Hz, with a duration of 10 s, demonstrating the existence of relationships between the EEG activity and the acoustic properties of stimuli.

The binaural phenomena have been studied for a very long time [16], they fall in the previously mentioned AEP area and refer to the perception of interaural differences in the binaural stimulus [9]. It means that the brain is inducted to interpret two tones, applied on the left and right ears, as a single tone of a frequency given by the difference in Hertz (Hz) between the frequencies of the two tones. The two tones that produce the single tone perceived by the brain are formally defined *carrier tone* and *offset tone* [41].

Their influence on the EEG activities is investigated in other works [34], where the study of average amplitudes of the spectral density function of brain waves strength signal generates some effects, mainly related to the components of the EEG signal characterized by the same frequency as the binaural beats. In more detail, a statistically relevant decrease in the average amplitudes of the spectral density function of the EEG strength signal related to the *Alpha* and *Beta* frequencies was detected in the presence of binaural beats.

Other studies [18] explored the effect of the low-frequency binaural beats (from 200 to 900 Hz) in the reduction of anxiety and the modification of some psychological conditions/states through the alteration of the cognitive processes and mood states. Regardless of the different approaches, according to the literature, the binaural beat frequencies should be lower than 1000 Hz [41], indicating a stimulation period of about 2 min [27]. The aforementioned works also underline how significant beat frequency responses are related to the use of 40 Hz binaural beat (obtained using a *carrier tone* = 380 Hz and an *offset tone* = 420 Hz), as well as to the same binaural beat obtained using a *carrier tone* = 390 and an *offset tone* = 430, or a *carrier tone* = 810 and an *offset tone* = 850. This evidences that we get a significant response when the brain is stimulated by pairs of tones afferent to both low and high frequencies. An interesting study [63] was aimed to evaluate the impact of binaural beats, discussing their positive and negative effects in several areas, such as education, health care, IT security, and entertainment, but without addressing the e-drug (digital drugs) effects, which are discussed in other works [5].

In this field, it should be mentioned the *steady-state visually evoked potential* (SSVEP), a stimulus-locked oscillatory reply to a series of periodic visual stimulation, which can be recorded by an EEG device [58]. This is an approach widely used due to its characteristics of noninvasiveness, high signal-to-noise ratio, and ease of use Silberstein et al. [77]. Another work [101] explores the feasibility of using a convolutional neural network to decode the EEG data for user authentication purposes, exploiting in this context the low-frequency components of the SSVEP.

Another type of stimulation with which the efficacy in the biometric field is being tested is *motor imagery* (MI), a technique based on a process in which the user imagines a certain action without performing it at the muscular level. The EEG signals related to four types of MI that involve three subjects are discussed in Hu [31], where the authors take into account two different cases of classification, including the user identification one, or in Das et al [21], where in the same context the authors exploit a *convolutional neural network* (CNN) for the automatic discriminative feature extraction and person identification.

In the context of the biometric user recognition systems based on the EEG data, in order to face the problems related to the usage of external stimuli that require the attention of the users, along with a relatively long time for the recognition process, several studies in the literature experimented the *resting state* (RS) as a possible solution. This is an approach where the EEG data collection is performed in a resting state of the user, without the application of external stimuli [15].

In accordance with the literature (i.e., that included in the period between 2017 and 2022), this study takes into account the most common and easy-to-use stimulation techniques: visual, auditory, and vibratory ones.

In this regard, it should be formalized that the *event-related potentials* (ERPs) [30] are the brain responses measured after certain sensory, cognitive, or motor events; then, they are an electrophysiological response to a stimulus. With regard to the EEG scenario, an ERP is recorded from the scalp of a user whose a sound or a visual stimulus is applied, and the *evoked potentials* and the *induced potentials* represent subtypes of the ERPs.

2.4 Evaluation metrics

The performance of a biometric system is mainly expressed based on two different error metrics: the *false acceptance rate* (FAR) and the *false rejection rate* (FRR) [19]. In the case of the FAR, it expresses how many times an unauthorized person is mistakenly allowed access, while in the case of the FFR, it expresses how many times an authorized person is mistakenly denied access. These two metrics are inversely proportional because the more secure the biometric system is, the less comfortable it is to use since authorized users could be more easily not recognized by the system. In other words, as the value of FAR decreases, the value of FRR increases, and vice versa. It should be noted that in real-world scenarios a false acceptance represents an undesirable result, whereas a false rejection is more tolerable.

Other largely used evaluation metrics in this field, which are based on the FAR and FRR metrics, are the *half total error rate* (HTER), calculated as $\mathrm{HTER} = \frac{(\mathrm{FAR}+\mathrm{FRR})}{2}$, and the *equal error rate* (EER), also known as *crossover error rate* (CER), which refers to the HTER evaluated when the FAR value is equal to FRR one.

Some other simple metrics frequently used in the biometric literature are the *Correct Recognition Rate* (CRR), which represents the percentage of correctly identified users over their total number, and the *true acceptance rate* (TAR), which is calculated as TAR = 1 − FRR.

The relation between FAR, FRR, and EER values is shown in Fig. 5, where *Threshold* is the value where we consider correct the prediction performed by the adopted evaluation model.

3 Literature review

In this section, we present the scientific literature on biometric recognition approaches based on evoked potentials. First, Sect. 3.1 presents the methodology we used to collect the papers. Then, Sect. 3.2 presents the selected works.

3.1 Methodology

Following, we present the methodology we use to collect the papers.

(1) First, we have drawn up a candidate list by using *Google Scholar* (https://scholar.google.it), as it represents one of the most inclusive search engines for scientific publications. After a series of tests aimed at identifying the best keywords to use, since initially we get thousands of works focused on other topics that addressed our topic only marginally (e.g., in the related work), we have identified the following as the optimal query:

```
allintitle: ("brain waves" | EEG) + (authentication |
biometric) + (stimulation | stimuli | evoked)
```

This because it performs the search only in the title of the works, allowing us to filter and extract only the relevant works. In addition, to identify other relevant works despite the absence of related keywords in the title, further searches were conducted without using the `allintitle` directive, manually filtering the results.

(2) We have selected the subset of papers relating to the last 6 years (i.e., from 2017 to 2022).

(3) In order to cross-check the authoritativeness of the works obtained through this search, we have excluded from our sample the papers that are not also indexed by *Scopus* and/or *Web of Science* (WOS).

(4) Then, we have selected the subset of papers that use approaches based on one of the following evoked potentials: auditory, visual, and vibratory.

(5) Finally, although we have tried to be as exhaustive as possible in the selection of the related literature papers, we have excluded some of these due to their not direct relevance to the subject of this work, or for their formalization of the experimental results that did not allow us to perform a comparative analysis.

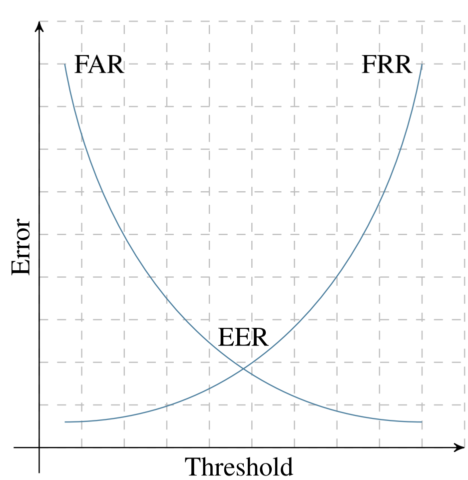


Fig. 5 FAR, FRR, and EER metrics

Regarding step four, it should be noted that our orientation in this work was to take into consideration only widely used stimulus techniques (EPs) that are suitable for use in the context of biometric recognition systems, then excluding techniques that did not meet this requirement, according to the related literature.

For this reason, we excluded stimulus techniques different from the auditory, visual, and vibratory ones. This allowed us to take stock of the situation of the last 6 years of research in a quite exhaustive manner with regard to the type of application taken into account, i.e., biometric user recognition systems based on EEG and EPs.

We believe that such an orientation represents an interesting scientific contribution since our work differs from the others in the literature, which usually are characterized by a more dispersive approach because they are not so sharply focused on a specific target. This also in the light of the following observations: (1) a generic search in the literature of EEG-based biometric systems leads toward thousands of results in the last 6 years, making an exhaustive analysis impossible and moreover useless for the purposes of our work; (2) a specific search in the literature carried out on Scholar in the period under consideration, according to the following query:

```
allintitle: ("brain waves" | EEG) + (authentication | biometric |
identification) + (motor | resting | steady)
```

It is aimed to detect all the works based on the stimulation techniques we did not considered, returns only 22 results, of which only six (resting-state-based = 4, motor-imagery-based = 1, steady-state-based = 1) focused on the biometric user identification systems [15, 37, 55, 58, 88, 89], and excluded by us for the reasons previously discussed (with the exception of the work [58], as it combines the steady state with a visual stimulus and meets our requirements), whereas all the other ones were oriented on secondary aspects such as the system robustness analysis [23], the minimization of the number of EEG channels [47], and so on.

It should be noted that, as regards 2022, at the time of writing this work there was only a work in the literature that met the requirements mentioned above, probably due to the publication time needed by many conferences and journals.

3.2 Analysis of literature works

The related literature works selected by following the criteria reported in Sect. 3.1 are shown in Table 3 sorted by date, where an identifier has been added (i.e., $W01, W02, \ldots, W26$) to quickly refer to these works later.

These works are discussed in the following with the same chronological order, starting with the indication of the identifier, the publication year, and the used stimulus (i.e., *auditory*, *visual*, or *vibration*).

[$W01$, 2017, *Visual*] in this work, the authors propose a biometric recognition approach based on the steady-state visually evoked potentials (SSVEPs) technique. In their work the EEG responses to SSVEP stimuli flickering at different frequencies are measured, using both the *mel-frequency cepstral coefficients* (MFCCs) and the *auto-regressive* (AR) reflection coefficients as discriminating features of the users. It should be noted that the *mel-frequency cepstrum* (MFC) is a representation of the short-term power spectrum of a signal and the *mel-frequency cepstral coefficients* (MFCCs) are coefficients that collectively compose the MFC.

In more detail, to identify a user they rely on the EEG data alterations inducted by repetitive stimuli characterized by a constant frequency, recording the result repeating the process at different frequencies. The validation process was performed using 25 users in the context of two different sessions repeated with an average interval of 15 days (disjoint-time sessions). The results indicate that combined use of multiple stimulation frequencies leads toward both to a significant improvement in recognition rates, and to the possibility of using fewer electrodes during the EEG data recording, thus highlighting its possible practical application in the biometric field. The experimental results show as best performance a CRR $= 96.00\%$ using MFCCs.

[$W02$, 2017, *Visual*] this work defines an EEG-based biometric system that exploits the brain waves data evoked by an invisible visual stimulation. According to it, a frame (target image) is inserted into a video displayed at a high frame rate, decreasing the target intensity simultaneously. The spectral differences are then measured on the EEG at different intensity conditions, and the results are used as features that characterize the user, verifying the identities through a Euclidean distance metric. The experiments, which involved 20 users, show that to improve the uniqueness of the patterns related to each user in evoked brain waves (with respect to the spontaneous brain waves), the invisible visual stimuli need to be calibrated for each user, then it is not possible to use the same stimulation for all the users. The experimental results show as best performance an EER $= 23.00\%$ under a certain configuration.

[$W03$, 2017, *Visual*] in their work, the authors formalize an online biometric system based on the combination of the EEG with a series of subject-specific self-referential visual stimuli, intending to get a more stable/reliable EEG identification pattern about a user. The stimulation is composed of self-face and the subject's relatives images, and the biometric task is performed using the relative spectral activity of the left and right hemispheres (band-invariant information of multiple frequency bands). The experimentation took place with 4 users and the results indicate an average biometric recognition accuracy of 87.50%, which indicates a practical application in the biometric field if this will be confirmed by subsequent experimentations carried out with a greater number of users. The experimental results show as best performance an CRR $= 87.50\%$, a FRR $= 12.50\%$, and a FAR $= 12.50\%$.

[$W04$, 2018, *Visual*] in this work, instead, the authors propose a biometric system for the user authentication that is based on the EEG stimulation through self-face and non-self-face photos. This approach, with the aim of improving the brain wave patterns stability, in the sequence of visual stimuli takes into consideration the sequence of self-face photos, including the first-occurrence position and the non-first-occurrence position. In order to overcome the

Table 3 Related scientific works from 2017 to 2022

ID	Year	Source	Title	References
W01	2017	IEEE	Steady-state visual evoked potentials for EEG-based biometric identification	Piciucco et al. [58]
W02	2017	IEEE	Biometric potential of brain waves evoked by invisible visual stimulation	Nakanishi and Hattori [51]
W03	2017	IEEE	EEG-based biometric authentication using selfreferential visual stimuli	Thomas et al. [86]
W04	2018	IMR	Application of a brain–computer interface for person authentication using EEG responses to photo stimuli	Mu et al. [48]
W05	2018	IEEE	The proposal and it's evalution of biometric authentication method by EEG analysis using image stimulation	Yamashita et al. [97]
W06	2018	IEEE	Convolution neural networks for person identification and verification using steady state visual evoked potential	El-Fiqi et al. [25]
W07	2019	MDPI	EEG-based identity authentication framework using face rapid serial visual presentation with optimized channels	Zeng et al. [103]
W08	2019	IEEE	EEG-based person authentication method using deep learning with visual stimulation	Puengdang et al. [60]
W09	2019	IEEE	A new approach for EEG-based biometric authentication using auditory stimulation	Seha and Hatzinakos [70]
W10	2019	IEEE	Biometric authentication using evoked potentials stimulated by personal ultrasound	Nakanishi and Maruoka [52]
W11	2019	IEEE	Individual identification based on code-modulated visual-evoked potentials	Zhao et al. [104]
W12	2020	FLAIRS	Music stimuli for EEG-based user authentication	Li et al. [42]
W13	2020	MDPI	Biometrics using electroencephalograms stimulated by personal ultrasound and multidimensional nonlinear features	Nakanishi and Maruoka [53]
W14	2020	IEEE	Wavelet transform and machine learning-based biometric authentication using EEG evoked by invisible visual stimuli	Miyake et al. [46]
W15	2020	IEEE	Biometric identification based on EEG signal with photo stimuli using hjorth descriptor	Wijayanto et al. [95]
W16	2020	IEEE	Introduction of fractal dimension feature and reduction of calculation amount in person authentication using evoked EEG by ultrasound	Mukai and Nakanishi [49]
W17	2020	IEEE	Individual identification using code-modulated visual potentials with left-and-right balance	Li and Huang [43]
W18	2021	Springer	Person authentication based on eye-closed and visual stimulation using EEG signals	Yap et al. [100]
W19	2021	Elsevier	Person-identification using familiar-name auditory evoked potentials from frontal EEG electrodes	Jijomon and Vinod [33]
W20	2021	Elsevier	Towards online applications of EEG biometrics using visual evoked potentials	Zhao et al. [105]
W21	2021	IOP	The wavelet packet decomposition features applied in EEG based authentication system	Rosli et al. [66]
W22	2021	IEEE	Single-channel EEG-based subject identification using visual stimuli	Katsigiannis et al. [35]
W23	2021	IEEE	Longitudinal assessment of EEG biometrics under auditory stimulation: a deep learning approach	Seha and Hatzinakos [71]
W24	2021	IEEE	Performance improvement in user verification using evoked electroencephalogram by imperceptible vibration stimuli	Nakashima et al. [54]
W25	2021	IEEE	Person verification using electroencephalograms evoked by new imperceptible vibration stimulation	Shindo and Nakanishi [75]
W26	2022	IEEE	Person authentication using brain waves evoked by individual-related and imperceptible visual stimuli	Rahman and Nakanishi [62]

performance of the canonical solutions, the authors used a *Fisher linear classifier* (FLC) and the *event-related potential* (ERP) technique for the analysis of the brain waves features. The validation phase, performed with 10 users (6 male and 4 female), shows the feasibility of the approach as a biometric authentication system; The experimental results show as best performance an CRR = 82.30% and a FRR = 11.20%.

[*W05*, 2018, *Visual*] also in this work, the authors face the biometric challenge by recurring to the image stimulation, extracting the features by the *cross-correlation coefficient* (CCC), and classifying them through the *support vector machine* (SVM) algorithm. In addition, some preprocessing techniques are adopted by the authors to improve the final performance. The experiments involved 31 users (male university students), and the results show that by increasing the stimulation by images, the EER value decreases, and the proposed method achieves a EER = 02.00% when five images are used. In addition, they experimented that the authentication performance improves by applying artifact countermeasure and digital filter, without the need to change the feature extraction and ML modalities. The experimental results show as best performance an EER = 00.94%.

[$W06$, 2018, *Visual*] the authors propose an approach that exploits a *convolutional neural network* (CNN) with raw SSVEPs, intending to design an automatic user identification system based on the EEG data. In such a context, they perform a comprehensive comparison between the CNN performance with raw signals and other canonical approaches, using two datasets composed, respectively, of 4 and 10 users. The validation process indicates that the proposed approach outperformed the other methods taken into account as competitors. The experimental results show an averaged identification accuracy = 96.80%, an averaged verification accuracy = 98.34%, a FAR = 01.53%, and a TAR = 97.09%.

[$W07$, 2019, *Visual*] this work implements a face image-based *rapid serial visual presentation* (RSVP) paradigm for the user authentication. It uses two different biometric aspects, face and EEG, which are combined to generate more specific and stable patterns for user authentication. The event-related potential (ERP) approach exploits self-face and non-self-face (familiar and not familiar), and the performed experiments evaluate the differences in terms of performance. In more detail, the approach uses an authentication approach based on the *hierarchical discriminant component analysis* (HDCA) and the *genetic algorithm* (GA) methods to define user-specific models with optimized fewer channels. The experimental results show as best performance a CRR = 94.26%, a FAR = 06.27%, and a FRR = 05.26%, under certain conditions.

[$W08$, 2019, *Visual*] this work proposes a combination of the *steady-state visually evoked potential* (SSVEP) and the *event-related potential* (ERP) features, to discriminate the distinction between users, exploiting a *long short-term memory* (LSTM), a type of recurrent neural network, for the analysis. In more detail, they start collecting raw EEG data related to 20 users stimulated by a square SSVEP at 7.5 Hz, using targeted and nontarget Snodgrass and Vanderwart pictures [80] as ERP stimuli, subsequently, they applied a series of preprocessing methods on this raw data (i.e., notch filter, band-pass filter, and eye blink artifacts removal), finally, they used an LSTM neural network to analyze the data and perform the user classification. The validation of this approach was made in terms of *false acceptance rates* (FAR) and *false rejection rates* (FRR), and the experimental results show a high verification accuracy, then its potential suitability in the biometric applications; The experimental results show as best performance a CRR = 91.44%, a FAR = 06.58%, and a FRR = 10.53%.

[$W09$, 2019, *Visual*] a novel approach for the user identification through EEG data has been followed in this work, where the authors take into account three different features, evaluating them based on the energy and the entropy measured in the EEG sub-band rhythms, recurring to a narrow-band Gaussian filter and a *wavelet packet decomposition* (WPD). The experimental phase involved 21 users, whose EEG has been recorded while they listened to modulated auditory tones, during a single- and two-session configuration. The final classification was based on the discriminant analysis, and the experimental results show as best performance a CRR = 97.18% and a EER = 04.30%. In addition, the authors experimented that, in the context of two-session setup, the WPD entropy features remain stable over time, differently from the other features with a decrease of 01.00%, and an increase of 00.45% related, respectively, to the CRR and EER value, an interesting aspect for what concerns the biometric applications of the proposed approach.

[$W10$, 2019, *Auditory*] the authors propose a biometric approach where EEG and ultrasound EP are combined. In more detail, the user features are extracted from the EEG power spectra through the *principal component analysis* (PCA) technique, and the verification process is instead performed using the SVM algorithm. The validation process involved 10 users, whose EEG data have been measured 10 times, and it was performed in the same environment, as well as the definition of the ultrasound stimuli. In more detail, three types of stimuli (created from high-resolution sounds) have been used: personal stimuli selected by the users, stimuli selected by other users, and stimuli that are the same for all users. The experimental results show as best performance an EER = 4.4%.

[$W11$, 2019, *Visual*] this work proposes an EEG-based individual identification approach that exploits *code-modulated visually evoked potentials* (CVEPs) In more detail, through a series of experiments, the authors compared eight CVEP patterns, involving 25 users, to test the feasibility of such an approach as a biometric recognition system. In addition, to further evaluate the influence of the inter-session variability, they recorded two data sessions for each user on different days, measuring the intra-session and cross-session performance. In such an experimental context, they obtained a CRR = 100.00% during the intra-session identification, using 05.25 s of EEG data (average of five trials), whereas they obtained a CRR = 99.43% during the cross-session identification, using 10.50 s of EEG data (average of ten trials). The results, therefore, indicate that the proposed approach can be profitably used in the context of biometric user recognition systems.

[$W12$, 2020, *Auditory*] the authors, based on their previous studies in this field, where they experimented with different EEG stimuli, propose a novel framework for the user authentication based on the EEG and music stimuli. The experiments involved the EEG data related to 16 users, recorded once a week for 3 weeks, and the stimuli are related to various types of music. The idea behind this approach is to recognize the users based on the different responses to the music, in terms of EEG data. The experimental results indicate an average accuracy across all recording weeks of 91.01%. The best performance are an CRR = 96.75% and a FAR = 03.72%.

[$W13$, 2020, *Auditory*] this work proposes a biometric user identification approach based on EEG data, ultrasound, and multidimensional nonlinear features. The approach used is similar to that of a previous work by the authors (i.e., $W10$), where to extract the individual features related to a user from the log power spectra of the EEG data, they adopted the *principle component analysis* (PCA), using SVM as ML classification algorithm. In addition, in this work, they introduced nonlinear features based on the chaos analysis, intending to improve the feature extraction process by adopting a multidimensional nonlinear features approach. In this regard, they join the results related to this approach (related to all electrodes) with the spectral features, reaching performance of EER = 00.00%, although this result requires a high computational cost, then it is not applicable in a real-world application context. Summarizing, in this new work of the authors, the validation process involved 10 users, and the obtained best performance for a single electrode is EER = 22.00%, whereas it is EER = 04.40% for multiple electrodes, where the results are combined by following a majority decision criterion. Experiments, therefore, indicate the possibility of using this approach in a biometric recognition system context.

[$W14$, 2020, *Visual*] in this work, the authors propose a mechanism of user authentication based on EEG altered by visual stimuli that exploit the wavelet transform as data analysis and feature extracting method (including time elements) to improve the accuracy in the user detection task. With the aim of further improving the performance, they experimented some approaches (i.e., SVM and ANN), achieving the best result of EER = 08.10% after training neural networks using ensemble learning with 30 ANNs.

[$W15$, 2020, *Visual*] the authors propose a biometric system for the user identification based on EEG data altered by photo stimuli. The validation process was performed by involving 5 users in the context of five EEG recording sections made through a *Muse* headband device, using a *backpropagation neural network* (BNN) under the K-fold cross-validation criterion (10 test data and 15 training data), adopting for the user EEG data characterization the *Hjorth Descriptor* [65], a method used for observing natural biological signals. The data is recorded from 5 users that have been stimulated by using a series of pictures for 1 min, repeating the session five times, and in such an experimental context, the best performance was CRR = 100.00% under the used configuration.

[$W16$, 2020, *Auditory*] this work exploits the ultrasound stimuli for the EEG stimulation, with the motivation of the authors that in this way the users are not distracted from their current activity during the recognition process, unlike what happens when audible stimuli are used. It should be noted that this work approach is in line with others previously experienced by the authors, the last of which is the one described in $W13$. The generation of the ultrasound stimuli was made by removing, through a digital high-pass filter, the frequency components of 20 kHz or less in the favorite songs of the users involved in the experiments (i.e., 10), playing the ultrasound in a silent environment for 30 s. The proposed approach introduces a new nonlinear feature, the fractal dimension, evaluating its introduction by measuring the performance on its own and in combination with the other conventional ones. Based on the performed experiments, they get an ERR = 00.00% using 5 features, 14 electrodes, and 70 SVM evaluation models, obtaining the same result when they reduce these models to 24.

[$W17$, 2020, *Visual*] the authors of this work combine the EEG data with a stimulus mode with the left-and-right balance to evoke CVEPs, to perform a user identification task. In more detail, they realize such stimuli using two sides of a screen placed, respectively, on the left and on the right visual field of the user, which flash at the same time according to two different sequences. The users are guided to gaze at the left side for the half time of the experiment, and at the right side for the other half of the time, and the related EEG data are used to define their unique brain waves patterns. The experiments involved 20 users, and the results show as best performance a CRR = 92.50%. An additional analysis made by the authors proves the stability over time of the proposed approach, which appears suitable for the biometric recognition application.

[W18, 2021, *Auditory*] this work proposes a feasible approach (in terms of acquisition time and low-cost EEG device) for the biometric identification of users based on two protocols: eyes closed (EC) and visual stimulation. It analyzes the pairwise correlation of the preprocessed EEG data related to each scalp electrode, defining in this way a feature vector, then the data are analyzed and classified using the *support vector machine* (SVM) algorithm. The validation process involved 8 users and the EEG recording was divided into two sessions, morning and afternoon ones. The experimental results show as best performance CRR $= 99.06\%$, under certain conditions.

[W19, 2021, *Auditory*] in this approach, the authors use single-trial familiar-name AEPs detected from two frontal EEG electrodes. The experiments involved 20 users and the proposed approach tests several different combinations of ANN architectures for feature extraction and classification. They get the best results using the 1D *convolutional neural network* (1D-CNN) with LSTM, demonstrating as a scientific contribution that the use of familiar-name AEPs from frontal EEG electrodes can simplify the acquisition process in terms of the required time. The experimental results show as best performance CRR $= 99.53\%$ and HTER $= 00.24\%$.

[W20, 2021, *Visual*]: a system framework for VEP-based biometrics, where the authors compare the performance of three types of VEP signals oriented to the user identification is proposed in this work. In more detail, FVEP, SVEP, and CVEP techniques have been tested on 21 users during two different days, to evaluate the related CRR. For this goal, the authors developed a template-matching-based recognition algorithm for VEP detection in a *brain–computer interface* (BCI) aimed for user identification. The experimental results show that the best performance (i.e., CRR $= 100.00\%$) is reached using the CVEP technique based on 03.15 s of VEP data, a result that indicates the potential feasibility of this approach for the user identification.

[W21, 2021, *Visual*]: this work proposes the use of EEG data as a biometric approach, in the context of which the *wavelet packet decomposition* (WPD) technique has experimented as a feature extraction method. The WPD is used to get new features that can improve the information extracted from the EEG data when visual stimuli (familiar and unfamiliar images) are displayed to the user, whereas the data have been processed by using the SVM, KNN, and RF algorithms. The experiments involved 13 users and the results have been evaluated in terms of *false acceptance rate* (FAR) and *false rejection rate* (FRR). The results show a FAR value lower than FRR in terms of error rate, and SVM as the best algorithm. The best performance are a CRR $= 92.80\%$, a FAR $= 00.41\%$, and a FRR $= 4.99\%$.

[W22, 2021, *Visual*]: the authors of this work proposes an approach for a biometric user identification based on the EEG data using a benchmark dataset related to EEG data acquired under different visual and non-visual stimuli through a low-cost EEG device. The used dataset contains EEG recordings from 21 users acquired during three separate sessions, each 1 week apart. Their results indicate that some EEG device electrodes provide effective information that leads to better accuracy, regardless of the features and the stimuli exploited in this process, observing that the best performance in this regard is related to the use of the *mel-frequency cepstral coefficients* (MFCCs). In other words, a certain combination of fewer electrodes potentially leads toward high performance in the user identification task, allowing us the use of low-cost EEG detection devices. The experimental results show as best performance an CRR $= 29.69\%$, obtained using the P8 electrode and the MFCC features for the flashing VEP at 07.00 and 10.00 Hz), observing that this approach underperforms the baseline approaches [4] based on all the electrodes, which offer an CRR $= 40.25\%$.

[W23, 2021, *Auditory*]: this work proposes a DL approach for the longitudinal assessment of EEG data aimed to design a biometric authentication system based on auditory stimuli. In more detail, such an approach records the EEG data from 13 users during three sessions, using about a year as the average time span between the last session and the first two. The EEG data are encoded into an embedding space, where the distance between cross-session features is minimized from the same users, whereas it is maximized from different users. In addition, the approach adopts an encoder with a custom convolution layer aimed to extract improved functional connectivity features over the standard convolution. The experimental results indicate that this approach overcomes the other state-of-the-art DL frameworks and BCI techniques in terms of EER and CRR, showing also a reduced acquisition time. The best performance is an EER $= 05.00\%$.

[W24, 2021, *Vibration*]: the authors propose a study aimed to detect stable EEG biometric data to use in the context of a user identification system. In this regard, they exploit imperceptible vibration EEG stimuli, introducing a method able to repeat these stimuli over a short time. The validation of the proposed approach involved 10 users, whose EEG data have been captured when they were in a resting, closed-eyed, and seated position. The experimental results show that using EEG data immediately after a short time of stimulation leads toward best performance than those obtained using continuous stimulation. The EEG data are processed recurring to the SVM algorithm, and the obtained best performance is an EER $= 11.00\%$.

[$W25$, 2021, *Vibration*]: also in this work is aimed to design an EEG-based user authentication system by exploiting imperceptible vibration stimuli. According to their previous knowledge of the EEG effects related to tactile stimulations, where they have experienced that the evoked responses occur in a short time, in this work they propose to measure evoked EEG data for 100 ms. The experimental results, which involved 10 users, demonstrate that the stimulation based on imperceptible tactile stimuli is effective to define a user identification EEG-based system. The measured best performance of EER $= 24.00\%$ outperforms that obtained in their previous work [76], where they exploited the imperceptible tactile stimuli in the same context.

[$W26$, 2022, *Visual*]: In this work, the authors exploit individual-related stimuli, instead of common ones, with the aim of improving the biometric system performance, using EEG data stimulated by imperceptible visual stimulation. In addition, the proposed approach exploits a time zone and frequency sub-bands feature extraction method in order to improve the verification performance. The results of the validation process, where have been involved 8 users, show EER $= 6.10\%$.

4 Discussion

In this section, we carry out an in-depth analysis of the literature works taken into consideration.

First, Sect. 4.1 discusses the main trends by delving into the most researched topics (Sect. 4.1.1) and the publication distribution (Sect. 4.1.2). Next, Sect. 4.2 focuses on model comparison, detailing algorithms (Sect. 4.2.1) and their performance (Sect. 4.2.2). We then further our comparison with Sect. 4.3, which reviews the architectures analyzing both the data collection protocols (Sect. 4.3.1) and the hardware used (Sect. 4.3.2). Next, Sect. 4.4 examines the challenges of this research field, discussing first the common challenges (Sect. 4.4.1) and then the specific ones (Sect. 4.4.2). Finally, Sect. 4.5 presents future research directions, dealing with emerging ideas (Sect. 4.5.1) and suggesting possible future developments (Sect. 4.5.2).

4.1 Main trends

This section describes the main trends in this research area. First, we start presenting the research directions which brain–computer interface researchers investigate. Later, we explore the publication distribution, comparing the distribution of brain–computer interface papers with the distribution of the works we selected.

4.1.1 Brain–computer interface research topics

As highlighted by the previously discussed works, as well as in several recent studies in the literature [10, 102], the main direction that characterizes research in the brain–computer interface (BCI) field is focused on the definition of systems capable of maximizing performance in terms of ease of use, low cost of hardware, and accuracy of identifications, while minimizing known problems through increasingly sophisticated protocols and techniques.

In more detail, BCI has interesting applications in very heterogeneous areas such as security, communications, control, transport, medicine, and entertainment [102]. The literature works show an increasing interest for these approaches by researchers around the world, with an interest in the development of applications even very distant from the canonical BCI area of the past (i.e., the medical one). Indeed, the majority of the works in the literature are not focused on the medical field (which was the reference domain in the past), with almost 60% of the works in different fields and about 30% in the medical one [3, 90].

In addition, in the field of biometric authentication systems, the literature highlights how systems based on EEG signals represent the best solution for the future, thanks to their portability, ease of use, and low cost compared to the security they offer [10]. This distribution is most likely due to the diffusion on the market of affordable hardware which has helped to give life to numerous types of research in other fields such as that of biometric identification of users that we have considered in this work.

4.1.2 Publication distribution

As regards the distribution of publications in the world, as underlined in several studies in the literature [90], Asia has the highest number of publications related to EEG-based BCI applications, followed by Europe and North America (i.e., between 2009 and 2019, 111 publications in Asia, 56 in Europe, and 27 in North America). However, it should be noted that despite Asia presenting the highest number of publications in this field, of the 37 countries involved in the world, the largest number of them are European (i.e., 18). Another important trend that emerges from the study of the literature is the growing cooperation between researchers from different countries, as well as the use of increasingly less invasive and easy-to-implement data acquisition techniques.

Focusing on the works we selected, the literature of the last 6 years indicates a growing interest in this research field, especially in recent years since we have eight works in 2021 against the three works in 2017 (we do not take in consideration 2022 because not all the related literature is visible due to publication times), with some works improved over the years by the same authors (e.g., *W*02, *W*10, and *W*13), and this interest is also evident in the context of university theses/dissertations [72]. As we already noted for the BCI publications, even in the case of the works we selected, we identify that Asia has the highest number of publications (21), followed by North America (3) and Europe (2).

4.2 Models

This section discusses the models proposed by the selected works, focusing on the algorithms (Sect. 4.2.1) and their performances (Sect. 4.2.2).

4.2.1 Algorithms

Recent literature in the BCI field shows a large use of models based on algorithms related to deep learning techniques, Bayesian networks, support vector machines, convolutional neural networks, and linear discriminant analysis, as they are able to limit the problems that affect the BCI systems (e.g., signal noise, training time, unstable patterns, etc.), improving the overall performance [102].

In more detail, a recent study in this field [90] shows that the most used classification algorithm in the BCI application based on EEG data is the one that exploits the linear discriminant analysis (35 of the 114 publications analyzed), followed by the support vector machine (24 of the 114 publications analyzed), whereas the remaining publications are distributed on numerous other methods (e.g., naive Bayes, random forests, etc.), as reported, in percentage terms, in Fig. 6.

Specifically, as regards the systems considered by us in this work, aimed at the biometric identification of users by exploiting the combination of EEG signals and EP stimuli, the literature examined shows a high level of heterogeneity as regards the used models. In more detail, many of the approaches combine multiple techniques, such as the mel-frequency cepstral coefficients (MFCCs) and the auto-regressive (AR) reflection coefficients to discriminate the features of the users (W1), the cross-correlation coefficient (CCC), and the support vector machine (SVM) algorithm (W5), the hierarchical discriminant component analysis (HDCA) and the genetic algorithm (GA) (W7), the narrow-band Gaussian filter and the wavelet packet decomposition (WPD) technique (W9), the principal component analysis (PCA) and the support vector machine (SVM) algorithm (W13), and the 1D convolutional neural network (1D-CNN) with long short-term memory (LSTM) (W19). In this context, there is a widespread use of techniques such as the principal component analysis (PCA) (W7, W10, and W13) and the wavelet packet decomposition (WPD) (W9, W14, and W21) for their capability to analyze complex information such as EEG data. For the same reason, various approaches make use of artificial neural networks (ANN), such as the convolutional neural network (CNN) (W6 and W23), the long short-term memory (LSTM) (W8 and W19), the backpropagation neural network (BNN) (W15), and the 1D convolutional neural network (1D-CNN) (W19). Further approaches are based on techniques such as the Fisher linear classifier (FLC) (W4), the mel-frequency cepstral coefficients (MFCCs) (W22), and other techniques/strategies such as Euclidean distance and fractal dimension.

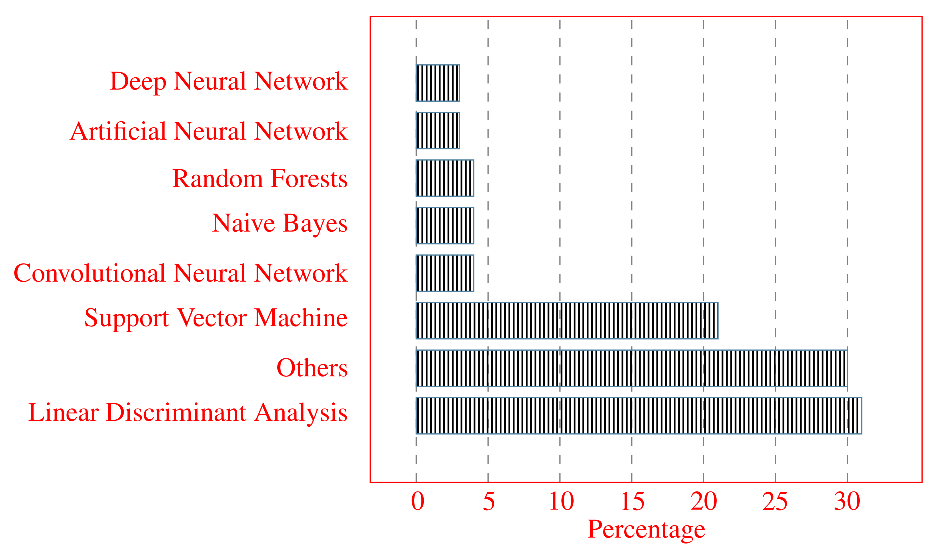


Fig. 6 EEG-based BCI application classification algorithm usage

An overall analysis of the used models indicates intensive use of techniques and/or strategies capable of breaking down and analyzing the EEG data in the most in-depth way possible, in order to minimize the problems due to the poor stability of the EEG patterns over time. In this regard, it is not easy to identify the best state-of-the-art architecture as the performances achieved by each work are strongly related to numerous parameters such as the number of users involved in the experiments, the number and the distance between the acquisition sessions, and so on. In any case, the comparison between the works of recent years and the more recent ones shows an effort by researchers toward models capable of exploiting low-cost, easily available, and simple-to-use hardware, as it is the only one that can allow widespread use as a biometric user identification approach. In light of the ever-increasing performance of low-cost EEG devices and the availability of ever more sophisticated and performing models capable of exploiting them, it is possible to foresee an increasingly widespread use of this type of biometric identification approach in the near future.

4.2.2 Performances

In this section, we analyze the performances of the selected works. Our analysis considers two fundamental aspects: the experimental environment and the biometric user recognition system performance. More specifically, we compare the following aspects: the number of users involved in the experiments, the number of data acquisition sessions, the data collection protocols adopted in these sessions, and the system's performance regarding the correct number of user identifications carried out.

According to this goal, Table 4 reports, for each of the works in Table 3, the number of users involved in the validation process, the exploited type of stimuli, and the measured performance. We highlight that, to compare the performance related to all the works, although most of them provided the value of CRR, we assume that CRR $= 1 - \text{EER}$ when CRR is not provided. In light of the different number of users involved in the experiments, we propose an assessment in terms of weighted average, using the metric formalized in Eq. 1, where for the literature work $w \in W$ the CRR performance and the involved

Table 4 Experimental results

Work ID	Publication year	Involved users (max)	Type of stimulus	Best CRR (%) performance
W01	2017	25	Visual	96.00
W02	2017	20	Visual	77.00
W03	2017	04	Visual	87.50
W04	2018	10	Visual	82.30
W05	2018	31	Visual	98.00
W06	2018	10	Visual	96.80
W07	2019	15	Visual	94.26
W08	2019	20	Visual	91.44
W09	2019	21	Visual	97.18
W10	2019	10	Auditory	95.60
W11	2019	25	Visual	100.00
W12	2020	16	Auditory	96.75
W13	2020	10	Auditory	95.60
W14	2020	20	Visual	91.90
W15	2020	05	Visual	100.00
W16	2020	10	Auditory	100.00
W17	2020	20	Visual	92.50
W18	2021	08	Auditory	99.06
W19	2021	20	Auditory	99.53
W20	2021	21	Visual	100.00
W21	2021	13	Visual	92.80
W22	2021	21	Visual	29.69
W23	2021	13	Auditory	95.00
W24	2021	10	Vibration	89.00
W25	2021	10	Vibration	76.00
W26	2022	08	Visual	93.80

Table 5 Weighted average CRR performance by stimulus type

Type of stimulus	Number of works	Weighted average CRR (%) performance
Visual	16	93.83
Auditory	7	97.45
Vibration	2	82.50

number of users in the experiments are denoted, respectively, with CRR_w and $|U|_w$.

$$\text{Performance} = \frac{\sum_{w=1}^{W}(\mathrm{CRR}_w \cdot |U|_w)}{\sum_{w=1}^{W}|U|_w} \quad (1)$$

The results are shown in Table 5: We exclude *W*22 (it uses visual stimuli) since, as previously discussed, its scientific contribution is not related to the best CRR. According to this metric, the best average performances calculated separately for each different type of stimulus are: 93.83% (16 works, excluding *W*22) for approaches using visual stimuli, 97.45% (7 works) for those using auditory ones, and 82.50% (2 works) for those using vibrations ones. The results therefore show performance in accordance with those of other widely used biometric systems, albeit with the limits before discussed.

The first evident aspect of the results is that four works get a CRR of 100% or an error rate of 0.00% (i.e., *W*11, *W*15, *W*16, and *W*20), as shown in Fig. 7, where the results of Table 4 are sorted in descending order of performance. This should mean that strategies able to provide ideal results have been identified, but actually these results are strictly linked to specific experimental environments and to a small number of users in the validation process (none of these four approaches use more than 25 users and none of the discussed approaches use more than 31 users). It must be underlined that the performances taken into consideration have to be considered as the *best case*, although, regardless they refer to particular experimental conditions,

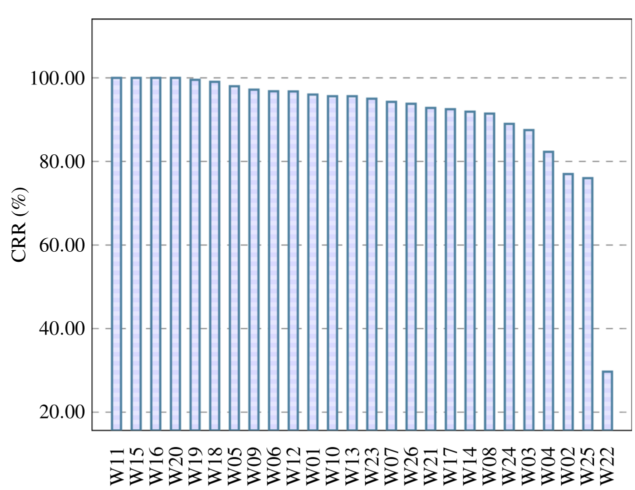


Fig. 7 Best CRR performance

they offer an interesting scientific contribution in the field of the biometric applications based on the EEG and evoked potentials.

A separate discussion must be made for the less performing approach (i.e., *W*22) since the authors' goal was to investigate the performance related to each individual EEG channel in the context of recognition systems based on low-cost consumer-grade EEG devices. For this reason, the scientific contribution is not related to the best CRR. In their study they demonstrate that a combined use of electrodes leads toward better performance than the single-electrode solutions, offering valuable information about the suitable combination of them. The best result they declared is related to the highest accuracy achieved using a single electrode.

Also in the case of two other works that share two authors (*W*24 and *W*25) it is necessary to make some differentiation, first of all with regard to the used stimulus (i.e., imperceptible vibrations), which reaches lower performances than the other ones, even if it exists a numeric difference concerning the number of works in literature, secondarily, because, even in this case, the real scientific contribution does not refer to the improvement of the state-of-the-art performance (they get a best average performance of 82.50%) but to the study of which is the best configuration during data acquisition (electrodes, discriminative features, etc.). In addition, in both works the authors indicate the need to increase the number of users in order to get valuable/reliable experimental results, confirming our opinion in this regard.

About the type of stimulus that has proved most effective, we can observe how the best approaches are related to different type of stimuli (respectively, CVEP, VEP, AEP, and VEP), indicating that the improvements are not mainly related to them but to the adopted experimental method and strategy, although it should be pointed out that the choice of the optimal parameters of these stimuli (e.g., frequency and duration) must be experimentally defined and it is strongly related to the experimental conditions (e.g., environment, users, etc.).

4.3 Architectures

This section studies the architecture of the surveyed works by inspecting protocols for collecting data (Sect. 4.3.1) and hardware (Sect. 4.3.2).

4.3.1 Data collection protocols

An important aspect that affects all the experiments carried out in the works we have taken into consideration and which determines the quality of the proposed work is the protocol used to collect the EEG data. The study of the literature shows a great heterogeneity in the protocols adopted by the authors, considering that they involve different elements, such as the number of involved users, the number of data collection sessions, the duration of each of these sessions, and the distance between them. The literature works of the last six years considered by us present large differences in these aspects: For instance, we observe an average number of users of 15, with cases in which there are only 4 [86] users and cases that instead involve 31 [97]. In this regard, analogously with any type of scientific experimentation, the value and validity of the results are strongly correlated with the number of samples (users) involved in the process, and this is an even crucial aspect in a domain such as that of the EEG data, which is characterized by a high degree of heterogeneity, as previously discussed in Sect. 4.4. However, it should be noted that some of the authors of the discussed literature work highlight this type of limitation, indicating the need to perform future works with a greater number of users involved in the experiments [54, 75].

In such a context, we compared the different experimental environments related to all the works in Table 3, reporting the results in Table 6. On the basis of them, we can observe that different data collection protocols have been adopted by the authors: In some cases, the EEG data acquisition sessions are few and little spaced from each other in terms of time, e.g., [53, 86, 95, 97]; in few cases, they involve a greater number of sessions but carried out consecutively, e.g., [52, 66]; in other cases, we instead have a considerable distance between sessions, a configuration usually aimed at verifying the stability of the EEG patterns over time, e.g., [42, 71, 104]. From the analysis of the tasks performed in each individual session, we can observe differences based on the type of stimulus used. The tasks using visual stimuli are characterized by a high number of trials, each of concise duration in which one or more images are shown to the users. Typically, the images shown alternate between images familiar to the user (e.g., chosen by the user before the session begins) and unfamiliar images. In contrast, auditory stimuli works have fewer trials and longer overall duration. The longer duration is also due to the use of prolonged pauses between stimuli; indeed, the literature indicates that such pauses are necessary to achieve greater accuracy in the results. Finally, the two works based on vibration stimuli perform the estimation for a short time (0.1 s) interspersed with 5-s pauses for a total number of trials of 100. For reasons of completeness, It should be added that some works in the literature discuss of the EEG data acquisition protocols in terms of acquisition modalities, usually distinguishing three of them: resting states, mental tasks, and tasks with external stimuli [7]. In the first two modalities (i.e., resting states and mental tasks) the acquisition process does not need additional hardware/software except those related to the EEG device, whereas the third modality (i.e., tasks with external stimuli) requires an appropriate hardware/software for the generation of the external stimuli. This categorization was not considered by us since all the discussed works fall into the third modality.

4.3.2 Hardware

The literature works considered by us (i.e., those relating to techniques that combine EEG signals with EP stimuli), show the use of hardware not included among the low-/medium-cost devices previously listed in Table 2, adopting more expensive (around several tens of thousands of euros) and/or professional hardware (i.e., W01, W04, W07, W09, W11, W12, W17, W19, W20), whereas three works (i.e., W06, W08, and W23) do not specify this information (the absence of information is indicated with *NS* in Table 7).

In any case, the literature works indicate that is possible to perform experiments and obtain interesting results in this research domain even using low-/medium-cost EEG hardware, as demonstrated by 13 of the 26 works taken into consideration, and highlighted by the percentage distribution of the hardware reported in Fig. 8.

4.4 Challenges

This section presents the challenging problems in the context of the approaches based on the EEG data, which we divide into domain challenges (Sect. 4.4.1) and specific challenges (Sect. 4.4.2).

4.4.1 Domain challenges

Following, we describe the open problems affecting all the applications that exploit the EEG data. *Data Complexity* most of the problems that make user recognition based on EEG data a challenge are mainly related to the nature of the data, as they are complex, nonlinear, and non-stationary [82]. In other words, the EEG data can be considered stationary only within short intervals, and for this reason usually is applied a short-time windowing approach to identify the local discriminating features, exploiting techniques such as the *stationary subspace analysis* (SSA), which is aimed to find a linear coordinate transformation that factorizes the input data into stationary and non-stationary components [91]. This work [12] investigates the

Table 6 Experimental environment

Work ID	Involved users	Number of sessions	Session details: trial duration and repetitions	Session configuration
W01	25	02	N.A.	2 sessions with an average time interval of 15 days
W02	20	10	6 s—55 times	2 sessions a day for 5 days
W03	04	10	17 s—20 times	6 sessions online and 4 sessions offline
W04	10	06	1.25 s—370 times	6 sessions over 6 weeks with the same time interval
W05	31	03	10 s—25 times	3 sessions in a day for each user
W06	10	03	N.A.	3 sessions with the 2nd and 3rd ones after 3 and 6 weeks
W07	15	02	3 s—200 times	2 sessions with an average time interval of 30 days
W08	20	02	10.3 s—5 times	2 sessions for each user made in different days
W09	21	02	360 s total	2 sessions with an average time interval of 30 days
W10	10	10	360 s total	10 sessions for each user with a different order of stimuli
W11	25	02	2 s—100 times	2 sessions with an interval between 1 and 103 days
W12	16	03	310 s total	1 session a week for 3 weeks
W13	10	04	300 s total	4 sessions for each user
W14	20	10	1 s—55 times	10 sessions for each user
W15	05	05	60 s total	5 sessions for each user
W16	10	08	30 s total	8 sessions for each user
W17	20	20	3 s—53 times	20 sessions for each user
W18	08	02	2 s—120 times	2 sessions for each user divided into morning and afternoon ones
W19	20	04	90 s—4 times	4 sessions for each user
W20	21	02	66.15 s total	2 sessions with an average time interval of 5 days
W21	13	07	720 s total	7 consecutive sessions for each user
W22	21	03	N.A.	3 sessions with a time interval of 7 days
W23	13	03	300 s total	3 sessions
W24	10	10	5.1 s—100 times	10 sessions for each user
W25	10	10	5.1 s—100 times	10 sessions for each user
W26	08	08	Several values	8 subjects$\times$3 datasets for training, 8 subjects$\times$8 datasets for testing

factors that influence the performance of the biometric systems based on EEG data, while this work [7] provides a survey on methods and challenges in EEG-based authentication;

User Heterogeneity a well-known problem in the literature further complicates data processing: There are huge differences among users in the EEG data, as demonstrated in this study [45] involving 150 users. In addition, the different types of EEG signals and their non-stationary and low signal-to-noise ratio often make it difficult to extract the information that needs for a specific task [93];

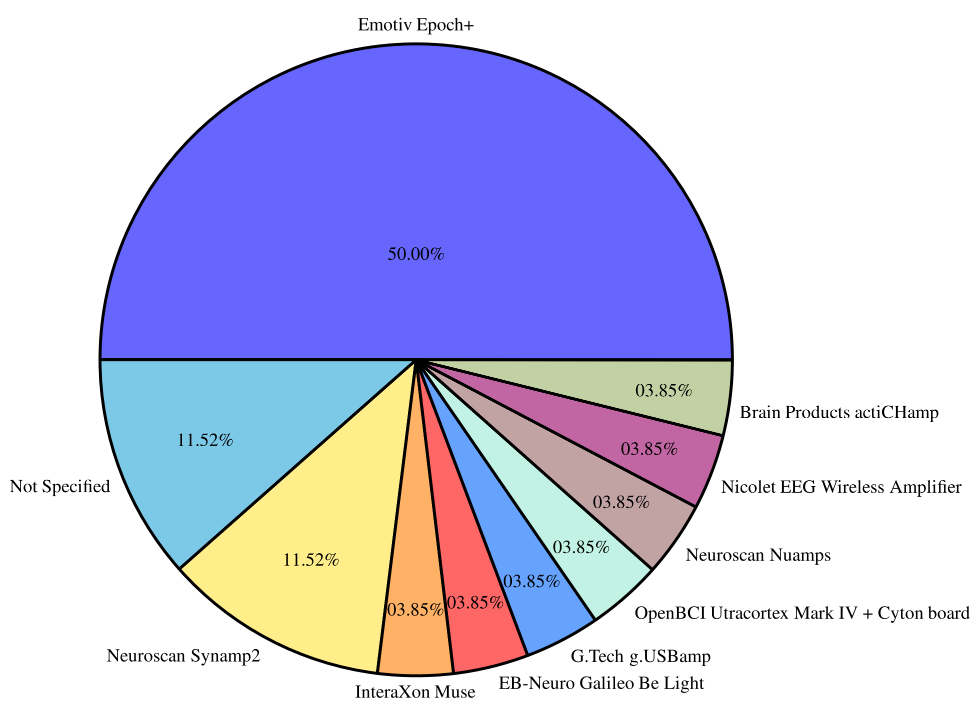
System Calibration another important problem is related to the fact that any EEG-based approach requires that, before the data acquisition session, users must undergo a system calibration. In such a context, this problem is faced by the *transfer learning* [93], a machine learning (ML) approach aimed to use a model defined for a task as starting point for a new model related to another task. In our case, it represents a method to reduce the calibration requirements of a biometric recognition system based on EEG data since it adjusts the evaluation model via prior knowledge to make it adaptable for our new task. This approach is largely used in different domains (e.g., image recognition, positioning systems, language translation, etc.). In the domain taken into consideration in this work it offers a twofold advantage because it reduces the information requirement, and allows us to define an adaptive models;

Data Stability a further transversal problem that affects all the EEG-based approaches, is related to the repeatability of the recognition process [36]. It occurs because the acquired data (brain waves patterns) are influenced by different elements such as the state of relaxation of the user during the data acquisition, the number of sessions used for the experiments, the movements of the user during the data acquisition, and so on. In addition, even under the same conditions, the data vary over time, and this implies the

Table 7 Experimental hardware

Work ID	EEG device	Used channels	Bit resolution	Sampling rate
W19	Brain products actiCHamp	64	24	500 Hz
W01	EB-Neuro Galileo be light	19	12	32 KHz
W02	Emotiv Epoch +	14	16	128 Hz
W03	Emotiv Epoch +	14	16	128 Hz
W05	Emotiv Epoch +	14	16	128 Hz
W10	Emotiv Epoch +	14	16	128 Hz
W13	Emotiv Epoch +	14	16	128 Hz
W14	Emotiv Epoch +	14	16	128 Hz
W16	Emotiv Epoch +	14	16	128 Hz
W18	Emotiv Epoch +	14	16	128 Hz
W21	Emotiv Epoch +	14	16	128 Hz
W22	Emotiv Epoch +	14	16	128 Hz
W24	Emotiv Epoch +	14	16	256 Hz
W25	Emotiv Epoch +	14	16	256 Hz
W26	Emotiv Epoch +	14	16	256 Hz
W07	G.Tech g.USBamp	16	24	2400 Hz
W15	InteraXon Muse	4	12	500 Hz
W04	Neuroscan Nuamps	40	22	1000 Hz
W11	Neuroscan Synamp2	9	24	1000 Hz
W17	Neuroscan Synamp2	9	24	1000 Hz
W20	Neuroscan Synamp2	9	24	1000 Hz
W09	Nicolet EEG wireless amplifier	7	24	12 KHz
W06	NS	8	NS	256 Hz
W08	NS	6	NS	250 Hz
W23	NS	7	NS	12 KHz
W12	OpenBCI utracortex mark IV + cyton board	8	24	250 Hz

Fig. 8 EEG hardware distribution



adoption of more sophisticated techniques than those commonly used with other biometric approaches [40]. A study aimed to investigate this problem was performed in Pham et al [57], where based on the experimental results the authors demonstrate that some emotions should be considered in order to improve the EEG data stability in the context of the biometric user authentication applications;

Electrodes Minimization last but not least is the problem related to the need to use a reduced number of electrodes during the biometric process of user recognition based on EEG data. This problem arises from the need to obtain good performance even using a reduced number of electrodes, an indispensable condition for the widespread use of the EEG data as a biometric user recognition system. In this regard it should be observed that the EEG devices used in many literature works use a high number of electrodes [7, 8] (an average of 33), whereas many EEG devices in the medical field also use 64 electrodes, then their number is much higher than that of the low-cost commercial devices. Several studies in the literature investigated about this problem, such as in Moctezuma and Molinas [47], where the authors propose a biometric system based on EEG data designed with a minimal subset of EEG channels, or in [38], which proposes a deep-learning-based technique to automatically search for the minimum number of EEG channels.

4.4.2 Specific challenges

In the context of biometric user identification mainly emerges a twofold type of problem, one related to the nature of the involved data and another related to the data acquisition process.

The first type of problem is related to the non-stability of the EEG patterns over time since the involved data are complex, nonlinear, and non-stationary, and these characteristics do not allow us to obtain useful information from these signals in the time domain, directly by observing them Subha et al. [82]. This is a challenge that has been faced in many works of the literature, in a parallel way to the works addressed to exploit the EEG data in the biometric field. In this regard, it should be noted that the stimulation of users (i.e., through the evoked potentials techniques) during the acquisition of EEG data is mainly aimed at reducing the effects of this problem, creating conditions in which the brain waves signals show greater repeatability compared to the EEG data acquired without any external stimulus, in accordance with what the discussed works discussed highlight.

The second problem instead refers to aspects such as the user heterogeneity in terms of EEG waves, and the need to perform a calibration of the acquisition/stimulation system. This is an aspect implicitly or explicitly reported in many of the discussed papers, which proposed approaches that are not suitable for real-world biometric user identification applications, precisely due to this issue. Some possible examples are the discussed works that use professional high-cost and big-sized EEG equipment, e.g., [33], where in addition to the high price (unsuitable for large-scale applications), they need a large number of electrodes, whose application on the user's scalp requires a long time, as well as the use of a conductive paste since they do not adopt the dry EEG electrodes technology that is used in almost all the low-cost EEG devices such as those reported in Table 2. In such a context, it should be underlined that a widely usable biometric user identification system should be based on hardware that does not require extensive and/or complicated preparation/calibration, in order to be used by the users themselves, without the need for an operator who manages the operations, similarly to the most common biometric recognition systems widely used today [14].

Representative examples of the effectiveness of some approaches/strategies in the considered literature can be found in Piciucco et al. [58], where the experimental results related to the proposed SSVEP approach demonstrate the existence of stable characteristics in the EEG response across several acquisition sessions, or in Mu et al. [48], where the experimental results prove that the proposed visual stimulation approach can improve the stability of the EEG signals over time. Other significant examples are the work in Zeng et al. [103], where the EEG-based user identification system stability has been tested for a 30-day averaged time interval, or that in Seha and Hatzinakos [70], where the authors use the wavelet packet decomposition to get more permanent patterns over time. Still in the context of the literature works taken into consideration, also some non-conventional auditory stimuli such as the musical one can lead toward a relatively stable accuracy in the context of user authentication systems, as demonstrated in Li et al. [42]. It should be noted that not all the discussed works present this characteristic in their experimental results, as some of them, such as in Yamashita et al. [97] or in El-Fiqi et al. [25], where the authors postpone to a future work the study of the EEG pattern stability over time.

4.5 Future research directions

Concerning the future research directions related to the area we taken into account in this work (i.e., that related to techniques that combine EEG signals with EP stimuli), the literature underlines the need to better validate the obtained results through experimental processes that involve a greater number of users, considering that many state-of-the-art works are based on a small number of participants.

Such an improvement during the experimental process, combined with the ever-increasing performance of acquisition devices and analysis techniques, could lead in the future to reliable and low-cost identification systems that allow us widespread use of EEG data, both individually and in combination with other biometric systems.

4.5.1 Emerging ideas

More generally, in the light of the problems previously discussed in Sect. 4.4, one of the ideas that are increasingly being taken into consideration is that of realizing hybrid systems capable of mitigating these issues, for example, by combining EEG signals with other signals (electrocardiogram data, eye-tracking data, etc.) [94].

This means that there is an increasing of multimodal biometric systems in the literature, which combine different techniques and biometric data, and this is not a recent research direction, as evidenced by the work in Yang and Ma [99], where the authors define a multimodal identification system based on palmprint and iris score level fusion and wavelet packet transform, or that in Murakami and Takahashi [50], where instead the authors propose an identification system based on face recognition, fingerprint, and iris biometric data.

Another class of approaches that seems to give good results in this application area is the one that exploits the functional near-infrared spectroscopy (fNIRS), a technique that measures the brain signals by measuring modifications in the properties of light as it shines through the skull and is refracted back to a particular sensor, or the functional magnetic resonance imaging (fMRI), a technique that measures the changes in blood flow that happens during the brain activity [90].

In light of the above, it is clear that research in this field will be increasingly multidisciplinary, involving areas such as neuroscience, engineering, computer science, and many others [3].

4.5.2 Possible future improvements

Although research in this area shows us an increasingly widespread use of EEG information in the biometric field in the future, it also shows the impossibility of directly using this type of biometric data (EEG signals) to identify users, differently from what happens with other biometric-type approaches (face recognition, voice recognition, fingerprint recognition, etc.). This occurs because EEG data alone fail to provide stable patterns capable of discriminating users unambiguously over time. For this reason, the evolution of techniques in the literature shows the involvement of increasingly sophisticated classification models but, above all, the combined use of other techniques/strategies (e.g., evoked potentials) and/or additional biometric information (e.g., heart rate, eye movements, etc.). What this scenario suggests for the future (at least for the foreseeable future) is therefore the use of EEG data in combined systems, where such information is mainly used to improve user identification performance in systems that adopt other types of biometric data.

A quite transversal problem that emerges from the literature, which affects many EEG-based approaches, is that related to the users' de-identification since some systems, such as those aimed at the user identification, should adequately protect the privacy of the involved biometric data [78].

5 Conclusion and future work

The evidence of the surveyed works related to the last six years shows the potential feasibility of a biometric approach based on EEG data under certain external stimuli, inviting researchers to continue experimenting with new techniques and strategies aimed at consolidating the studies carried out so far. In particular, the number of literature works indicates a growing interest in this type of approach, year by year: Indeed, the actual number of publications is much greater, as in this work, we have considered only those that exploit both EEG signals and EP stimuli and meet our methodology requirements.

We are convinced that each new work in the literature offers an interesting contribution to the improvement of such EEG-based identification systems, and that a future combination of these contributions can lead toward the definition of ever more accurate systems. The potential of such a biometric approach opens up stimulating scenarios related to the improvement in the security field, with repercussions also for what concerns a better knowledge of the mechanisms of EEG response to external stimuli, which can be profitably used, transversely, in other areas.

Unlike other similar works in the literature, this work has been focused on a specific research field where the EEG data are combined with the most widespread stimulation technologies to create biometric user identification systems able to reduce the issues related to the EEG patterns instability, i.e., it is focused on precise software/hardware applications. This approach allowed us to evaluate the literature of the last six years in a quite exhaustive way, offering a valuable tool to the research community for verifying the state of the art, and evaluating the feasibility of such biometric systems in real-world contexts.

Based on our study, we provide recommendations below on what we believe to be priority goals for future research developments.

1. *Improving experimentation* In Sect. 4.2.2, we have shown that despite some outstanding results, the

number of user involved is generally low, from which we infer that some results may be overly optimistic and need further experimentation to be confirmed. Accordingly, more in-depth experiments need to be carried out, especially experiments that involve a more significant number of users.
2. *Enhancing practical usability* Although substantial academic fermentation is at this stage, we have noticed that some methods require conditions that are difficult to be applied in a real-world context. Moreover, it is also challenging to reproduce the experiments described in some papers for the same reasons. Accordingly, we recommend considering the practical applicability in a real-world context when developing new methods.
3. *Combining biometric systems* One promising approach that researchers should explore further is combining the biometric systems based on EEG data with other biometric systems to improve the overall performance or define multilevel user identification systems [56].
4. *Experiment with new stimulation approaches* Similar to the effort to use low-cost and easy-to-use hardware for acquiring EEG data, future research in this field (EEG + EP) should consider that the large-scale use of such systems for biometric user identification goals cannot be based on dedicated EP hardware devices. More specifically, it should be able to exploit already available stimuli generated by a computer until the market makes available low-cost dedicated devices, as happened for EEG data acquisition devices. Some examples of possible stimuli are images, sounds, or their combination.

As future work, in accordance with what was formalized in our recent position paper [69], we intend to design and implement a biometric user identification system based on low-cost and easy-to-find EEG devices, as well as on external stimuli techniques that do not require particular hardware (e.g., based on images and sounds generated by a computer), focusing our research more on the feasibility of the approach (i.e., simple operative environment in terms of hardware and number of electrodes, and reasonable detection times), rather than only on the mere performance of the system, searching the right balance between these two aspects. In this context, concerning the process of characterization and identification/classification of the EEG patterns, we would also like to experiment with some of the approaches/strategies we have adopted with interesting results in other domains, such as the *local feature engineering* (LFE) [13] strategy, the *discretized extended feature space* (DEFS) [68], and the *discretized enriched data* (DED) [67] models.

Acknowledgements This research was partially funded and supported by Visioscientiae Srl.

Data availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declaration

Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Abed SS, Abed ZF (2020) User authentication system based specified brain waves. J Discrete Math Sci Cryptogr 23(5):1021–1024
2. Alarcao SM, Fonseca MJ (2017) Emotions recognition using EEG signals: a survey. IEEE Trans Affect Comput 10(3):374–393
3. Al-Nafjan A, Hosny M, Al-Ohali Y et al (2017) Review and classification of emotion recognition based on EEG brain-computer interface system research: a systematic review. Appl Sci 7(12):1239
4. Arnau-González P, Katsigiannis S, Arevalillo-Herráez M et al (2021) Bed: a new dataset for EEG-based biometrics. IEEE Internet Things J 8(15):12219–12230
5. Baakek YNEH, Debbal SMEA (2021) Digital drugs (binaural beats): how can it affect the brain/their impact on the brain. J Med Eng Technol 45(7):546–551
6. Bayrak Ş, Yücel E, Takçi H (2019) Classification of extracranial and intracranial EEG signals by using finite impulse response filter through ensemble learning. In: 2019 27th signal processing and communications applications conference (SIU). IEEE, pp 1–4
7. Bidgoly AJ, Bidgoly HJ, Arezoumand Z (2020) A survey on methods and challenges in EEG based authentication. Comput Secur 93(101):788
8. Bidgoly AJ, Bidgoly HJ, Arezoumand Z (2022) Towards a universal and privacy preserving EEG-based authentication system. Sci Rep 12(1):1–12
9. Blauert J (2013) The technology of binaural listening. Springer, Berlin
10. Brocal F (2023) Brain-computer interfaces in safety and security fields: risks and applications. Saf Sci 160(106):051
11. Campisi P, La Rocca D (2014) Brain waves for automatic biometric-based user recognition. IEEE Trans Inf Forensics Secur 9(5):782–800
12. Carrión-Ojeda D, Fonseca-Delgado R, Pineda I (2021) Analysis of factors that influence the performance of biometric systems based on EEG signals. Expert Syst Appl 165(113):967
13. Carta S, Podda AS, Recupero DR et al (2020) A local feature engineering strategy to improve network anomaly detection. Future Internet 12(10):177
14. Chan HL, Kuo PC, Cheng CY et al (2018) Challenges and future perspectives on electroencephalogram-based biometrics in person recognition. Front Neuroinform 12:66
15. Choi GY, Choi SI, Hwang HJ (2018) Individual identification based on resting-state EEG. In: 2018 6th international conference on brain–computer interface (BCI). IEEE, pp 1–4
16. Colburn HS, Durlach NI (1978) Models of binaural IEG interaction. Handb Percept 4:467–518

17. Coull BM, Pedley TA (1978) Intermittent photic stimulation. Clinical usefulness of non-convulsive responses. Electroencephalogr Clin Neurophysiol 44(3):353–363
18. da Silva Junior M, de Freitas RC, dos Santos WP et al (2019) Exploratory study of the effect of binaural beat stimulation on the EEG activity pattern in resting state using artificial neural networks. Cogn Syst Res 54:1–20
19. Dahel S, Xiao Q (2003) Accuracy performance analysis of multimodal biometrics. In: IEEE systems, man and cybernetics society, information assurance workshop, 2003. IEEE, pp 170–173
20. Das R, Maiorana E, Campisi P (2016) EEG biometrics using visual stimuli: a longitudinal study. IEEE Signal Process Lett 23(3):341–345
21. Das R, Maiorana E, Campisi P (2018) Motor imagery for EEG biometrics using convolutional neural network. In: 2018 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, pp 2062–2066
22. Di GQ, Fan MC, Lin QH (2018) An experimental study on EEG characteristics induced by intermittent pure tone stimuli at different frequencies. Appl Acoust 141:46–53
23. Di Y, An X, He F et al (2019) Robustness analysis of identification using resting-state EEG signals. IEEE Access 7(42):42113–42122
24. Donoghue T, Dominguez J, Voytek B (2020) Electrophysiological frequency band ratio measures conflate periodic and aperiodic neural activity. Eneuro 7(6)
25. El-Fiqi H, Wang M, Salimi N et al (2018) Convolution neural networks for person identification and verification using steady state visual evoked potential. In: 2018 IEEE international conference on systems, man, and cybernetics (SMC). IEEE, pp 1062–1069
26. Fraschini M, Pani SM, Didaci L et al (2019) Robustness of functional connectivity metrics for EEG-based personal identification over task-induced intra-class and inter-class variations. Pattern Recognit Lett 125:49–54
27. Goodin P, Ciorciari J, Baker K et al (2012) A high-density EEG investigation into steady state binaural beat stimulation. PLoS ONE 7(4):e34789
28. Grana M, Aguilar-Moreno M, De Lope Asiain J et al (2020) Improved activity recognition combining inertial motion sensors and electroencephalogram signals. Int J Neural Syst 30(10):2050053
29. Gui Q, Ruiz-Blondet MV, Laszlo S et al (2019) A survey on brain biometrics. ACM Comput Surv (CSUR) 51(6):1–38
30. Handy TC (2005) Event-related potentials: a methods handbook. MIT press, Cambridge
31. Hu Jf (2009) New biometric approach based on motor imagery EEG signals. In: 2009 international conference on future biomedical information engineering (FBIE). IEEE, pp 94–97
32. Jayarathne I, Cohen M, Amarakeerthi S (2017) Survey of EEG-based biometric authentication. In: 2017 IEEE 8th international conference on awareness science and technology (iCAST). IEEE, pp 324–329
33. Jijomon C, Vinod A (2021) Person-identification using familiar-name auditory evoked potentials from frontal EEG electrodes. Biomed Signal Process Control 68(102):739
34. Kasprzak C (2011) Influence of binaural beats on EEG signal. Acta Phys Pol A 119(6):986–990
35. Katsigiannis S, Arnau-González P, Arevalillo-Herráez M et al (2021) Single-channel EEG-based subject identification using visual stimuli. In: 2021 IEEE EMBS international conference on biomedical and health informatics (BHI). IEEE, pp 1–4
36. Kaur B, Kumar P, Roy PP et al (2017) Impact of ageing on EEG based biometric systems. In: 2017 4th IAPR Asian conference on pattern recognition (ACPR). IEEE, pp 459–464
37. Kim D, Kim K (2019) Resting state EEG-based biometric system using concatenation of quadrantal functional networks. IEEE Access 7(65):745-65–756
38. Kim HS, Ahn MH, Min BK (2021) Deep-learning-based automatic selection of fewest channels for brain–machine interfaces. IEEE Trans Cybern 52:8668–8680
39. Kora P, Meenakshi K, Swaraja K et al (2021) EEG based interpretation of human brain activity during yoga and meditation using machine learning: a systematic review. Complement Thera Clin Pract 43:101329
40. Lebedeva N, Karimova E (2020) Stability of human EEG patterns in different tasks: the person authentication problem. Neurosci Behav Physiol 50(7):874–880
41. Lee M, Song CB, Shin GH et al (2019) Possible effect of binaural beat combined with autonomous sensory meridian response for inducing sleep. Front Hum Neurosci 13:425
42. Li S, Marino L, Alluri V (2020) Music stimuli for EEG-based user authentication. In: The thirty-third international flairs conference
43. Li W, Huang Z (2020) Individual identification using code-modulated visual potentials with left-and-right balance. In: 2020 13th international congress on image and signal processing, biomedical engineering and informatics (CISP-BMEI). IEEE, pp 699–703
44. Llanos F, Xie Z, Chandrasekaran B (2019) Biometric identification of listener identity from frequency following responses to speech. J Neural Eng 16(5):056004
45. Matthews G, Reinerman-Jones L, Abich J IV et al (2017) Metrics for individual differences in EEG response to cognitive workload: optimizing performance prediction. Personal Individ Differ 118:22–28
46. Miyake T, Kinjo N, Nakanishi I (2020) Wavelet transform and machine learning-based biometric authentication using EEG evoked by invisible visual stimuli. In: 2020 IEEE region 10 conference (TENCON). IEEE, pp 573–578
47. Moctezuma LA, Molinas M (2020) Towards a minimal EEG channel array for a biometric system using resting-state and a genetic algorithm for channel selection. Sci Rep 10(1):1–14
48. Mu Z, Yin J, Hu J (2018) Application of a brain–computer interface for person authentication using EEG responses to photo stimuli. J Integr Neurosci 17(1):113–124
49. Mukai K, 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). IEEE, pp 567–572
50. Murakami T, Takahashi K (2011) Fast and accurate biometric identification using score level indexing and fusion. In: 2011 international joint conference on biometrics (IJCB). IEEE, pp 1–8
51. Nakanishi I, Hattori M (2017) Biometric potential of brain waves evoked by invisible visual stimulation. In: 2017 international conference on biometrics and Kansei engineering (ICBAKE). IEEE, pp 94–99
52. Nakanishi I, Maruoka T (2019) Biometric authentication using evoked potentials stimulated by personal ultrasound. In: 2019 42nd international conference on telecommunications and signal processing (TSP). IEEE, pp 365–368
53. Nakanishi I, Maruoka T (2020) Biometrics using electroencephalograms stimulated by personal ultrasound and multidimensional nonlinear features. Electronics 9(1):24
54. Nakashima H, Shindo Y, 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). IEEE, pp 109–113

55. Nishimoto T, Azuma Y, Morioka H, et al (2017) Individual identification by resting-state EEG using common dictionary learning. In: International conference on artificial neural networks. Springer, pp 199–207
56. Pham T, Ma W, Tran D et al (2014) Multi-factor EEG-based user authentication. In: 2014 international joint conference on neural networks (IJCNN). IEEE, pp 4029–4034
57. Pham T, Ma W, Tran D et al (2015) A study on the stability of EEG signals for user authentication. In: 2015 7th international IEEE/EMBS conference on neural engineering (NER). IEEE, pp 122–125
58. Piciucco E, Maiorana E, Falzon O et al (2017) Steady-state visual evoked potentials for EEG-based biometric identification. In: 2017 international conference of the biometrics special interest group (BIOSIG). IEEE, pp 1–5
59. Prathibha R, Swetha L, Shobha K (2017) Brain computer interface: design and development of a smart robotic gripper for a prosthesis environment. In: 2017 international conference on networks and advances in computational technologies (NetACT). IEEE, pp 278–283
60. Puengdang S, Tuarob S, Sattabongkot T, et al (2019) EEG-based person authentication method using deep learning with visual stimulation. In: 2019 11th international conference on knowledge and smart technology (KST). IEEE, pp 6–10
61. Purnamasari PD, Junika TW (2019) Frequency-based EEG human concentration detection system methods with svm classification. In: 2019 IEEE international conference on cybernetics and computational intelligence (CyberneticsCom). IEEE, pp 29–34
62. Rahman MA, Nakanishi I (2022) Person authentication using brain waves evoked by individual-related and imperceptible visual stimuli. In: 2022 international conference of the biometrics special interest group (BIOSIG). IEEE, pp 1–5
63. Rajan A, Hashim A, Akre V, et al (2018) The impacts of binaural beats. In: 2018 Fifth HCT information technology trends (ITT). IEEE, pp 353–357
64. Reshmi K, Muhammed PI, Priya V et al (2016) A novel approach to brain biometric user recognition. Procedia Technol 25:240–247
65. Rizal A, Hadiyoso S (2015) ECG signal classification using hjorth descriptor. In: 2015 international conference on automation, cognitive science, optics, micro electro-mechanical system, and information technology (ICACOMIT). IEEE, pp 87–90
66. Rosli FA, Saidatul A, Abdullah AA et al (2021) The wavelet packet decomposition features applied in EEG based authentication system. In: Journal of physics: conference series. IOP Publishing, p 012035
67. Saia R, Carta S, Recupero DR et al (2019a) A discretized enriched technique to enhance machine learning performance in credit scoring. In: KDIR, pp 202–213
68. Saia R, Carta S, Recupero DR et al (2019b) A discretized extended feature space (DEFS) model to improve the anomaly detection performance in network intrusion detection systems. In: KDIR, pp 322–329
69. Saia R, Carta S, Fenu G, et al (2022) Brain waves and evoked potentials as biometric user identification strategy: an affordable low-cost approach. In: SECRYPT. SCITEPRESS, pp 614–619
70. Seha SNA, Hatzinakos D (2019) A new approach for EEG-based biometric authentication using auditory stimulation. In: 2019 international conference on biometrics (ICB). IEEE, pp 1–6
71. Seha SNA, Hatzinakos D (2021) Longitudinal assessment of EEG biometrics under auditory stimulation: a deep learning approach. In: 2021 29th European signal processing conference (EUSIPCO). IEEE, pp 1386–1390
72. Seha SNA (2021) Brain biometrics under auditory stimulation for human identity recognition. Ph.D. thesis, University of Toronto (Canada)
73. Seo NJ, Lakshminarayanan K, Bonilha L et al (2015) Effect of imperceptible vibratory noise applied to wrist skin on fingertip touch evoked potentials-an EEG study. Physiol Rep 3(11):e12624
74. Sharif M, Raza M, Shah JH et al (2019) An overview of biometrics methods. Handbook of Multimedia Information Security: Techniques and Applications, pp 15–35
75. Shindo Y, Nakanishi I (2021) Person verification using electroencephalograms evoked by new imperceptible vibration stimulation. In: 2021 IEEE 3rd global conference on life sciences and technologies (LifeTech). IEEE, pp 282–286
76. Shindo Y, Nakanishi I, Takemura A (2019) A study on person verification using electroencephalograms evoked by unperceivable vibration stimuli. In: 2019 seventh international symposium on computing and networking workshops (CANDARW). IEEE, pp 416–419
77. Silberstein RB, Schier MA, Pipingas A et al (1990) Steady-state visually evoked potential topography associated with a visual vigilance task. Brain Topogr 3(2):337–347
78. Shopon M, Hossain Bari A, Bhatia Y et al (2022) Biometric system de-identification: Concepts, applications, and open problems. Handbook of Artificial Intelligence in Healthcare: Vol 2: Practicalities and Prospects, pp 393–422
79. Skoric MK, Jerbic AB, Krois I et al (2015) Vibratory evoked potentials. In: 6th European conference of the international federation for medical and biological engineering. Springer, pp 505–508
80. Snodgrass JG, Vanderwart M (1980) A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity. J Exp Psychol Hum Learn Mem 6(2):174
82. Soni YS, Somani S, Shete V (2016) Biometric user authentication using brain waves. In: 2016 international conference on inventive computation technologies (ICICT). IEEE, pp 1–6
83. Subha DP, Joseph PK, Acharya UR et al (2010) EEG signal analysis: a survey. J Med Syst 34(2):195–212
84. Thakor NV, Sherman DL (2013) EEG signal processing: theory and applications. In: Neural engineering. Springer, pp 259–303
85. Thomas KP, Vinod A (2017) Toward EEG-based biometric systems: the great potential of brain-wave-based biometrics. IEEE Syst Man Cybern Mag 3(4):6–15
86. Thomas KP, Vinod AP (2018) EEG-based biometric authentication using gamma band power during rest state. Circuits Syst Signal Process 37(1):277–289
87. Thomas KP, Vinod A, et al (2017) EEG-based biometrie authentication using self-referential visual stimuli. In: 2017 IEEE international conference on systems, man, and cybernetics (SMC). IEEE, pp 3048–3053
81. van Son D, De Blasio FM, Fogarty JS et al (2019) Frontal EEG theta/beta ratio during mind wandering episodes. Biol Psychol 140:19–27
88. Valizadeh SA, Riener R, Elmer S et al (2019) Decrypting the electrophysiological individuality of the human brain: identification of individuals based on resting-state EEG activity. NeuroImage 197:470–481
89. Valsaraj A, Madala I, Garg N et al (2020) Motor imagery based multimodal biometric user authentication system using EEG. In: 2020 international conference on cyberworlds (CW). IEEE, pp 272–279
90. Värbu K, Muhammad N, Muhammad Y (2022) Past, present, and future of EEG-based BCI applications. Sensors 22(9):3331
91. Von Bünau P, Meinecke FC, Scholler S, et al (2010) Finding stationary brain sources in EEG data. In: 2010 annual

international conference of the IEEE engineering in medicine and biology. IEEE, pp 2810–2813
92. Walsh P, Kane N, Butler S (2005) The clinical role of evoked potentials. J Neurol Neurosurg Psychiatry 76(suppl 2):ii16–ii22
93. Wan Z, Yang R, Huang M et al (2021) A review on transfer learning in EEG signal analysis. Neurocomputing 421:1–14
94. Wang M, Yin X, Zhu Y et al (2022) Representation learning and pattern recognition in cognitive biometrics: a survey. Sensors 22(14):5111
95. Wijayanto I, Hadiyoso S, Sekarningrum FA (2020) Biometric identification based on EEG signal with photo stimuli using hjorth descriptor. In: 2020 8th international conference on information and communication technology (ICoICT). IEEE, pp 1–4
96. Xavier G, Ting AS, Fauzan N (2021) P-eg002. An exploratory study of brain waves and corresponding brain regions of fatigue post-call doctors using quantitative electroencephalogram. Clin Neurophysiol 132(8):e78
97. Yamashita M, Nakazawa M, Nishikawa Y (2018) The proposal and it's evalution of biometric authentication method by EEG analysis using image stimulation. In: 2018 eleventh international conference on mobile computing and ubiquitous network (ICMU). IEEE, pp 1–4
98. Yang S, Deravi F (2017) On the usability of electroencephalographic signals for biometric recognition: a survey. IEEE Trans Hum-Mach Syst 47(6):958–969
99. Yang F, Ma B (2007) Notice of retraction: two models multimodal biometric fusion based on fingerprint, palm-print and hand-geometry. In: 2007 1st international conference on bioinformatics and biomedical engineering. IEEE, pp 498–501
100. Yap HY, Choo YH, Mohd Yusoh ZI et al (2021) Person authentication based on eye-closed and visual stimulation using EEG signals. Brain Inform 8(1):1–13
101. Yu T, Wei CS, Chiang KJ et al (2019) EEG-based user authentication using a convolutional neural network. In: 2019 9th international IEEE/EMBS conference on neural engineering (NER). IEEE, pp 1011–1014
102. Zabcikova M, Koudelkova Z, Jasek R et al (2022) Recent advances and current trends in brain–computer interface research and their applications. Int J Dev Neurosci 82(2):107–123
103. Zeng Y, Wu Q, Yang K et al (2019) EEG-based identity authentication framework using face rapid serial visual presentation with optimized channels. Sensors 19(1):6
104. Zhao H, Wang Y, Liu Z et al (2019) Individual identification based on code-modulated visual-evoked potentials. IEEE Trans Info Forensic Secur 14(12):3206–3216
105. Zhao H, Chen Y, Pei W et al (2021) Towards online applications of EEG biometrics using visual evoked potentials. Expert Syst Appl 177(114):961