Brain Waves Combined with Evoked Potentials as Biometric Approach for User Identification: A Survey

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Abstract. The growing availability of low-cost devices able of performing an Electroencephalography (EEG) has opened stimulating scenarios in the security field, where such data could be exploited as a biometric approach for user identification. However, a series of problems, first of all, the difficulty of obtaining unique and stable EEG patterns over time, has made this type of research a hard challenge that has forced researchers to design ever more efficient solutions. In this context, one of the approaches that has proved most effective is the one based on the application of external stimuli to the user during the EEG data collection, a stimulation method named Evoked Potentials (EPs), which is long used for other purposes in the clinical setting, in this context used to increase the EEG patterns stability. The combination of EEG and EP has generated an ever-increasing number of literature works but their heterogeneity makes it difficult to take stock of the state-of-the-art, so this work aims to analyze the literature of the last six years, providing information useful for directing the research of those who work in this field.

Keywords: Biometric, User Identification, Security, EEG, EP.

1 Introduction

Nowadays, the availability on the market of affordable and easy-to-use sensors capable of detecting EEG data has opened many new research directions ranging from the canonical ones related to health [60,34], up to the once unthinkable ones concerning applications in various fields such as, for example, those concerning security, where these data are used to create biometric systems [27]. Formally named Electroencephalogram (EEG) [52], the EEG data are captured by analyzing the brain electrical activity through some electrodes positioned on the user's head, electrodes which vary in number and positioning depending on both the applicative scenario and the used hardware. In more detail, they are placed on the user's scalp in a non-invasive way, directly or through a conductive paste. Also in this case it depends on the scenario and hardware: most of the low-cost devices do not require any paste or manual positioning, as they are applied to the user through a light headband/headset, whereas other more professional devices (e.g., those used in the medical field) usually require a manual positioning and a greater number of electrodes applied through a conductive paste.

The cortex is the largest area of our brain, it is made up of four lobes. The *frontal* lobe refers to executive functions (e.g. conscious thought). The *temporal* lobe relates to language, understanding, and memory and processes complex stimuli (e.g., scene and face recognition). The *parietal* lobe refers to sensory information integration related to different senses and the manipulation of objects. Finally, the *occipital* lobe refers to the vision activity. Moreover, we also have the *cerebellum*, which controls motor skills and is located at the back of the brain (below the occipital and temporal lobes).

In an adult user, the brain electrical activity measured by the EEG is typically from 10 to 100 millivolts. The electrodes are placed on the scalp according to the *International 10-20 System* reported in Fig. 1, where each electrode placement is identified by letters and numbers that refer to the lobe and the hemisphere location. In more detail, the letters C, F, P, O, and T refer to the lobes (Central, Frontal, Parietal, Occipital, and Temporal). Notably, the Central lobe does not exist and is used only for reference). In contrast, the even numbers refer to the right hemisphere, and the odd numbers refer to the left hemisphere. The letter z is used to indicate an electrode located on the centerline; in addition, smaller numbers indicate values closer to the median line. The point between the forehead and nose is called Nasion, while the point at the back of the skull is the Inion.

The human brain contains billions of neurons, each connected to thousands of others, creating a massive network of brain circuits that communicate through electrical signals in the order of microvolts. The activation of a neuron generates electrical pulses, and this activity is called brain waves. The brain waves are related to five areas, each denoted using a Greek letter and characterized by a different frequency range (from 4 to 100 Hz), and all operate simultaneously. Accordingly, the EEG activity is divided into frequency bands: The Delta wave is less than 4 Hz. The Theta wave is in the range between 4 and 8 Hz. The Alpha wave is in the range between 8 and 12 Hz. The Beta wave is in the range between 12 and 30 Hz. The Gamma wave is greater than 30 Hz. The literature indicates a strong correlation between the slowest rhythms of the brain waves and the inactive brain state, and the fastest rhythms of them and the brain processing of information, as well as that the deep sleep status has low frequency and high amplitude oscillations. On the other hand, the wakefulness status has high frequency and low amplitude oscillations.

1.1 Motivations and Contributions

Compared to other biometric systems, such as, for instance, those based on fingerprints or retinal, few works in the literature propose biometric systems based on EEG that are suitable for large-scale utilization. This is due to some limitations, for instance, the acquisition protocols that result unsuitable for user identification applications (e.g., due to positioning and number of electrodes, acquisition time, etc.) and the difficulty of obtaining stable patterns over time. In light of these aspects and based on the evaluation metrics primarily used in biometrics, in this work, we aim to explore the literature related to the biometric approaches that combine EEG and EP in the period from 2017 to 2022 to take stock of the situation, providing useful findings for anyone working in this research field. The scientific contributions of our work are reported in the following:

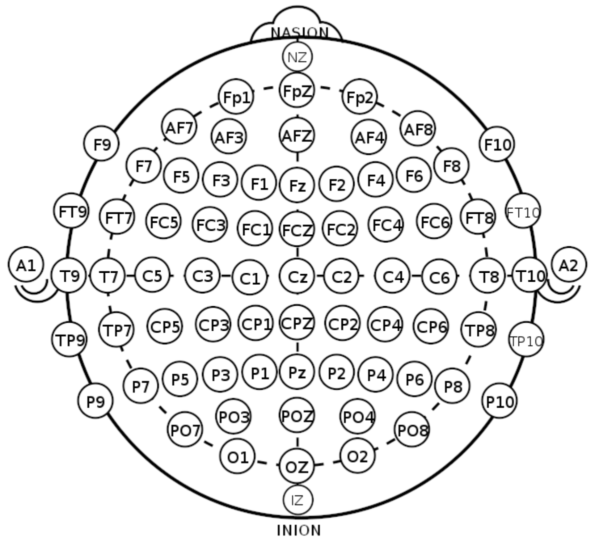

Fig. 1. 10-20 system EEG Electrode Placement.

- It analyzes the last six-year state of the art of biometric systems that use EEG data and EP stimuli (i.e., visual, auditory, and vibration ones) to evaluate the practical feasibility of these systems for large-scale biometric user identification applications.
- It surveys these literature works concerning the hardware devices, the adopted techniques, the open problems, the assessment metrics, and the data collection protocols.
- It compares the performance of these works, underlining the current challenges and indicating the direction taken by researchers in the development of these systems.

2 Research Scenario

This section starts by introducing the widespread low/medium-cost devices capable of acquiring EEG data (Section 2.1), continuing with providing information about the different biometric methods aimed to perform the user identification task (Section 2.2), the related open problems (Section 2.4), the different EP techniques (Section 2.3), concluding by discussing the assessment metrics largely used in the biometric systems area (Section 2.5).

2.1 EEG Data Acquisition

Table 1 reports the popular low/medium cost devices capable of acquiring EEG data, all of them usually characterized by a construction that allows easy use. This means that the electrodes do not require any conductive paste for the application and they are positioned on the users' skull through a sort of headband/headset, and the connections are made wirelessly. It should be noted that some of the cited manufacturers (e.g, *OpenBCI*), also produce and sell high-price devices, which we do not take into account, as they do not allow us a widespread use, due to the high cost, the size and the high number of electrodes involved. In addition, it is necessary to specify that the discussed devices follow the placement shown in Fig. 1 but they use fewer electrodes.

Table 1. Widespread Low/Medium-Cost EEG Acquisition Devices

Manufacturer	Device name	Bits resolution	Range (Hz)	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 S	12	0.20−45	04
InteraXon	Muse-2	12	0.20−45	04
Neurowsky	MindWave Mobile 2	12	3.00−100	01
OpenBCI	Cyton Biosensing Board	24	1.00−50	08

Although many devices provide additional sensors besides EEG ones (e.g., Photoplethysmogram, Pulse Oximetry, Gyroscope, Accelerometer, etc.), as they are not related to the scope of this work, they will not be taken into consideration by us. In addition to the low cost and ease of use of these devices, one of the most important aspects for those working in this research area is the growing availability of libraries for the development of applications based on them, e.g., the framework *Brains@play* (https://brainsatplay.com), the Python libraries *Brainflow* (https://brainflow.org), and the tools for acquiring, viewing, and recording EEG data *Muse LSL* (https://github.com/alexandrebarachant/muse-lsl).

2.2 Biometric Methods

A biometric user identification method has the purpose of comparing the data detected by one or more biometric sensors to those stored in a database (unique characteristics of the involved users), using techniques and strategies aimed at reducing the false negatives and false positives number. A typical EEG data process is carried out through three distinct steps, in the first of these the raw EEG data are acquired through the adopted hardware, in the second step the EEG patterns are extracted according to a previously defined protocol, and these patterns are analyzed in the last step according to a certain objective. There are several biometric methods and each of them presents advantages and disadvantages [46].

In recent years, the literature shows a growing interest in biometric approaches based on EEG data [62]. Some works address the problem on a practical level [53,54,9], whereas other ones face secondary but equally important aspects such as, for example, the choice of the most suitable evaluation metrics for measuring the performance of these systems [12], or hybrid techniques that combine EEG with different data to get better results in the biometric system [50].

In the context of biometric systems designed for user identification based on EEG data, to obtain univocal EEG patterns stable over time, some literature works propose approaches based on external user stimulation during the acquisition process of EEG data, getting interesting results. However, in many cases it is not possible to use these combined approaches on large-scale applications due to some limitations such as, for instance, the high cost of the involved hardware and/or the long times required for the data acquisition [13]. An interesting overview of these systems is provided by the authors of this work [26], as well as in this one [26] where the EEG data is acquired during an invisible visual stimulation, or in this other one [1], which proposes a system for the user identification based only on the *Gamma* and *Beta* waves.

2.3 Evoked Potentials

Evoked Potentials (EPs) [57] are defined in the literature in terms of electrical potentials measurable in areas of the nervous system (primarily in the brain) after the application of external stimuli. There are different techniques to generate such stimuli, for example, the *Visual Evoked Potentials* (VEPs) that use visual stimuli [7], the *Auditory Evoked Potentials* (AEPs) that employ acoustic stimuli [33], and the *Vibratory Evoked Potentials* [49], where vibrations are used [49]. They have numerous applications in the clinical field, mainly to diagnose neurological disorders, and their intensity is in the order of microvolts. The generation of stimuli is performed employing different devices such as, just to give some examples: in the case of VEPs, through a sort of glasses capable of producing visual stimuli [6]; in the case of AEPs, through the production of sounds at certain frequencies in a headphon [10]; in the case of the *Vibratory Evoked Potentials*, through devices capable of producing vibrations [48]. Although other stimulation approaches also exist, for the scope of this work we will consider only the widespread and easy-to-use ones used in the literature (i.e., auditory, visual, and vibratory approaches) in the period from 2017 to 2022.

2.4 Open Problems

Some problems make it difficult to use EEG for biometric user identification approaches. The first of these is the complexity of the data at stake as they are composed of very complex, non-linear, and non-stationary signals [51].

This data scenario forces to use of even very complex approaches to deal with the problem as, for example, in this work [56], where the authors employ a *Stationary Subspace Analysis* (SSA) technique to extract stationary and non-stationary EEG data, separately. A survey that discusses approaches and challenges related to the EEG data used in biometric field is provided in [2], and a study aimed at the identification of the elements able to improve or worsen the performance of these biometric systems is instead provided in [4].

Another relevant problem that complicates the problem of the non-stationary nature of the data is related to the diversity that characterizes the EEG data of the users under equal conditions, making the definition of a common acquisition protocol very complex [21]. A further complication is given by the fact that system noise is very loud compared to the EEG signal, making it difficult the exploitation of EEG data in a reliable way [58].

The needed calibration of the hardware used for the acquisition of EEG data represents another problem in the biometric identification systems, which should be characterized by quick use. In the literature, this problem is tackled using several approaches such as, for example, the one based on *transfer learning* [58] technique, where a model previously created for an objective is used as the base for the creation of a new model for another one, effectively reducing the calibration time. In other words, this approach modifies an evaluation model via prior knowledge, a technique already used in other scenarios (e.g., positioning systems, image recognition, etc.), which is used to face the mentioned problem of system calibration.

Another type of problem, which is transversal to this kind of approaches, is the poor repeatability of the EEG pattern under equal conditions of acquisition [16], a crucial aspect investigated in this study [31], in which the authors demonstrates that in order to obtain greater stability of the EEG patterns it is necessary to take into account some emotional states of the users. This is because many factors influence the EEG data acquisition such as, for example, the movement of the users and their state of relaxation, factors that make the acquired EEG data different, even with the same acquisition conditions, and that require the adoption of techniques and strategies to face the problem [18].

Last but not least, it is the problem related to the number of electrodes necessary for an optimal acquisition of EEG data, since many works in the literature characterized by good performance employ acquisition hardware that requires a number of electrodes not compatible with a large-scale usage of these systems [2,3]. This is a problem discussed and faced in [23], where the authors use few electrodes while achieving good performance, or in this another work [17], where the authors propose a technique capable of identifying the optimal/minimum number of electrodes to use.

2.5 Evaluation Metrics

According to the literature, the biometric systems performance is primarily assessed through the *False Rejection Rate* (FRR) and the *False Acceptance Rate* (FAR) [8] metrics. These two metrics provide the measure of access granted by mistake to unauthorized users (FAR), as well as that of access denied to authorized users (FFR). They are therefore two inversely proportional metrics since as the value of one increases, that of the other one decreases and vice versa. it should be highlighted that for a user identification system, a bad FRR value is more tolerable than a FAR one, for obvious prudential reasons. Other metrics used in this field, which are based on the two previously mentioned, are the *Half Total Error Rate* ($HTER = \frac{(FAR+FRR)}{2}$), and the *Equal Error Rate* (EER), which represents the value of HTER when $FAR = FRR$. The *Correct Recognition Rate* (CRR) and the *True Acceptance Rate* (TAR) are other two metrics used in some literature works. The first metric gives us a measure of the users identified correctly with regard to the total of them, whereas the second one is formalized as $TAR = 1 - FRR$.

3 Research Methodology

We collected the literature works that combine EEG and EP to implement biometric user recognition approaches according to the following five steps:

1. We extract a first list through *Google Scholar* (https://scholar.google.it) by using a series of keywords able to identify only the literature works actually centered on the type of biometric system we have taken into consideration, i.e., we have defines as optimal query: `allintitle: ("brain waves" | EEG) + (authentication | biometric) + (stimulation | stimuli | evoked)`, since it takes into account the keywords only in the title of the work, excluding, for instance, those cases when they are present only in the related work. However, at the end of the process, a further search was carried out by us without using the `allintitle` directive to include other relevant works that do not have our keywords in the title.
2. We applied a filter on the candidate list previously defined, with the aim to keep only the works related to the period from 2017 to 2022;
3. Another filter was applied by us to remove the less authoritative works, considering only those indexed on *Scopus* or/and *Web of Science* (WOS).
4. The list was further filtered in order to keep only the works based on the combination of EEG data and auditory, visual, or vibratory EP. The criterion adopted in this work is to consider only EP techniques suitable for use in a biometric user identification system, thus excluding those that do not satisfy this requirement. This criterion allows us to provide an exhaustive view of the systems designed for user identification tasks that are based on approaches that are more suitable for large-scale use, unlike some works in the literature which are instead characterized by purely theoretical approaches.
5. In the last step, we removed those works that did not allow us a comparative analysis, limiting this exclusion only to works that did not allow us such a comparison in any way, either directly or indirectly.

The results of the previous steps are shown in Table 2, where the selected works are sorted by date, and each of them has been assigned an identifier (i.e., $P01, P02, \ldots, P26$) to provide a quick reference. We can observe that for the year 2022, when we wrote this work there was only a work in the literature that met the requirements previously mentioned, and this we believe is probably due to the publication time.

4 Literature Analysis

Premising that to allow the comparison of all the works, when the CRR value is not provided by the authors, it will be calculated assuming that $CRR = 1 - EER$, on the basis of their analysis we can perform the following considerations:

- The literature indicates a growing interest over the years in the research sector considered in this work, and some of these works are approaches of the same authors improved over the years (e.g., $P02$, $P10$, and $P13$).

Table 2. List of papers selected for the survey.

Paper	Publisher	Year	Bibliography
P01	IEEE	2017	[32]
P02	IEEE	2017	[26]
P03	IEEE	2017	[55]
P04	IMR	2018	[24]
P05	IEEE	2018	[61]
P06	IEEE	2018	[11]
P07	MDPI	2019	[64]
P08	IEEE	2019	[35]
P09	IEEE	2019	[44]
P10	IEEE	2019	[27]
P11	IEEE	2019	[66]
P12	FLAIRS	2020	[19]
P13	MDPI	2020	[28]
P14	IEEE	2020	[22]
P15	IEEE	2020	[59]
P16	IEEE	2020	[25]
P17	IEEE	2020	[20]
P18	Springer	2021	[63]
P19	Elsevier	2021	[14]
P20	Elsevier	2021	[65]
P21	IOP	2021	[37]
P22	IEEE	2021	[15]
P23	IEEE	2021	[45]
P24	IEEE	2021	[29]
P25	IEEE	2021	[47]
P26	IEEE	2022	[36]

- The information reported in Table3 shows that many literature approaches do not employ low/middle-cost EEG devices, adopting instead expensive/professional hardware (i.e., works P01, P04, P07, P09, P11, P12, P17, P19, P20). In addition, the P06, P08, and P23 work do not specify the hardware being used (this is denoted with *NS*).

Table 3. Hardware Employed for the Experiments

Paper	Device	Channels	Sampling rate	Resolution (bit)
P01	EB-Neuro Galileo Be Light	19	32 KHz	12
P02	Emotiv Epoch +	14	128 Hz	16
P03	Emotiv Epoch +	14	128 Hz	16
P04	Neuroscan Nuamps	40	1000 Hz	22
P05	Emotiv Epoch +	14	128 Hz	16
P06	NS	8	256 Hz	NS
P07	G.Tech g.USBamp	16	2400 Hz	24
P08	NS	6	250 Hz	NS
P09	Nicolet EEG Wireless Amplifier	7	12 KHz	24
P10	Emotiv Epoch +	14	128 Hz	16
P11	Neuroscan Synamp2	9	1000 Hz	24
P12	OpenBCI Utracortex Mark IV + Cyton board	8	250 Hz	24
P13	Emotiv Epoch +	14	128 Hz	16
P14	Emotiv Epoch +	14	128 Hz	16
P15	InteraXon Muse	4	500 Hz	12
P16	Emotiv Epoch +	14	128 Hz	16
P17	Neuroscan Synamp2	9	1000 Hz	24
P18	Emotiv Epoch +	14	128 Hz	16
P19	Brain Products actiCHamp	64	500 Hz	24
P20	Neuroscan Synamp2	9	1000 Hz	24
P21	Emotiv Epoch +	14	128 Hz	16
P22	Emotiv Epoch +	14	128 Hz	16
P23	NS	7	12 KHz	NS
P24	Emotiv Epoch +	14	256 Hz	16
P25	Emotiv Epoch +	14	256 Hz	16
P26	Emotiv Epoch +	14	256 Hz	16

- Despite these cases, the literature shows that it is still possible to achieve design effective EEG-based approaches even using low/middle-cost devices, according to the usage percentage shown in Table 4.
- Another consideration should be made about the experimental requirements for some approaches, which appear incompatible for large-scale user identification systems (e.g., long times required to acquire data), providing only a theoretical contribution.
- Some literature works taken into account (i.e., $P11$, $P15$, $P16$, and $P20$) appear to be infallible, with CRR=100% or with an error rate equal to zero, so as reported in Table 5. Unfortunately, this does not only depend on the effectiveness of the proposed approach but also on the not optimal validation process that, for instance, involves a low number of users, preventing the generalization of the reached perfor-

Table 4. Hardware Distribution

Hardware	Number	Usage (%)
Emotiv Epoch+	13	50.00
Neuroscan Synamp2	03	11.52
Not Specified	03	11.52
OpenBCI Utracortex Mark IV + Cyton board	01	03.85
EB-Neuro Galileo Be Light	01	03.85
G.Tech g.USBamp	01	03.85
InteraXon Muse	01	03.85
Neuroscan Nuamps	01	03.85
Nicolet EEG Wireless Amplifier	01	03.85
Brain Products actiCHamp	01	03.85

mance. In this regard, only four of all the considered literature works employ more than twenty-five users and, in any case, none of them employ more than thirty-one users.

- The analysis of the literature approaches also show that there is no direct correlation between the approach performance and the adopted technique of stimulation, as this mainly depends on the technique/strategy with which the biometric system was designed.
- Because the number of users involved in the validation process of the works taken into consideration is different, we thought it appropriate to evaluate the approach performance (AP) according to the weighted criterion shown in Equation 1, where the CRR performance of a paper $p \in P$ is denoted as CRR_p, and the involved users are denoted as $|U|_p$.

$$AP = \frac{\sum\limits_{p=1}^{P} (CRR_p \cdot |U|_p)}{\sum\limits_{p=1}^{P} |U|_p} \tag{1}$$

- Based on the AP metric previously formalized, we calculated the best average performance related to the different types of stimulus, obtaining for the approaches that use visual stimuli a value of 96.72% (16 works, not considering $P22$ since its aim was not to get the best CRR performance but a study aimed at investigating the performance of each single EEG channel), whereas for the those that use auditory stimuli a value of 97.45% (7 works), and for those that use vibration stimuli a value of 82.50% (2 works).

4.1 Data Acquisition Protocols

The data acquisition protocols deserve a separate discussion, since the reliability of the experimental results depends on them. In this regard, the works in the literature appear very heterogeneous since each work is characterized by different parameters as regards crucial elements such as, for instance, the acquisition sessions and the users involved, as well as regarding the duration and the break between sessions. A significant example of this high degree of heterogeneity is given by the number of users involved (one of the most important parameters), considering that some works involve only four users [55], whereas in other ones thirty-one users [61], with an average number of users for all works of fifteen. In addition, only some authors underline the limitation given by the low number of users involved in the experiments, proposing to increase them in future works [29,47] For the above reasons, in Table 5 we carried out a comparison of all the works on the basis of the main experimental parameters used by the authors.

Table 5. Experimental environment, performance, and parameters.

Paper	Stimulus	Max CRR	Total subjects	Total sessions	Session duration and repetitions	Average session time interval
P01	Visual	96.00	25	02	N.A.	15 days
P02	Visual	77.00	20	10	6 s - 55 times	2 sessions per day
P03	Visual	87.50	04	10	17 s - 20 times	N.A.
P04	Visual	82.30	10	06	1.25 s - 370 times	1 week
P05	Visual	98.00	31	03	10 s - 25 times	3 sessions per day
P06	Visual	96.80	10	03	N.A.	3 and 6 weeks
P07	Visual	94.26	15	02	3 s - 200 times	30 days
P08	Visual	91.44	20	02	10.3 s - 5 times	N.A.
P09	Visual	97.18	21	02	360 s total	30 days
P10	Auditory	95.60	10	10	360 s total	N.A.
P11	Visual	100.00	25	02	2 s - 100 times	between 1 to 103 days
P12	Auditory	96.75	16	03	310 s total	1 week
P13	Auditory	95.60	10	04	300 s total	N.A.
P14	Visual	91.90	20	10	1 s - 55 times	N.A.
P15	Visual	100.00	05	05	60 s total	N.A.
P16	Auditory	100.00	10	08	30 s total	N.A.
P17	Visual	92.50	20	20	3 s - 53 times	N.A.
P18	Auditory	99.06	08	02	2 s - 120 times	2 sessions per day
P19	Auditory	99.53	20	04	90 s - 4 times	N.A.
P20	Visual	100.00	21	02	66.15 s total	5 days
P21	Visual	92.80	13	07	720 s total	7 consecutive sessions
P22	Visual	29.69	21	03	N.A.	7 days
P23	Auditory	95.00	13	03	300 s total	the last one after one year
P24	Vibration	89.00	10	10	5.1 s - 100 times	N.A.
P25	Vibration	76.00	10	10	5.1 s - 100 times	N.A.
P26	Visual	93.80	08	08	Several values	N.A.

Moreover, Table 5 shows also the heterogeneity of parameters, with few data acquisition sessions close to each other in some works ([55,61,28,59]), or a more significant number of sessions without any distance in time ([27,37]), or even very spaced out in time ([66,19,45]). There are also differences according to the type of stimulus used, as those based on visual stimulation have a high number of trials and a short overall duration, unlike those based on auditory stimulation, which instead have fewer but longer trials, whereas, in the two approaches that exploit the vibration stimuli, we have a short time of acquisition with short pauses.

4.2 Limitations

What was previously discussed in Section 2.4 regarding some well-known limitations affecting this research field, together with the analysis of the literature of the considered period, underline three main problems:

i) the first problem refers to the type of data (complex, non-stationary, and non-linear), which makes it difficult to obtain stable EEG patterns over time, a stability necessary for a biometric user identification system. This is a problem faced in the literature in different ways and which seems to be able to be effectively countered through the use of EP techniques, as they can create the conditions to ensure greater repeatability of the patterns compared to the EEG data acquisition carried out without any stimulus [24]. Although of great importance, the problem of the stability of EEG patterns has been considered only in some of the works discussed by us (e.g., [61,11]);
ii) the second problem is instead given by the diversity of users despite using the same data acquisition protocol, a transversal aspect that strongly limits the definition of a common evaluation model, a problem that requires even very sophisticated approaches to be reduced;
iii) another problem concerns the hardware calibration required by many biometric approaches in the literature, which is not compatible in terms of time with a large-scale use, differently from other biometric systems (e.g., those based on recognition speech or fingerprints), and this is further complicated by those approaches that require many electrodes and/or a conductive paste for their application;
iv) a last problem that somehow involves all the previous ones is the heterogeneity of the experimental environments related to the works in the literature, as they differ, often in a very marked way, in terms of software, hardware, system configuration, number of users, sessions and acquisition times, as well as other minor parameters, thus making it difficult for those working in this research sector to take stock of the situation.

5 Conclusions

The literature works have shown the possibility of realizing biometric systems for the users' identification based on EEG data influenced by external stimuli (EP), although it must be noted that among all the proposed solutions very few are suitable for large-scale use as a biometric system for the users' identification due to some intrinsic limitations. In any case, we have to take into account that this is a relatively new research area, although very promising as the literature shows a growing interest that bodes well for the future.

The intrinsic limitations are mainly attributable to the data acquisition protocols that are often incompatible with practical use in real-world biometric applications, as well as the difficulty to get the same performance measured during the experimental phase, varying the environment and/or the users. Each work in the literature, regardless of its theoretical or practical approach, represents a step forward toward the definition of reliable biometric systems to be used on a large scale, also by considering the continuous evolution of EEG devices and data analysis techniques. In addition, some of the approaches discussed in this work, although they present limitations, could be exploited to design hybrid biometric approaches to improve the effectiveness of the user identification process [30].

Unlike other works in the literature, the present work is focused on a precise sub-area where EEG and EP are combined to face some well-known problems (mainly that of EEG pattern instability). To our best knowledge, it is a sub-area that has never been considered alone in the literature but only in a more dispersed way. For this reason, the exhaustive and targeted analysis provided in this work can offer valuable information for those who work in this research field.

An extension of this work was carried out by us after the writing of this work in order to deepen all the concepts briefly exposed here due to issues of available space [40]. A next work (theoretically formalized in [38]) will be to design a biometric approach aimed to perform user identification tasks by adopting only low-cost EEG and EP devices, focusing our attention on the definition of a system suitable for large-scale use, therefore taking into account not only the cost of the hardware but also other characteristics (e.g., required electrodes, ease of use, acquisition time, etc.). In this regard, we would also like to experiment with techniques/strategies already used with interesting outcomes in other domains [42,41,5,39,43].

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