A Survey on Brain Biometrics

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Brainwaves, which reflect brain electrical activity and have been studied for a long time in the domain of cognitive neuroscience, have recently been proposed as a promising biometric approach due to their unique advantages of confidentiality, resistance to spoofing/circumvention, sensitivity to emotional and mental state, continuous nature, and cancelability. Recent research efforts have explored many possible ways of using brain biometrics and demonstrated that they are a promising candidate for more robust and secure personal identification and authentication. Although existing research on brain biometrics has obtained some intriguing insights, much work is still necessary to achieve a reliable ready-to-deploy brain biometric system. This article aims to provide a detailed survey of the current literature and outline the scientific work conducted on brain biometric systems. It provides an up-to-date review of state-of-the-art acquisition, collection, processing, and analysis of brainwave signals, publicly available databases, feature extraction and selection, and classifiers. Furthermore, it highlights some of the emerging open research problems for brain biometrics, including multimodality, security, permanence, and stability.

CCS Concepts: • **Security and privacy** → *Biometrics*; • **Computing methodologies** → *Machine learning approaches*; • **Applied computing** → *Psychology*;

Additional Key Words and Phrases: Biometric, brain, brainprints, identification, authentication

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1 INTRODUCTION

Means of authentication and identification can be classified into three groups: something the user knows, something the user has, and something the user is [123]. Traditionally widely used methods in the categories of something the user knows and has, like passwords and ATM cards, have

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demonstrated clear weaknesses. Tokens the user knows or has can be forgotten, lost, or stolen, leading to unsuccessful authentication or information leakage. Biometrics, which is a means that the user is, can overcome these drawbacks. Biometrics do not require any memorizing because they are innate physiological or behavioral parts of the individual. Biometrics cannot be lost or stolen for the same reason.

Currently, conventional biometrics, such as fingerprint, face, iris, voice, and DNA, have been extensively studied in literature and widely adopted in real-life scenarios. However, these biometrics each possess their weaknesses [59]. For example, DNA can be easily stolen from any surface a target has touched. Fingerprints can be faked through plastic molds, latex milk, and wood glue [99]; by a 2D picture of a fingerprint made by a normal inkjet printer [21]; and even through high-resolution photography [23]. Fingerprints, face, and iris are all noncancelable. This means that if they are stolen, they cannot be replaced: a user cannot grow a new finger or eye or change the shape of her face volitionally. A biometric more secure than any of these would therefore meet two criteria: it would be more difficult to steal, and it would be cancelable. Brain electrical activity measured at the scalp (through an electroencephalogram or EEG) may meet these criteria.

Since EEG was first developed in 1929, many studies have shown that brain activity can be influenced by many genetic and nongenetic factors and have demonstrated high individuality of EEG and Event-Related Potentials (ERPs) (please see Section 4.1 for differences between EEG and ERP) among different people [170]. This finding indicates that the brainwave signal could be unique for each individual and thus has the potential to be a biometric [19]. The EEG has several unique advantages compared with other conventional biometrics. First, in order to produce EEG, a person must be alive—the lack of an EEG is the primary clinical indicator of brain death [175, 176]. This is not the case for DNA, fingerprint, and face, all of which can be maintained even after people die, or the iris, which, though eventually changing after death, is still valid for recognition for a few hours post mortem [149, 169]. In this respect, brain biometrics also protect the user, as the user has to be alive and conscious state to produce valid EEG data. Second, brain electrical activity is measured as a voltage which falls off dramatically with distance from the brain. Therefore, the electrodes to record brain activity must be placed either on the scalp, using wet or dry noninvasive sensors [25, 26], or close to the scalp, using remote measurement of electric fields [48]. Current sensors are large and invasive enough that it would be impossible to collect the EEG without a person's knowledge [96, 142]. Thus brain biometrics meet the criteria of being “more difficult to steal.” Third, recent research suggests that brain biometrics may be cancelable [142] because they can be elicited by numerous distinct brain systems. For example, when the stored brain biometric identifier of an authorized user is lost, stolen, or disclosed, a different brain biometric identifier can be generated from a distinct form of brain activity and response (e.g., ERP evoked by a distinct set of visual stimuli) and thus can be used to replace the compromised and corrupted one. Fourth, the EEG is very sensitive to stress [22]. This is another factor that may protect the user of a brain biometric system: Any attempt at coercion that would place stress on the user would invalidate the brain biometric. Finally, high-accuracy identification can be achieved with nonvolitional features of the EEG, meaning that brain biometrics are not disclosable: A user cannot reveal a biometric feature that they are not aware of [142, 146]. Given the unique and superior advantages described above, brain biometrics holds the potential to be used in the scenarios demanding a very high security level, such as in defense and financial agencies.

Despite the many advantages of brain biometrics, they are still not widely adopted because substantial research still must be done, and reviewing the areas of necessary research is one focus of this review. There are seven factors—universality, uniqueness, permanence, collectability, performance, acceptability, and circumvention [58, 59]—that evaluate how reasonable a biometric is as an authentication or identification method. Many prior research efforts have demonstrated

Table 1. Comparison Between Brain Biometrics and Some Popular Biometrics

Biometric Identifier	Universality	Uniqueness	Permanence	Collectability	Performance	Acceptability	Circumvention
DNA	H	H	H	L	H	L	L
Face	H	L	M	H	L	H	H
Fingerprint	M	H	H	M	H	M	M
Iris	H	H	H	M	H	L	L
Brainwave	H	H	H	M	H	M	H

satisfactory uniqueness, permanence, and universality for brain biometrics. Recent research has also shown that brain biometric is resistant to spoofing and circumvention from the perspectives of signal acquisition and synthesis [45]. However, more research is needed to improve the collectability, performance, and acceptability of brain biometrics [19]. Table 1 compares the brain biometrics against some popular biometrics in terms of the seven factors defined in Jain et al. [59]. However, there are very few existing surveys that comprehensively review the scientific rationale of brain biometrics and the various protocols for eliciting, acquiring, processing, and analyzing brain activity signals. Some existing surveys, such as those by Khalifa et al. [70], Pozo-Banos et al. [134], and Campisi and La Rocca [19], discussed feature extraction, protocol design, and classifiers for brain biometric systems from multiple perspectives. As brain biometrics are becoming more feasible, it is important to take stock of what is and is not known about them. The goal of this survey is to expand on previous surveys by:

- (1) reviewing state-of-the-art brain biometric acquisition devices and methods,
- (2) reviewing publicly available databases for brain biometric studies,
- (3) presenting preprocessing and postprocessing methods useful for biometric applications,
- (4) describing effective methods for channel/feature selection and dimensionality reduction that reduce the complexity of the authentication problem,
- (5) reviewing existing statistical and machine learning classifiers for brain biometrics,
- (6) exploring multimodal biometric systems that include brain biometrics, and
- (7) reviewing what is known about the security, permanence, and stability of brain biometrics.

In this article, we survey the recent literature (primarily between 2007 and 2017) and outline the scientific work conducted on brain biometric systems. This includes review of the acquisition, processing, and analysis of the EEG. This article is organized as follows: We first give a brief introduction to brain biometric systems (Section 2). Then we describe each part of the typical system in detail, including EEG acquisition devices and methods (Section 3), collection protocols and publicly available databases (Section 4), preprocessing/postprocessing techniques (Section 5), frequently used features (Section 6), channel/feature selection and dimensionality reduction selection (Section 7), and classifiers (Section 8). In conclusion, we highlight some of the open research areas in the field, including multimodal biometrics which have EEG as one of the biometric traits, and work investigating the security, permanence, and stability of brain-based biometrics (Section 9).

2 BRAIN BIOMETRIC RECOGNITION SYSTEM

Biometric *authentication* is the security process that verifies an individual's identity through unique physiological or behavioral characteristics. This process basically compares a biometric data capture against stored, confirmed authentic data in the database. Biometric *identification*, in contrast, represents the security process of identifying and labeling the identity of an individual by

Fig. 1. General structure of brain biometric identification and authentication.

searching against a biometric database to find the distinctive biometric characteristics attributable to a single individual [57].

Brain biometric systems typically contain two parts, both for authentication [71] and identification applications [30]. These are (i) the data acquisition part and (ii) the decision part. Figure 1 shows a schematic architecture of brain biometric systems. In the data acquisition stage, EEG sensors capture brain electrical activity, while the user engages with some protocols, such as resting, pass-thought, visual stimulation, or imagery. Data are transferred for digitization and decision-making; this can occur wirelessly or with wired sensors. Once the data are digitized, the decision-making stage begins. Because the collected EEG data are usually contaminated with different kinds of noise and EEG data have a relatively low Signal-to-Noise Ratio (SNR), the first step in decision-making often involves signal preprocessing to enhance signal quality. Then various computational features are extracted. More often, the channel/feature selection and dimensionality reduction methods are adopted to reduce the dimensionality and computational complexity of the EEG data, which are typically large-dimensional [96]. When the feature set has been determined and confirmed, the biometric computations are performed. These may be simple statistical analyses or more complex machine learning approaches (e.g., Neural Network [NN], Support Vector Machine [SVM]). When the system is performing authentication, its output will be a binary acceptance/rejection. When the system is performing identification, its output will be the identity label of the user. More often in recent literature, nonlinear classifiers, like NN and SVM, can complete both the matching score calculation and decision-making in one classifier. Thus, they combine the matcher module and decision-making module into one module. In the following sections, we will review each of the steps just described. This includes review of EEG devices, EEG acquisition protocols, preprocessing, feature extraction, channel/feature selection and dimensionality reduction selection, and classifiers.

3 EEG DEVICES AND COLLECTABILITY

Collectability of the brainwaves specifies and requires that they should be practically and quantitatively measurable [19]. The brain's electrical currents were first observed from the exposed brains of rabbits and monkeys by an English physician named Richard Caton in 1875. In 1924, Hans Berger, a German neurologist, first recorded human brain electrical activity. The technology necessary for acquiring the EEG has thus been available for nearly a hundred years, although, of course, it has undergone substantial refinement since its initial discovery [12, 56, 161, 165].

Table 2. Commercially Available EEG Devices in Brain Biometric Studies

Device (Company)	Channels	Sampling Rate	Bandwidth	Connectivity	Battery Life	Papers
ActiveTwo (Biosemi)	256	2/4/8/16 kHz	DC up to 3200 Hz	Cable	5 hrs to 1 week (battery box)	[35, 100, 118]
BrainAmp (Brain Vision)	up to 256	5 kHz	0-1,000 Hz	Cable	up to 30 hrs (powerpack)	[20, 24, 79, 80, 142]
ENOBIO (Neuroelectronics)	8/20/32	500 Hz	0-125 Hz	Bluetooth	16/15/14 hrs	[66, 138]
EPOC (Emotiv)	14	128 Hz/256 Hz	0.2-43 Hz	Bluetooth	up to 12 hrs	[7, 49, 61, 67, 73, 75, 76, 109, 168, 186]
Galileo BE Light (EB Neuro)	37	up to 32 kHz	N/A	Cable, Wi-Fi	N/A	[32-34, 92, 97, 130]
g.MOBILab+ (G.Tech Medical Engineering GmbH)	8	256 Hz	0.5-100 Hz	Bluetooth	25-100 hrs	[1]
g.USBamp (G.Tech Medical Engineering GmbH)	16	up to 38.4 kHz	0-2,400 Hz	Cable	N/A	[24, 36, 124, 177, 178]
MindWave (Neurosky)	1	512 Hz	3-100 Hz	Bluetooth	8 hrs	[2, 28, 30, 62]
SynAmps 2/RT (Compumedics/NeuroScan)	64/128/256	up to 20,000 Hz	DC up to 3,500 Hz	Cable	N/A	[50, 51, 89, 182]

To capture the EEG, an EEG device must include sensors that can make conductive contact with the scalp, a bioamplifier that enables online filtering and common mode rejection, an A/D converter, and a PC to store the digitized data. Table 2 lists several commercially available EEG devices used in the studies of brain biometrics. A typical complete system for EEG recording, such as the ActiveTwo system by BioSemi (Amsterdam, Netherlands)¹, is usually a wired system that can accommodate as many as 256 channels. In the ActiveTwo system, sensors are placed in an electrocap and a conductive gel is applied to make contact between the sensors and the scalp. The ActiveTwo system uses active amplification, which means that signals are preamplified on the sensor before being passed to the bioamplifier. This reduces the impact of electrical noise that is induced in the wires connecting the sensors to the amplifier. The ActiveTwo system enables high-density recordings from as many as 256 sensors. This is an advantage because it provides more spatial coverage of the scalp and, consequently, a richer dataset.

A disadvantage of high-density recording, however, is that the preparation process is long. A conductive connection with the scalp must be made individually for each sensor. This is time-consuming. High-density recordings are also more expensive, as, obviously, each sensor adds to the cost of the unit. Research-grade systems, in general, are too expensive for consumer use, which is another disadvantage. The main cost is the bioamplifier.

Recent advances in large-scale integrated circuits and wireless communication have resulted in the development of cheaper, more consumer-friendly EEG devices. Examples of these are the ENOBIO developed by Neuroelectronics (Barcelona, Spain)², the EPOC/EPOC+ wearable

¹<http://www.biosemi.com/>.

²<http://www.neuroelectronics.com/>.

neuroheadset developed by Emotiv Systems, Inc. (San Francisco, USA)³, and the MindWave wearable headset developed by NeuroSky, Inc. (San Jose, USA)⁴. Consumer devices, however, typically do not allow recordings that are as high density as research-grade devices. And the cheaper sensors and bioamplifiers typically result in substantially reduced signal quality. There is thus a tradeoff between consumer- and research-grade systems. Consumer systems are cheaper and more user friendly, but produce poorer data. Research-grade systems produce high-density, high-quality data but are more expensive and less user friendly. These factors contribute to the “collectability” of brain biometrics. However, compared with extensively deployed fingerprint sensors or face recognition cameras, EEG devices still demand significant improvement in affordability, ease-of-use, and portability.

4 DATA COLLECTION PROTOCOLS

4.1 Protocols

EEG can be collected while a participant engages in any type of cognitive task or while the user simply rests with their eyes open (RO) or eyes closed (RC). The task the participant is engaging in will impact the nature of the data recorded, so it is important to define the task, or protocol, used in any biometric system. Table 3 summarizes the protocols used in a selection of published brain biometric approaches, and Table 4 lists some publicly available databases, including their protocols. Generally, protocols can be categorized into two types: resting states and cognitive tasks.

Resting-state EEG is acquired when the participant is simply at rest during data collection, not performing any particular task. Resting-state protocols are therefore simple and can be collected continuously. For this reason, resting-state protocols are common in brain biometrics [1, 20, 30, 78–81, 95–97, 157].

Cognitive protocols are more complex. In cognitive protocols, the participant engages in some specific tasks while the EEG is acquired. These tasks are many and varied in the literature and may involve specialized procedures. One type is mental tasks. These include pass-thoughts [28, 62] and mental imagery, such as mental rotation or imagining body movements [4, 7, 100, 112, 117]. In pass-thought and mental imagery protocols, the EEG is acquired while participants perform some internal, volitional tasks (e.g., imagining opening and closing a fist). It is also possible to acquire the EEG while participants are externally stimulated and capture the participants’ nonvolitional response. The form of stimulation can vary, but the most common format is the presentation of human faces. Faces are used for multiple reasons. First, a person’s brain response to his or her own face is different from his or her response to faces of others, and this information can be individuating [105, 177, 178, 182]. Second, individuals differ in how attractive they find the faces of others, and this information can also be individuating [142].

Biometric systems using a cognitive protocol typically rely not on the raw EEG time series, but instead on the time-locked ERPs. ERPs refer to the scalp-recorded voltage fluctuations locked in time to an externally defined event. ERPs are formed when segments of the EEG time-locked to several instances of a stimulating event are averaged. For example, an ERP is formed when several EEG segments all locked to the presentation of a different face are averaged together. Other types of stimulation-evoked brain responses include Visual Evoked Potentials (VEP), Auditory Evoked Potentials (AEP), and Somatosensory Evoked Potentials (SSEP). Some prior brain biometric studies have also used the VEP protocol. Because VEPs are limited to the brain’s visual cortex activities, they require very careful experimental design to lower the impact of other brain activities, such as semantic or auditory input. This is difficult to achieve; here, we use the concept of a wider scope

³<http://emotiv.com/>.

⁴<http://neurosky.com/>.

Table 3. Typical EEG Collection Protocols

Papers	Sbjs*	Chs*	Protocols	Sampling Rates	Sessions
[6, 43, 146]	45	6	acronym	500 Hz	1 (30 sbjs) 2 (15 sbjs, 5-40 days) 3 (9 sbjs, 134-188 days)
[8, 89]	20	64	Revised Snodgrass and Vanderwart object pictorial set	1000 Hz	1
[20, 78, 80]	48	56	RC	200 Hz	1
[28, 62]	15+3I*	1	breathing task simulated finger movement sports task song/passage recitation task eye and audio tone task object counting task passtthought task	512 Hz	2 (separate days)
[32–34]	50	19	geometric shapes letters & digits	256 Hz	1 2 (1 week) 3 (25-49 days)
[42, 44]	37	4	words, pseudowords, acronyms, illegal strings	500 Hz	1
[46, 142, 143]	50	30	sine gratings low frequency words black and white food black and white celebrity faces color version of black & white images color food	500 Hz	1 2 (20 sbjs, 48-516 days)
[50, 51]	7	19	blocking virtual target balls	1000 Hz	1
[79]	9	54	RC, RO	200 Hz	2 (1-3 weeks)
[92]	45	19	RC, RO, mathematical computation, speech imagery	256 Hz	1 2 (about 1 week) 3 (about 1 month) 4 (about 7 months) 5 (about 16 months) 6 (30 sbjs, about 36 months)
[95–97]	60	19	RC, RO	256 Hz	1 2 (50 sbjs, about 1 week) 3 (50 sbjs, about 34 days)
[108, 110]	30	1	driving scenes in virtual environment	128 Hz	10 (twice a day, 5 days)
[113, 128]	40	23	free	167 Hz	1
[157–160]	40	1	RC (water/coffee)	200 Hz	6 (water) 6 (coffee)
[177, 178]	15+30I	16	self-face, non-self-face	2400 Hz	2 (30 days)

*Abbreviations used in all following tables: Sbjs – Subjects, Chs – Channels, I – intruders/imposters.

of ERP to include brain responses to not only visual stimuli, but also sensory, cognitive, motor, or other events.

ERPs have two clear advantages over the EEG for biometric use. First, the EEG is relatively unspecific: That is, when EEG is collected outside of a cognitive task, there is no way to know what the participant is thinking about or what state their brain is in. ERPs, in contrast, represent very specifically the brain's response to the stimulation that they are time-locked to. In the case of facial stimulation, for example, a face ERP represents precisely and only the brain's response to

Table 4. Representative Publicly Available EEG Databases

Databases	Sbjs	Chs	Protocols	Sampling Rate	Sessions	Papers
Alcoholism	122	64	Snodgrass & Vanderwart picture set	256 Hz	1	[55, 60, 87, 113, 181, 188]
ATR	51	64	RO, left & right attention	256 Hz	9	[114]
DEAP	32	32, GSR, BVP, respiration, skin temperature, ECG, EMG, EOG	music video	160 Hz	1	[86, 103, 129]
EEGMMIDB	109	64	RO, RC open/close fists/feet imagery opening/closing fists/feet	160 Hz	1	[4, 10, 29, 40, 64, 81, 140, 152, 166, 167, 179, 186]
Graz IIIa	3	60	imagery left/right hand, feet or tongue movements	250 Hz	1	[113]
Graz A	9	22, EOG	imagery left/right hand, feet or tongue movements	250 Hz	2	[74, 111, 113, 127]
Graz B	9	3, EOG	motor imagery left/right hand movement	250 Hz	5	[111–113, 127]
Keirn & Aunon	7	6, EOG	RO, RC Complex problem solving 3-D geometric figure rotation Mental letter composing Visual counting	250 Hz	1	[117, 139]
Two-class MI BNCI Horizon 2020	14	7	motor imagery of right hand & feet	512 Hz	1	[74]

the face it has just been presented. This is advantageous for biometric use because the brains of users of ERP protocols can be directed into states that are likely to be individuating (e.g., those corresponding to the recognition of their own face). The second advantage of ERPs over EEG for biometric use regards SNR properties. As ERPs are an averaged signal, their SNR is better than that of the EEG, which is not averaged. The primary disadvantage of ERPs, as compared to EEG, is that the protocols for their elicitation are more complex. EEG can be acquired with no special stimulation of the user, whereas ERPs can only be acquired when the user is stimulated in a specific and well-controlled manner.

4.2 Publicly Available Databases

Instead of collecting live EEG data from human subjects, many prior brain biometric studies in the literature have used and relied on publicly available EEG databases. Development and testing of a robust brain biometric method require databases of sufficient sample size and carefully controlled protocols. In this section, we will review several representative EEG databases and describe the characteristics and contents of each (Table 4).

4.2.1 Alcoholism Database. The Alcoholism Database⁵ [187] studies the correlates of genetic predisposition to alcoholism in terms of EEG activity. The data were measured using a cap containing 64 electrodes, with a sampling rate of 256 Hz. One hundred twenty-two human subjects, including both alcoholics and controls, were presented with the Snodgrass and Vanderwart picture

⁵ Available online at <https://archive.ics.uci.edu/ml/datasets/EEG+Database>.

set [154], one or two pictures at a time. When two pictures were shown, they could be the same or different ones. Each subject completed 120 trials where different stimuli were shown. There are three versions of the dataset available: (i) the Small Data Set, containing data for 2 subjects, one alcoholic and the other control; (ii) the Large Data Set, containing data for 10 alcoholic subjects and 10 control subjects; and (iii) the Full Data Set, containing data for all 122 subjects.

4.2.2 ATR Dataset. The ATR dataset⁶ [104] recorded EEG signals from 51 participants using 64 channels at a sampling rate of 256 Hz. Each subject was guided to perform one 5-minute resting-state session first and followed by another session of 8 tasks. Each task session had 24 blocks, where each block included three phases: a 6- to 10-second rest phase, 4-second control phase, and 8-second attention phase. The subjects were asked to covertly attend to left or right without eye movement according to the visual stimulus cues.

4.2.3 DEAP. DEAP⁷ [72] is a multimodal database for human emotion analysis. The database is composed of recordings from 32 participants and includes 32-channel EEG, Galvanic Skin Response (GSR), respiration amplitude, skin temperature, electrocardiogram (ECG), Blood Volume Pressure (BVP) by plethysmograph, electromyogram (EMG) of the zygomaticus and trapezius muscles, electrooculogram (EOG), and 22 participants' face videos. During the experiments, each participant performed 40 trials by being presented with 40 1-minute excerpts of music videos selected through a web-based subjective assessment experiment. Each trial consisted of four steps: a 2-second screen displaying the current trial number for progress indication, a 5-second baseline recording, a 1-minute display of the music video, and, finally, the participant's self-assessment for arousal, valence, liking, dominance, and familiarity.

4.2.4 EEG Motor Movement/Imagery Database (EEGMMIDB). The EEG Motor Movement/Imagery Database⁸ comprises EEG recordings obtained from 109 volunteers on 64 channels using the BCI2000 instrumentation system [150]. It is available in PhysioNet [41]. All subjects participated in 14 experimental runs, including 6 types of tasks: 2 resting-state tasks, 2 motor movement tasks, and 2 imagery tasks. At the very beginning, two 1-minute resting-state tasks, one with eyes open and the other with eyes closed, were recorded. Then, four types of motor movement and imagery tasks were performed in 2-minute runs in the order of opening and closing left or right fist, imagining opening and closing left or right fist, opening and closing both fists or both feet, and imagining opening and closing both fists or both feet according to a target's position on the screen (left, right, top, or bottom). These four runs were repeated three times. All the experimental runs formed the dataset of more than 1,500 1- and 2-minute EEG segments.

4.2.5 BCI Competition Datasets. The BCI competitions, with the goal of testing and evaluating brain signal processing and classification methods for Brain-Computer Interfaces (BCIs), have been held four times (2001 [148], 2003 [13], 2005 [14], 2008 [163]). The first competition website is unaccessible; the other three are available, and the last two have been used in EEG biometric research.

BCI Competition 2005, dataset IIIa⁹ [151, 171], contains EEG data from 3 subjects and 60 channels at a sampling rate of 250 Hz with a bandpass filter in the range of 1 to 50 Hz and notch filter on. Each subject performed 60 trials on the tasks of motor imagery of left hand, right hand, foot, and tongue according to the cue of arrow directions displayed on the screen.

⁶ Available online at <http://biomark00.atr.jp/modules/xoonips/listitem.php?indexid=181>.

⁷ Available online at <http://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html>.

⁸ Available online at <http://www.physionet.org/pn4/eeegmmidb/>.

⁹ Available online at <http://www.bbc.de/competition/iii/>.

BCI Competition 2008, Graz dataset A¹⁰ [17], recorded EEGs from 9 subjects with a sampling frequency of 250 Hz. Besides the 22 EEG channels, 3 EOG channels were also recorded for the purpose of artifact removal sampled at the same frequency with a bandpass filter set between 0.5 Hz and 100 Hz and a notch filter of 50 Hz. The eye movement artifacts were particularly assessed at the beginning of each session, where data from 2 minutes of eyes open, 1 minute of eyes closed, and 1 minute of eye movements were recorded. Each subject was instructed to complete two sessions of recordings on different days. Each session had six runs, and each run included four cue-based motor imagery tasks (12 trials for each task): movement imagination of the left hand, right hand, both feet, and tongue.

BCI Competition 2008, Graz dataset B¹¹ [85], consists of EEG recordings from 9 subjects. It used the same sampling rate, filters, and EOG recording strategy as the Graz dataset A. The differences are the channels for recording, imagery tasks, and session numbers. Three channels, C3, Cz, and C4, were adopted. All subjects completed 5 sessions in two separate days. In each session, there were six runs of 10 trials of two types of motor imagery tasks (i.e., left hand and right hand movements).

4.2.6 Keirn & Aunon's Database. The Keirn & Aunon's Database¹² [68] was motivated to find brainwave changes in morphology and spectral density across different hemispheres and electrodes. Electrodes were placed on six different locations of scalp (i.e., O1, O2, P3, P4, C3, and C4) with an additional electrode for EOG recording. Five subjects were instructed to perform 5 mental tasks without overt movements in two sessions on separate weeks. The 5 distinct mental tasks were (i) resting with both eyes opened and closed for baseline measurements; (ii) solving nontrivial multiplication problems for which immediate answers were not apparent silently and without movement; (iii) mentally visualizing the rotations about one axis of the complex 3-D block figure learned 30 seconds earlier; (iv) mentally and silently composing a letter to a friend or relative; and (v) silently imagining writing numbers on an imagined blackboard sequentially after the previous one was erased. Since each task had both open- and closed-eyes conditions, 10 different experimental conditions were performed. Each task lasted for 10 seconds. The EEG data were sampled at 250 Hz with a hardware bandpass filter of between 0.1 and 100 Hz.

4.2.7 BNCI Horizon 2020 Project Database. The BNCI Horizon 2020 Project Database¹³ included several datasets, and the Two-class Motor Imagery (Two-class MI) dataset [156] was adopted in the literature for biometric purpose. It recorded 14 subjects using 7 electrodes (C3, Cz, and C4 at the central region and 4 additional electrodes around the center) at a sampling rate of 512 Hz. Participants were instructed to perform 5-second kinesthetic motor imagery of the right hand and of the feet. There was only one session for data recording, with 8 runs and 20 trials for each run.

5 PREPROCESSING AND POSTPROCESSING

The raw EEG is typically contaminated with electrical artifacts. The most common of these are 50/60 Hz noises from nearby electronics and muscular artifacts from the movements of the face and eyes. It is typical to preprocess the EEG to reduce or remove these artifacts in order to improve signal quality. Artifacts can be either rejected outright based on some criterion or corrected. We next discuss common methods of artifact rejection and correction.

¹⁰ Available online at <http://www.bbc.de/competition/iv/>.

¹¹ Available online at <http://www.bbc.de/competition/iv/>.

¹² Available online at http://www.cs.colostate.edu/eeg/main/data/1989_Keirn_and_Aunon.

¹³ Available online at <http://bnci-horizon-2020.eu/database/data-sets>.

Table 5. Description of EEG Subbands

Name	Frequency (Hz)	Description
Delta	0.5 – 4	predominant oscillatory activity during deep or slow wave sleep related to attention to internal processing
Theta	4 – 8	related to memory demands
Alpha	8 – 14	most dominant rhythm which emerges in normal subjects, most pronounced in the parieto-occipital region
Beta	14 – 30	consciously perceived stimuli of alertness and focused attention
Gamma	>30	transient functional integration of neural activity across brain areas

5.1 Artifact Rejection

The simplest criterion-based method of artifact rejection is to discard data that exceed some voltage thresholds. Eye movements and blink contamination are pervasive problems in ERP research [63]. Muscular artifacts are typically orders of magnitude larger than cortical activity (e.g., a blink artifact may be on the order of 200 μ V while an ERP effect may be on the order of 4 μ V), so thresholds of around 100 μ V are often used [16, 109, 116, 120, 121, 136]. The threshold was also considered to be sensitive to electrode location and sensor type. In Chen et al. [24], the threshold was set to 75 μ V for the wet electrodes placed in the frontal region and 150 μ V for all the dry electrodes. Threshold rejection procedures are relatively crude, however, and more sophisticated rejection procedures, such as those based on a peak-to-peak window or on the slope across time points, are preferred [90].

5.2 Artifact Correction: Filters

Powerline noise is caused by the AC power supply. Thus, a notch filter which is a band-stop filter with a narrow stopband at 50 Hz or 60 Hz depending on the AC frequency, was adopted to remove powerline noise [1, 36, 52, 105, 105, 138, 147].

Moreover, useful brain activities are primarily in the lower frequency ranges (see Table 5). As summarized in Campisi and La Rocca[19], the delta wave is a predominant oscillatory activity in the frequency range of 0.5–4 Hz during deep or slow wave sleep and is related to attention to internal processing; the theta wave is in the range of 4–8 Hz and more related to memory access; the alpha wave in the frequency band of 8–14 Hz is more likely to be generated in the parietooccipital region during relaxation with eyes closed; the beta band in 14–30 Hz is related to consciously perceived stimuli; and the gamma band is in the frequency range over 30 Hz and is related to the transient functional integration of neural activity across brain areas. Different brain tasks can be reflected in different brain rhythms. Therefore, removing less related brain activities can improve the signal quality, and various filters can be an effective way to keep the most relevant information. Low-pass filters of 40 Hz [24, 177, 178], 41 Hz [95, 96], and 50 Hz [81], or bandpass filters of 0.01–50 Hz [27], 0.01–100 Hz [31], 0.1–42 Hz [172], 0.1–55 Hz [98], 0.1–100 Hz [36], 0.5–8 Hz [33], 0.5–30 Hz [78, 79], 0.5–40 Hz [114, 130], 0.5–45 Hz [168], 0.5–50 Hz [9], 0.5–70 Hz [138, 147], 1–30 Hz [133], 1–50 Hz [143], 2–47 Hz [74], 2–50 Hz [65, 83], 2–55 Hz [64], 4–52 Hz [4], 5–100 Hz [50, 51], 8–30 Hz [52, 54, 92, 162], 14–50 Hz [53], 20–50 Hz [120], and so on, were implemented to keep the data within a specific frequency range. The Butterworth filter, which has the maximally flat magnitude in the passband, is also popular for EEG preprocessing. The 10th-order Butterworth filter in the 3dB passband of 30–50 Hz [116, 121, 136, 188] was a popular setting, while the 5th-order of 6–35 Hz Butterworth filter [76], the 3rd-order of 1–50 Hz [124], and the 4th-order of 0.5–30 Hz

[106] were also adopted. Elliptic filters have equalized ripple (equiripple) behavior in both the pass-band and the stopband. Abo-Zahhad et al. [2] utilized the 3rd-order elliptic bandpass filter with a pass-band ripple of 0.1dB and stop-band attenuation of 50dB. Ashby et al. [7] used a 2nd-order 2 Hz cutoff elliptic high-pass filter. And Palaniappan [117] adopted an elliptic Finite Impulse Response (FIR) filter of 0.5 Hz highpass, 30dB minimum attenuation in the stop-band, and 0.5dB ripple in the pass-band. The surface Laplacian filter, which filters out spatially broad features, was adopted by Marcel and Millán [100].

5.3 Artifact Correction: Independent Component Analysis

Independent Component Analysis (ICA) is a Blind Source Separation (BSS) method used to find individual source signals from mixed multidimensional data. Given the mixed signal matrix X , with each row representing channels and each column representing the time points, ICA finds the component matrix W to unmix the original data X and get the source matrix U by solving the problem of $U = WX$. It has been demonstrated that ICA can decompose multichannel EEG signals into different components, including EOG, ECG, EMG, different frequency bands, and ERP [115]. Thus, ICA has been widely adopted in the preprocessing stage for artifacts removal [8, 35, 50, 51, 89, 174].

5.4 Artifact Correction: Principal Component Analysis

Principal Component Analysis (PCA) is a statistical technique that can convert a set of correlated observations into linearly uncorrelated orthogonal components. Since the first few principal components represent most information of the original data, PCA is implemented to remove noise and increase the SNR by ignoring the less important components and to reconstruct the input signal using the first few components [121, 136].

5.5 Postprocessing

The temporal nature of the ERP signals means that the epochs from the same person appear consecutively. Currently used machine learning algorithms (e.g., NN, SVM, etc.) are all static classifiers, which means that they are memoryless classifiers and do not consider timing. However, classifiers that take time into account, like Recurrent Neural Network (RNN), Time Delay Neural Network (TDNN), or reservoir computing, have complex training procedures and thus can not always converge properly. To resolve this issue, a postprocessing strategy was proposed [37] which remembered past output labels and used these labels and current output to correct those elements thought to be unreasonable outputs. Results showed that postprocessing can improve accuracy.

6 FEATURE EXTRACTION

Feature extraction represents one of the most important stages in the processing and analysis of EEG signals because how well the extracted features represent the EEG signals influences the performance of the recognition system. The adopted features can be classified into groups of domains (i.e., time domain, frequency domain, and time-frequency domain) or channels (i.e., single-channel and two-channel). Here, the widely used features in time domain, frequency domain, and time-frequency domain are described.

6.1 Time Domain

The Autoregressive (AR) model is a widely used time-domain feature in EEG biometrics. The AR model represents a type of random process by specifying that the output variable depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term). Denoting that $x(n)$ is the current values of one channel, a_i is the AR coefficients at delay i , $e(n)$ is the error

at time n , and p is the order, the AR model is shown in Equation (1):

$$x(n) = - \sum_{i=1}^p a_i x(n-i) + e(n). \quad (1)$$

Compared to the Yule-Walker method, which applies a p th order AR model to the windowed input signal by minimizing the forward prediction least square error and solving the autoregressive parameters directly, Burg's method was selected much more frequently for its lower computational complexity [122]. It estimates the parameters using the Levinson-Durbin algorithm based on the last autoregressive-parameter estimated from each model order p by minimizing the forward and backward prediction error. In order to determine the optimal order of the AR model, there are generally three methods: minimizing the error of the predictor equation through experimental results with different orders, minimizing the Akaike Information Criterion (AIC), and based on the eigenvalues of the matrix $\tilde{R}$ in the Yule-Walker equations [5, 54, 69, 118].

Although AR is a popular method to extract EEG feature, it can only fit into one time-series data stream. However, sometimes the prediction not only depends on the historical trend of the same time series, but also the previous data of other time series. Thus, a multivariate AR (mAR) model [50] was proposed. Defining that N is the total number of channels, $x_c(n)$ represents the current values of channel c where $1 \leq c \leq N$, p is the model order, a_{ci} is the mAR coefficient at delay i for channel c , and $e_c(n)$ is the error at time n of channel c , the mAR model is shown in Equation (2). From this equation, the calculation of the present value of one channel involves all the history of all the channels. Thus mAR can find information on interactions among brain regions and enhance performance:

$$x_c(n) = \sum_{i=1}^p a_{c1}(i)x_1(n-i) + \cdots + \sum_{i=1}^p a_{cN}(i)x_N(n-i) + e_c(n). \quad (2)$$

A bilinear model used by Poulos et al. [132] is another extension of the AR model. The difference is that it has extra bilinear components $\{x(n-i)e(n-j)\}$ with coefficients b_{ij} and order k and m as shown in Equation (3):

$$x(n) + \sum_{i=1}^p a_i x(n-i) = \sum_{i=1}^k \sum_{j=1}^m b_{ij} x(n-i)e(n-j) + e(n). \quad (3)$$

6.2 Frequency Domain

As described in Section 5.2, EEG signals can be separated into different frequency bands which are related to various brain activities. Converting EEG data into the frequency domain can extract and distinguish the dominant frequency components.

Power Spectral Density (PSD) describes the signal strength distribution in the frequency domain. Fourier Transform (FT) is an effective way to transform the EEG signal from the time domain into the frequency domain. Based on the PSD obtained through squaring of the absolute value of Fourier-transformed data in each segment, the concavity of spectral distribution [107], variance of spectral power, and the nondominant region of the power spectrum [102] were calculated as EEG features for further recognition purpose. Fractional Fourier Transform (FRFT), seeking one-dimensional time-frequency distribution, was used to extract fractional spectral coefficient values for each segment of normalized EEG data [139].

In addition to the FT method, Welch's method is another popular algorithm to estimate the PSD. Welch's method first splits the input signals into overlapping segments and then, based on the segments, the periodogram is calculated by the squared magnitude of the Discrete Fourier

Transform (DFT) results. The individual periodograms are averaged to reduce the variance of the individual power measurements. This method has been adopted in several studies [112, 127, 128].

Spectral Power (SP) and energy are another two frequency domain features based on the PSD. They are calculated using Parseval's Theorem. Other features based on PSD (e.g., maximum power and frequency in alpha band) were also adopted. Spectral coherence connectivity, which is estimated by coherence, was also used [81] to quantify the level of synchrony between two stationary signals at a specific frequency. Interhemisphere Power Difference (IHPD) and Interhemispheric Channel Linear Complexity (IHLC) values, which are the entropy of the eigenvalues of the covariance matrix of the IHPD and measure the degree of spatial synchronization of data, were also features on the basis of the PSD [7].

6.3 Time-frequency Domain

Wavelet Packet Decomposition (WPD) is a wavelet transform algorithm providing both time and frequency information on the signals. In WPD, the signal passes through more filters to build the complete wavelet packet tree, with both the detail and approximation coefficients being decomposed, and thus it is more robust than Discrete Wavelet Transform (DWT) where only the previous approximation coefficients are used to pass through quadrature mirror filters. Cai et al. [18] decomposed the EEG signals using 6-level Daubechies 4 (DB4) WPD and extracted the mean energy and variance of each subband as features. Kumari and Vaish [76] also used 5-level DB4 WPD to extract the subband features of mean, standard deviation, and energy. Gui et al. [43] used 4-level WPD to separate the EEG signals into 5 subbands, including delta, theta, alpha, beta, and gamma, and then used the mean, standard deviation, and entropy as the features. Morlet wavelets [80, 114, 174] were used to transform the EEG signal into the time-frequency domain because this wavelet has a symmetrical and smooth Gaussian shape in both the time and frequency domains. Bump modeling was adopted to reduce the parameter size of a time-frequency map.

6.4 Others

In addition to the frequently used features just discussed, other features have also been studied. The EEG signal is approximately stationary in a short period of time between 5 ms and 100 ms. But over a long time period, the signal is nonstationary. The signals change to reflect different brain activities. Based on this "quasi-stationarity," which is also observed in speech signals, features used in speech signals, like Mel-Frequency Cepstral Coefficients (MFCC), energy, pitch, zero crossing measure, probability of voicing, jitter, and shimmer, were extracted for EEG-based biometric classification [113]. Ma et al. [91] extracted spectrum topographies so that the features were image-based and the biometric recognition problem was converted to image classification problem. Other features were also explored in various studies, like skewness and kurtosis [147], two-channel features of Mutual Information (MI) [138, 147] and Coherence (COH) [87, 138, 147], and so on. More features are summarized in tables in Section 8.

7 CHANNEL/FEATURE SELECTION AND DIMENSIONALITY REDUCTION

Although many studies on EEG biometrics directly feed the extracted features to the classifiers for decision-making, channel selection, feature selection, and feature dimensionality reduction are also important for improving the performance and computational efficiency of biometric recognition systems. Data captured by a large number of channels or too many extracted features—the extracted feature dimension can easily reach over thousands—can contain a high degree of irrelevant and redundant information which may greatly degrade the performance of learning algorithms [183, 184]. Furthermore, this could result in a significant challenge in computational complexity, especially for real-time recognition. Nowadays, EEG sensing is more likely to use wearable

devices for raw data acquisition and wireless data transmission, even for web-based applications [30]. These could lead to another limitation in terms of data transmission rate. Thus, selecting most relevant data by using more effective channels, more representative features, or containing most of the feature information but compressing it to a lower dimension are possible solutions. It is worth noting that some papers use the term “feature selection” even though the actual selection operation is to use features to choose those channels with best performance. Hence, here we categorize these as “channel selection.” Only those scenarios involving the addition or removal of features without channel selection are considered “feature selection.”

7.1 Channel Selection

Placing EEG electrodes onto the most effective brain region according to the testing protocols or on selected places from different regions is an efficient way to use fewer channels. For example, the occipital lobe is the visual processing center of the human brain; thus EEG signals collected from this region may give better results than others when doing VEP biometric recognition tasks.

But it can happen that the selected channels could be unstable, with bad signal quality or even no signal due to noise, movements, disconnections, and many other reasons. In those cases, more channels can provide more reliable and robust data collection. Altaht et al. [4] selected channels according to their stability values, defined as the difference between the “within person distance” (intra-subject distance, distance distribution of the feature vectors for the same person, same channel and same mental task) and the “between person distance” (inter-subject distance, distance distribution of the feature vectors for the same channel and same mental task, but different persons). Using a sequential forward selection algorithm, the process starts with the channel having the highest stability value to get authentication accuracy, then sequentially includes the next highest channel. If the newly added channel does not improve performance by a set threshold, it is removed since the channel feature is redundant. This procedure ends when all channels have been tested. Then the final retained channel set is considered the optimal selection. The result suggested that 8 channels is sufficient to reach the competitive HTER instead of using all 64 channels. Li et al. [86] also used the intra-subject and inter-subject strategy based on Euclidean distance to select 8 channels from 32 EEG channels and 8 physiological channels and reached an identification accuracy of 94%. Another statistical channel selection method, particularly used in authentication scenarios with self-face and non-self-face visual stimuli, was the pointwise biserial correlation coefficient. With the selected 5 or 6 channels, authentication accuracy was up to 92.4% [177, 178, 182].

SVM Recursive Feature Elimination (SVM-RFE) is another technique for feature selection. It finds the feature ranking list through iterations based on the following steps. First, the weight vector of dimension length of surviving features is computed from the SVM training model on the surviving features. Then the ranking criteria is computed. The feature with smallest ranking criterion is found, and the feature rank list is updated. The feature with smallest ranking criterion is eliminated, and the new surviving feature subset is formed. Moreover, SVM-RFE can be generalized to remove more than one feature per step to increase its speed [47]. Liu et al. [89] and Bai et al. [8] used SVM-RFE to select the most effective channels. Results showed that the selected 32 channels obtained a higher identification accuracy of 97.25% than the 96.25% reached by using all 64 channels.

The Genetic Algorithm (GA) is an adaptive, probabilistic search method for global optimization originating in biological natural selection. It consists of three basic operations: selection, crossover, and mutation. During the “selection” stage, the channel features with the highest accuracy were selected to breed a new generation. “Crossover” represented the analogous process to mating in a biological system and formed new offspring by varying the programming of a chromosome or

chromosomes from one generation to the next. Part of the new individuals were created through the “mutation” process, analogous to biological mutation, which randomly changed the allele values in the chromosome and helped maintain genetic diversity from one generation of a population to the next. When a new generation of individuals was produced through these three operations, the process is repeated until a termination condition is fulfilled, such as when the iteration process reaches a pre-set generation or when the fitness metric no longer rises. Bai et al. [8] applied this algorithm to optimize channels, and the classification accuracy was improved from 96.25% to 97% by reducing the number of channels from 64 to 37.

The Fisher Discriminant Ratio (FDR) was adopted to evaluate the discrimination level of features and to select the most discriminatory features [8]. Based on such evaluations, it was shown that there was no optimization on the channel number, which was still all 64 channels, and therefore the accuracy of 96.25% was not changed.

The Davies-Bouldin Index (DBI) evaluates feature importance by the number of clusters in the data and was adopted in Palaniappan and Mandic [120] to select the more representative features to optimize recognition accuracy since, for each channel, only the gamma band energy was extracted and each channel had one feature value. Therefore, sorting the DBI of the features from the 61 channels indicated the importance of the channel. Using this method, the optimal number of channels was 35, with a GAR of 98.56% compared to using all 61 channels with about 99% accuracy.

The Flower pollination algorithm [180] is a global optimization method motivated by the pollination process of flowers based on four rules: (i) biotic cross-pollination is the global pollination, and Lévy flights constrain pollen-carrying movements; (ii) abiotic pollination and self-pollination are the local pollination; (iii) pollinators contribute to flower constancy; and (iv) interaction of local pollination and global pollination is controlled by a probability between 0 and 1 and slightly biased to local pollination. The binary flower pollination algorithm was adopted in Rodrigues et al. [140], where the search space is binary instead of continuous, and it selected less than half of 64 channels but maintained a recognition accuracy of up to 87%.

A rough set is a method to learn data dependence and evaluate the quality of a feature subset. Rough set neighbor and rough set entropy were adopted in Moreno-Revelo et al. [103] and selected 12 more relevant channels out of 32 EEG channels and 8 peripheral channels for person identification. The best accuracy could reach 100%.

7.2 Feature Selection

More often, the number of electrode channels used is small, and it is thus less persuasive to select one or a few channels. The final result will largely rely on the features extracted from the raw signals. It is thus imperative to select the most representative features.

Linear Discriminative Analysis (LDA) is a method based on intra-class and inter-class means to find those directions having the maximum linear separability of classes. The highest recognition accuracy was achieved when using LDA on the optimized Eigenbrains (EBs) and Eigentensorbrains (ETBs) after discriminative analysis [96]. It was also mentioned by Cai et al. [18] that using LDA can reduce feature dimensionality. However, no further details, like performance, were presented. Considering one feature of one channel as a feature attribute, Lee et al. [83] used intra- and inter-subject mutual information to select features. Out of 112 features (7 features $\times$ 16 channels), 9 features were selected to achieve an identification accuracy of 95%.

One-Way Analysis of Variance (ANOVA) is a statistic model to analyze the differences of means and variance among classes. Thus it can be applied to explore the intra-class and inter-class variance of features. La Rocca et al. [80] used this method to select more discriminant parameters and shrank feature size from 39 to 13.

7.3 Dimensionality Reduction

PCA linearly transforms a set of variables into a new set of orthogonal variables called *principal components* in which most data information is retained in the first few principle components. Wang and Najafizadeh [174] used PCA to identify the most relevant 48 channels from 128 channels. The identification accuracy was 53.5%–99.73%, compared to 51.09%–99.14% when using all 128 channels. Palaniappan [117] used PCA to reduce the feature dimensions from 126 to 11 while retaining 99.99% of the variance. Koike-Akino et al. [73] selected 100 PCA components out of 1,442 feature dimensions to maintain 90% of the data variance, as well as using the partial least-squares method to explain 65% of the variance using 100 components. Falzon et al. [36] used 15 principle components to retain 90% of the total variance. PCA and Multilinear PCA (MPCA) were used in brain biometric recognition [95, 96], as well as for PSD feature projection (EB and ETB) [96].

The Johnson-Lindenstrauss Transform used in He et al. [50] is also a robust and time-efficient dimensionality reduction method. It is based on the lemma that n points in the Euclidean space can be projected down to the dimension of $O(\epsilon^{-2} \log(n))$ with a distortion within the range of $1 \pm \epsilon$ ($0 < \epsilon < 1$), in the pairwise distance. Using this transform, the feature size was reduced from 256×4 to 100×4 .

8 CLASSIFICATION

When evaluating the performance of a specific biometric approach, multiple metrics were proposed and adopted [19], including the Correct Recognition Rate (CRR) in the identification case, False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Authentication Rate (GAR), Half Total Error Rate (HTER=(FAR+FRR)/2), and Equal Error Rate (EER), which is the HTER when FAR=FRR in the authentication case. Moreover, the CRR in this survey also referred to the accuracy in authentication scenarios. In some papers, chance accuracy was used, and it was calculated based on predefined confidence probabilities according to similarity ranks, considering that the correct labels were not in the first rank but very close to it [144].

8.1 Similarity-Based Pattern Recognition

Similarity-based pattern recognition is a straightforward classification category to authenticate or identify individuals based on the selected similarity evaluation metrics [126]. For the authentication case, during enrollment, the system identifies both intra- and inter-class similarity ranges and then finds a proper threshold based on similarity values to separate the specific person from others. But for the identification case, the classification results are not simply acceptance or rejection by using a threshold. K-Nearest Neighbors (kNN), which make final decisions by majority rule on the closest or most similar points to the inputs, were usually selected for identification. Specifically, prior studies tried different similarity metrics in kNN for recognition, as summarized in Table 6. If the similarity metric was not explicitly specified in the paper, it was marked as “kNN.” Commonly used similarity measurements, like Cross-Correlation (CC) [6, 142–146, 167, 168, 172, 173], Cosine Similarity [28, 32, 62, 95–97, 106], Euclidean Distance [9, 10, 16, 39, 42, 44, 64, 95–97, 109, 121, 124, 174, 181], Mahalanobis Distance [81, 95, 96, 166, 167], Manhattan Distance [54, 95–97, 117, 119, 121, 130, 136], and Bhattacharyya Distance [83] have been investigated in the literature.

Moreover, it has been acknowledged that ERP patterns often had some sort of unintended misalignment or distortion. Thus Dynamic Time Warping (DTW) [34, 38, 42] was adopted to mitigate this problem. Because the extracted EEG features may not have the contributions equal to the classification results, and the intra-class features may have large variations due to changes in recording conditions, it is difficult for the regular Euclidean distance-based kNN to provide

Table 6. Performance of Similarity-Based Methods

Papers	Sbjs	Chs	Protocols	Features	Similarity	Performance
[6]	30	1	ERP	raw ERP	CC	Chance accuracy: 92%
[9]	9	61	RC	peaks	Euclidean	EER: 11.17%
[10]	52	64	RC, RO, Mental	PSD	Euclidean	EER: 22.97%-29.36%
[16]	120 6	64 106	ERP Mental	AR	Euclidean	CRR: 93.24%-96.34% CRR: 98.52%-99.41%
[18]	40,33,11	1	RC	AR, PSD, WPT	kNN L-LMNN	CRR: 50.99%-93.94% CRR: 58.47%- 98.03%
[28]	15	1	RC, Mental	PS	Cosine	HTER: 1.1%-43.3% CRR: 22%
[31]	20	20	ERP	LDA	kNN	CRR: 97%
[32]	50	6, 17	ERP	raw ERP	Cosine	EER: up to ~22%
[34]	50	6, 17	Mental	raw EEG	DTW	EER: 7%-25%
[36]	8	32	ERP	variance	kNN	GAR: 91.7% FAR: 1%
[38]	12	1	Mental	MPA, MSP, MSV, PF, PFM, SP, VAZ, ZCR	DTW	EER: 14.7%-67.6%
[39]	109	64	RC, RO	nodal EC	Euclidean	EER: up to 14.4%
[42]	30	1	ERP	raw ERP	Euclidean DTW	CRR: 53.33%-81.17% CRR: 33.83%-67.17%
[44]	37	1	ERP	raw ERP	Euclidean	CRR: 47.3%-67.57%
[54]	50	19	RC, RO	AR	Manhattan	CRR: up to 95%
[64]	109	34	RC, RO	EC, MaxLyp, MPC, PE, PLI, PSD, SE	Euclidean	FRR@1% FAR: 0.92%-2.2% EER: 0.63%-1.8%
[62]	15+3I	1	RC, Mental	PS	Cosine	HTER: 1%
[81]	108	56	RC, RO	COH, PSD	Mahalanobis	CRR: 75.86%-90.49%
[83]	7	6	RC	PSD	Bhattacharyya	CRR: 95%
[87]	10	10	ERP	CC, COH, MA	FRNN	CRR: 90.17%
[95]	60	19	RC	EB, LDA, PSD	Cosine, Euclidean, Manhattan, Mahalanobis	CRR: up to 97.68%
[96]	30	19	RC, RO	EB, ETB, LDA, PSD	Cosine, Euclidean, Manhattan, Mahalanobis	CRR: up to 90.49%
[97]	50	19	RC, RO	AR, COH, PSD	Manhattan Euclidean, Cosine	CRR: up to ~86%
[102]	23	1	RC	FFT	User define	GAR: 70%-79%
[106]	15+5I	2	RC	AR, PSD	Cosine	FAR: 1%-2.3% FRR: 13.7%-32.2% HTER: 7.3%-17.2%
[107]	23	1	RC	FFT	User define	EER: 11%
[108]	30	1	driving scenes, route tracing	PS	User define	EER: 22%-52%
[109]	20	14	ERP	spectral differences	Euclidean	EER: 23%-56%

(Continued)

Table 6. Continued

Papers	Sbjs	Chs	Protocols	Features	Similarity	Performance
[110]	23	1	driving scenes	PS	User define	EER: 27%-37%
[117]	5	6	Mental	AR, IHLC, IHPD, NLC	Manhattan	FRR: 0-1.5% FAR: 0
[119]	102	61	ERP	MUSIC	Manhattan	CRR: 95.00%-96.13%
[121]	20	61	ERP	GBSP	Euclidean Manhattan	CRR: 66.12%-91.54% CRR: 65.64%-94.18%
[124]	10	18	Motor	COH	Euclidean	EER: 7.5%
[130]	25	19	ERP	AR, MFCC	Manhattan	CRR: up to 100%
[136]	20	61	ERP	GBE	Manhattan	CRR: 70.88%-92.04%
[142]	50	1	ERP	raw ERP	CC	CRR: 60%-86%
[143]	20	26	ERP	raw ERP	CC	CRR: 100%
[144]	32	1	ERP	raw ERP	CC	CRR: 56%
[145]	32	1	ERP	raw ERP	CC	Chance accuracy: 90%
[146]	9	1	ERP	raw ERP	CC	CRR: up to 100%
[158–160]	40	1	RC (water/coffee)	PSD	kNN	CRR: 93.75%-97.5%
[166]	109	64	RC, RO	AE, SE	Mahalanobis	CRR: up to 99.7%
[167]	109	19	RC, RO	DBP, IAF, IAFP	CC, Mahalobonis	CRR: 90.21%
[168]	4	14	ERP	PSD	CC	FAR: 12.5% FRR: 12.5%
[172]	6	19	ERP	raw ERP	CC	GAR: 73.33%-96.67%
[173]	4+21	8	Mental	topological plot	2-D CC	FAR: 1.01%-50.48%
[174]	4	128	RC	CWT	Euclidean	CRR: 51.09%-99.73%
[181]	20	61	ERP	AR, PSD	Euclidean	CRR: up to 100%
[188]	70	8	ERP	Energy	kNN	GAR: 31.3%-95.1% FAR: 0.9%-6.4%

good performance. Thus the Local Large Margin Nearest Neighbor (L-LMNN) [18] was proposed to find the relative importance and correlations of each feature dimension, minimizing the intra-class distance while maximizing inter-class distance. The Fuzzy-Rough Nearest Neighbors (FRNN) [87] algorithm combines fuzzy sets, rough sets, and the nearest neighbor classification. It determines an input test feature class according to its membership value calculated from the fuzzy upper and lower approximations. In addition to these commonly used similarity evaluation metrics, user-defined approaches, in which the similarity was evaluated according to some custom-defined metrics by combining extracted features, were also adopted [102, 107, 108, 110].

8.2 Support Vector Machine

An SVM uses a hyperplane to separate two classes of data by maximizing the margin, which is the distance between the nearest training points from different classes, and has a good generalization capabilities. Because the ordinary SVM classifier can only separate two classes, in multiclass problem, there are two ways to implement the multiclass SVM: One-Against-One (OAO) and One-Against-All (OAA). OAA separates the data into two groups: a random class as one group and all other classes as the other group. Then the question is converted into a two-class problem. Thus the final decision is made according to the highest output. OAO chooses any two classes for classification. After this, by combining the results from each classifier, the class with the most votes

Table 7. Performance of SVM Methods

Papers	Sbjs	Chs	Protocols	Features	Kernels	Performance
[6]	30	1	ERP	raw ERP	SVM	Chance accuracy: 83%
[7]	5	14	Mental	AR, IHPD, IHLC, PSD, SP	Linear	FRR: 0-11.3% FAR: 0-2% CRR: 97.69%
[8]	20	64	ERP	AR, FPS, PLV, TPS	SVM	CRR: 88.63%-97.25%
[11]	9	5	RC	ABS, MSD, WPES, WPS	SVM	GAR: 44.44%-94.44%
[16]	120 6	64 106	ERP Mental	AR	Linear	CRR: 98.96% CRR: 99.76%
[30]	16	1	RC	Energy distribution, index, PSD	RBF	CRR: 93.73%
[35]	20	128	video	Cepstral coefficients	Linear	CRR: up to ~99%
[37]	13	20	ERP	SP	Linear, RBF	Error: 15.67%-65.94%
[67]	60	14	ERP	DB4 wavelets, RMS, std	Linear	CRR: 93.83%
[69]	104	6	RC, RO	AR	SVM	CRR: 97.43%
[73]	25	14	ERP	raw ERP	Linear	CRR: ~20%-50%
[75]	20+30I	14	Mental	DFT, mean, std	SVM	FAR: 18%-59% HTER: 9%-29.5%
[89]	20	64	RC, ERP	AR, TPS, FPS, PLV	RBF	CRR: 67.37%-96.25%
[106]	15+5I	2	RC	AR, PSD	Linear, RBF Sigmoid Polynomial	FAR: 0.3%-1.4% FRR: 10.7%-50% HTER: 5.5%-25.7%
[111]	9 9 40	3 3 8	Mental Mental free	AR, PSD	RBF	EER: up to ~37%
[113]	3, 9, 9 40 20, 122	8, 8, 3 8 8	Mental Free ERP	Energy, MFCC, Pitch, probability of voicing, ZCR, Jitter & shimmer	RBF	CRR: 46.24%-99%
[127]	9, 9	3	Mental	AR, PSD	RBF	EER: 0-3.3%
[182]	10	18	ERP	signal difference, time derivative	RBF	GAR: 86.1% FAR: 13.9% FRR: 13.9%

would be the instance classification [37]. Table 7 summarizes brain biometric studies using SVM classifiers. If the kernel was presented as “SVM,” then the kernel type was not listed in the paper. Linear kernel is computationally efficient, and it was adopted in several studies [7, 16, 35, 37, 67, 73, 106]. Sometimes, it is impossible for the linear hyperplane to separate classes. Thus, nonlinear decision boundaries could help in this situation. Nonlinear kernels are introduced to map data to another space to make them more separable while increasing the classifier’s complexity. One frequently used kernel is the Radial Basis Function (RBF) [30, 37, 89, 106, 111, 113, 127, 182]. Other kernels, like sigmoid and polynomial, were also tested [106].

8.3 Neural Network

The NN, one of the most important and popular machine learning techniques, seeks to find a function that can map inputs to outputs. The classic structure to implement the NN is the multi-layer perception NN, which generally has three types of layers: input layer, hidden layer, and output layer. It uses the feedforward and back-propagation algorithm to train the data and calculate the weight matrix. Based on the weight matrix, the result can be predicted. Several papers using NNs to make decisions in brain biometric recognition are listed in Table 8. Many studies used the

Table 8. Performance of NN Methods

Papers	Sbjs	Chs	Protocols	Features	Types	Performance
[1]	10	1,2,4	RC, RO	AR	DNN	CRR: 70%-97%
[27]	120	64	RC, RO, ERP	raw EEG	DNN	CRR: 62.2%-92.9%
[43]	32	1	ERP	WPD	NN	CRR: up to 47.5% GAR: up to 94.04%
[52]	15	2	Relax, Mental	PSD	NN	CRR: 78.6%
[53]	6	2	Relax, Mental	PSD	NN	CRR: 94.4% to 97.5%
[55]	45 122	64	ERP	RMS	NN	CRR: 100% CRR: 95.08%
[60]	20	64	ERP	1D-LBP, 1D-LGP	NN	CRR: 62.7%, 88.9%
[73]	25	14	ERP	raw ERP	DNN	CRR: ~35%-65%
[76]	6	14	Mental	DWT	LVQ	CRR: ~90%
[86]	32	32	ERP	DB4 wavelets	DNN	CRR: 88%
[105]	10	2	ERP	fuzzy entropy	NN	CRR: 87.3% FAR: 5.5% FRR: 5.6%
[116]	20	61	ERP	GBSP	NN	CRR: 99.06%
[118]	5	19	ERP	energy	NN	CRR: 80.6%-90%
[119]	102	61	ERP	MUSIC	ENN	CRR: 96.77%-98.12%
[120]	40	61	ERP	Energy	ENN	CRR: 98.06%-98.56%
[121]	20	61	ERP	GBSP	SFA	CRR: 66.26%-92.84%
[131]	4+75I	1	RC	SP	LVQ	GAR: 80%-100% FAR: 10%-20%
[132]	4+75I	1	RC	AR, bilinear	LVQ	GAR: 76%-88% FAR: 16%-24%
[133]	4+75I	1	RC	AR	LVQ	GAR: 72%-84% FAR: 18%-22%
[135]	14	N/A	Mental	DB4 wavelets	NN	CRR: 91.4%-93.8%
[136]	20	61	ERP	Energy	SFA	CRR: 71.14%-92.84%
[139]	7	6	RC, RO, Mental	FRFT	RBNN	GAR: ~80%
[153]	3	4	RC	DFT, WPD	NN	CRR: 87%-93%
[162]	9	15	Mental	Energy	NN	CRR: 92.52%, 90.12%

one-hidden layer NN, which was constructed using one input layer, one hidden layer, and one output layer [43, 52, 53, 55, 60, 105, 116, 118, 135, 153, 162]. Besides the conventional one-hidden-layer NN, the Deep Neural Network (DNN) with two or more hidden layers, was also investigated. Two-hidden-layer NNs with 100 and 1000 nodes on each hidden layer were adopted in Abdullah et al. [1] and Koike-Akino et al. [73] respectively. Four hidden-layer NN was implemented in other work [27, 86], while the output layer in Chu et al. [27] was set to three types: softmax, multiclass SVM, and Random Forest (RF).

In addition to the classic NN, Kohonen's LVQ is another type of NN that has been used during the very early stage of brain biometric studies by Poulos et al. [131–133]. The basic architecture of LVQ has two neuron layers: the competitive layer and the linear layer. It sorts data to the class whose Euclidean distance from the sample vector is smallest, and it has the ability of nonlinear separability. The output function is based on the winner-takes-all principle. Other types of NNs were also adopted, such as the Elman Neural Network (ENN) [119, 120] with the addition that the hidden layer outputs are delayed and fed back into the network; the Simplified Fuzzy ARTMAP

Table 9. Performance of DA Methods

Papers	Sbjs	Chs	Protocols	Features	Types	Performance
[2]	31	1	Eye blink, RC, ERP	AR	LDA	CRR: up to 99.68% EER: 0.89%-4.4%
[24]	29	28/16	ERP	point-biserial correlation coefficients	regularized LDA	GAR: 100% FAR: $3.33 \times 10^{-3}\%$
[61]	12	14	Mental	CSP	LDA	GAR: up to 96.97%
[73]	25	14	ERP	raw EPR	LDA, QDA	CRR: up to 96.7%
[74]	9	22	Mental	PLV, degree of brain networks	LDA	CRR: 93.7%-96.8%
	14	7	Mental			
	20	16	ERP			
	12	15	Driving			
[80]	36	3	RC	bump modeling	LDA	CRR: up to 99.69%
[84]	4	1	RC	α frequency, MP, SP	LDA	CRR: 86.7%-100%
[106]	15+5I	2	RC	AR, PSD	LDA	FAR: 2.3%-3.7% FRR: 25.9%-44.8% HTER: 14.1%-24.2%
[118]	5	19	ERP	energy	LDA	CRR: 76.9%-93.5%
[121]	20	61	ERP	GBSP	LDA	CRR: 84%-96.5%
[138]	51+36I	2	RC	AR, CC, COH, FT, MI	LDA, D-LDA, QDA, D-QDA	EER: 3.4%
[147]	50+20I	2	RC	AR, CC, COH, FT, MI, skewness & kurtosis, 3rd autocovariance, ICA, time reversibility, centroid frequency, max power frequency	LDA, D-LDA, QDA, D-QDA	EER: 2.4% CRR: 93.8%
[179]	108	9	RC, RO, Mental	WPD	LDA	CRR: up to 99% EER: 4.5%

(SFA) [121, 136], which consists of a fuzzy ART module for receiving the input features, a category layer with output classes, and an inter=ART module for learning the mapping between input features and corresponding output classes; and the Radial Basis Neural Network (RBNN) [139], which has one hidden radial basis layer and lower training time.

8.4 Discriminant Analysis

The aim of Discriminant Analysis (DA), more commonly Linear Discriminant Analysis (LDA), is to use hyperplanes to separate the data of different classes by projecting the data into a lower dimensional space. It maximizes the inter-class distance with the assumption that the data are normally distributed so that the covariance matrices are equal for different classes. Table 9 summarizes studies that adopted DA methods. In addition to LDA [2, 24, 61, 73, 74, 80, 84, 106, 118, 121, 147, 179], other DA variants are available, such as Diagonal Linear Discriminant Analysis (D-LDA), which is similar to LDA but with diagonal covariance matrices; Quadratic Discriminant Analysis (QDA), which fits multivariate normal density with covariance that is not identical for each class; and Diagonal Quadratic Discriminant Analysis (D-QDA), which is similar to QDA but with diagonal covariance matrices [73, 138, 147].

8.5 Other Supervised Learning Classification Methods

In addition to the mentioned frequently adopted classifiers, other supervised learning classification methods for person recognition have also been investigated; these are listed in Table 10.

Table 10. Performance of Other Supervised Learning Classification Methods for Brain Biometrics

Papers	Sbjs	Chs	Protocols	Features	Classifiers	Performance
[4]	106	8	RC, RO, Motor, Mental	PSD	GMM, UBM	HTER: 14.69%
[20]	48	3	RC	AR	Polynomial classifier	CRR: up to 96.08%
[50]	4	16	Mental	mAR	NBM	HTER: 1.5%-9.8%
[51]	7	17	Mental	AR	NBM	HTER: 0-12%
[66]	40	4	RC	AR, PSD	NBM	EER: 4.16%
[67]	60	14	ERP	WPD, RMS, std.	HMM	CRR: 97.5%
[75]	20+30I	14	Mental	DFT, mean, std.	HMM	FAR: 0-18.89% HTER: 0-9.445%
[78]	45	2, 3, 5	RC	AR	Polynomial classifier	CRR: up to 98.73%
[79]	9	3, 5	RC, RO	AR	Linear classifier	CRR: up to 100%
[92]	45	19	RC, RO, Mental	AR, MFCC, bump modeling	HMM	EER: up to 10%
[100]	9	8	Mental	PSD	GMM, MAP	HTER: 0-52.1%
[112]	9	3	Mental	AR, PSD	RBF SVDD GMM	EER: 0.25%-16.99% EER: 0.13%-19.64%
[128]	40	8	RO, RC	AR, PSD	SS2LM-SVDD	DET curve
[129]	32	8	Music videos	AR, PSD	RBF SVDD	EER: 15%-32.5%
[157]	40	1	RC	AR, PSD	NBM	EER: 4.16%
[188]	70	8	ERP	Energy	RBF SVDD	GAR: 44.2%-98.5% FAR: 1.7%-10.1%

8.5.1 Gaussian Mixture Model (GMM). In the GMM, all feature vectors are assumed to be independent. Denoting that λ is the parameter set for client C and $-\lambda_C$ is the parameter set for a non-client, a claim for client C 's identity is supported by the feature vectors X , $P(X|\lambda_C)$ is the likelihood of the claim made by the true client, and $P(X|-\lambda_C)$ is the likelihood of the claim coming from an impostor, then the authentication score $\Lambda(X)$ on the claim is shown in Equation (4). When the threshold is set to τ , the claim is accepted when $\Lambda(X) \geq \tau$ and rejected otherwise [4, 100, 112].

$$\Lambda(X) = \log P(X|\lambda_C) - \log P(X|-\lambda_C). \quad (4)$$

8.5.2 Hidden Markov Model (HMM). HMM is used to process nonstationary signals and consists of three probability states: initial, transition, and observation, denoted by $\lambda = (\pi, A, B)$. For a model λ , an observation sequence $O = (O_1, O_2, \dots, O_T)$ is modeled by GMM from a state sequence $Q = (Q_1, Q_2, \dots, Q_N)$, then HMM seeks to find the best likelihood of $P(O|\lambda)$ [67, 75, 92].

8.5.3 Linear & Polynomial Classifier. Denoting the feature vector as x , which is the observed feature vector of length M in the linear terms of $x = [x_1, x_2, \dots, x_M]^T$, and the transformation matrix as G , the linear classifier estimates the class labels $\hat{y}$ using a linear transformation so that $\hat{y} = x^T G$, where the transformation matrix G is solved by minimizing the mean square error [79].

The polynomial classifier is similar to the linear classifier, except that it uses a polynomial format, quadratic terms, cubic terms, and so on, along with the linear terms of the feature vector. Instead of $x = [x_1, x_2, \dots, x_M]^T$, the vector $z(x) = [1, x_1, x_2, \dots, x_M, x_1^2, \dots, x_M^2, x_1x_2, x_1x_3, \dots, x_1^3, \dots, x_M^3, \dots, x_1x_2x_3, \dots, x_1^2x_2, \dots]$ is used. Then the polynomial classifier makes predictions using $\hat{y} = z^T(x) \cdot G$ [20, 78].

8.5.4 Naïve Bayes Model (NBM). NBM [137] is a probabilistic model based on the Bayes theorem with the assumption that features are strongly (naïve) independent. It has good performance when the dimension of the feature vectors is high. Assume that each element x_i of the feature vector X of dimension M follows the Gaussian distribution and is statistically independent from each other; then the parameter θ of NBM can be estimated through Maximum Likelihood Estimation (MLE) using the training data. The likelihood of a claim is calculated as Equation (5). Given a threshold τ , the authenticate claim will be accepted if $P(X|\theta) \geq \tau$, and otherwise rejected [50, 51, 66, 157].

$$P(X|\theta) = \prod_{i=1}^M P(x_i|\theta_i). \quad (5)$$

8.5.5 Support Vector Data Description (SVDD). The key idea of SVDD [164] is to find a close boundary in which the targets are located. This is different from SVM, which aims to find a hyperplane to separate different classes. SVDD with an RBF kernel was adopted in several studies [112, 129, 188]. In order to reduce both the false acceptance rate and the false rejection rate simultaneously, Pham et al. [128] adopted the Small Sphere Two Large Margins Support Vector Data Description (SS2LM-SVDD), which constructed an optimal hypersphere in the feature space with one margin to include EEG the data of one person and with the remaining margins to exclude the EEG data belonging to other individuals.

8.6 Unsupervised Feature Learning-Based Recognition

So far, most of the methods used in brain biometric authentication and identification can be categorized into two types: similarity-based and supervised learning-based recognitions. Similarity-based methods measure the distances among the features for decision-making. However, the high noise level of the EEG signals could lower the accuracy of identifying individuals, and the computation efficiency decreases significantly as the sample size increases. For the supervised learning-based methods, features are extracted first from the EEG data before the supervised algorithms are adopted to train a model for prediction. Although supervised learning has shown its advantage in brain biometric recognition at fair computation times, its performance can be significantly affected by the quality of manually chosen features. If the feature represents the data well, a supervised learning algorithm can get good performance. Otherwise, the results will be unsatisfactory. Due to the complex nature of brain activities, EEG signals include a lot of noise, and random brain activities could influence the quality of the extracted features. Thus, unsupervised feature learning approaches that have achieved great success in the computer vision domain could be adopted in brain biometrics as well.

The Divergent Autoencoder (DIVA) [77] was used to reconstruct the ERPs automatically using an autoencoder, which is a three-layer network that has one input layer, one hidden layer, and one output layer; it tries to learn a function that directly maps the inputs to themselves. Based on this characteristic, autoencoder can reconstruct the input signal at the output. Then, DIVA was used to compare the similarity between the reconstructed input and stored templates during enrollment and made the decision. The identification accuracy was 54% [144] and chance accuracy was 89% [6, 145].

A Convolutional Neural Network (CNN) [82], which is another method to learn intrinsic features automatically through the training process, has gained increasing attention recently due to its extraordinary capabilities of feature learning and classification and has also been explored for EEG-based user recognition. The convolution layers in CNN apply sets of filters to process small local parts of the input data, and these filters were replicated along the whole input space. Through a training process, features of the input data can be learned by these filters. Using “INPUT,”

“CONV,” “AVGPOOL,” “MAXPOOL,” “FC,” “DROPOUT,” “RELU,” “ELU,” “SOFTMAX,” “mSVM,” and “RF” to denote the possible layers (i.e., input, convolution, average pooling, max pooling, fully connected, dropout, relu, elu, softmax, multi-class SVM, and random forest, respectively), the network structure is presented in “[]” with “->” connecting adjacent layers, and a duplicate structure would be presented by the repeated number followed by the structure in “()”. Chu et al. [27] investigated several deep learning models, including CNN, ANN, and RNN ending with the softmax, mSVM, and RF classifiers. The network architectures of CNN, ANN, and RNN were [INPUT-> 3 (CONV-> ELU-> MAXPOOL-> DROPOUT)-> 3 (FC-> ELU-> DROPOUT)-> SOFTMAX/mSVM/RF], [INPUT-> 4 (FC-> RELU-> DROPOUT)-> SOFTMAX/mSVM/RF], and [INPUT-> RNN-> FC-> SOFTMAX/mSVM/RF] correspondingly. Testing on 40 characteristics in high-risk individuals, 40 clinically stable first-episode patients with schizophrenia, and 40 healthy controls, respectively, using 64 channels under protocols of RC, RO, and watching video of news with neutral contents, the accuracy was 58.8%–83.9%, 62.2%–92.9%, and 74.9%–99.2% for RNN, ANN, and CNN, respectively. The results showed that CNN performed best and RNN had the worse accuracy. Das et al. [33] used the CNN structure of [INPUT-> 2 (CONV-> MAXPOOL)-> CONV-> RELU-> FC-> SOFTMAX] to identify 40 subjects using 17-channel ERP data under the “geometric” protocol, and the CRR was in the range between 80.65% and 98.8%. Gui et al. [46] proposed a one-dimensional CNN architecture to identify ERPs. From input to output, the CNN was composed of [INPUT-> CONV-> RELU-> MAXPOOL-> FC-> DROPOUT-> SOFTMAX]. Based on the dataset of 33 subjects of 30 channels using visual stimuli, the single-channel accuracy can reach between 99.6% and 100%. Ma et al. [91] extracted spectrum-topographies under the resting state with eyes closed and open protocols as the 2-D inputs to the CNN, which consisted of [INPUT-> 2 (CONV-> AVGPOOL)-> FC-> SOFTMAX], and obtained an accuracy of up to 88% in identifying 10 subjects. Mao et al. [98] used the CNN structure of [INPUT-> 2 (CONV-> RELU-> MAXPOOL)-> 2 (FC-> DROPOUT)-> FC-> SOFTMAX]. Testing on 100 subjects using 64 channels during a driving experiment, the CRR was 97%. Schons et al. [152] used the CNN architecture of [INPUT-> 3 (CONV-> MAXPOOL)-> 4 (FC)-> DROPOUT-> SOFTMAX]. After finishing the training, the last three layers were removed and the output of the third FC layer was set as the features for verification. Testing on 109 subjects using 64 channels during RC and RO, the EER was in the range of 0.19% to 11.2%. Wu et al. [178] adopted the CNN structure of [INPUT-> 2 (CONV-> MAXPOOL)-> FC-> SOFTMAX] to authenticate 15 genuine users and 25 intruders using 16 channels using visual stimuli of self-face and non-self-face. The authentication accuracy was 92.4% with a FAR of 5.75%–6.71% and an FRR of 7.07%–8.49%.

An attention-based encoder-decoder recurrent NN was implemented in Zhang et al. [186] to learn deep features for user identification. The feature learning modules included three components: the encoder formed by multiple fully connected layers and one recurrent Long Short-Term Memory (LSTM) layer, the attention module accepting the final hidden states and calculating better intermediate attention weights, and the decoder obtaining the learned deep features. Then, an extreme gradient boosting classifier, fused by a set of classification and regression trees, used the deep features learned from a delta band EEG for user identification. In testing on multitrial and single-trial datasets collected from 8 subjects and 14 channels under the RC protocol and the public EEGMMIDB database, the accuracies were 98.2%, 98.82%, and 99.89% respectively.

9 OPEN RESEARCH AREAS

9.1 Brain-Based Multimodal Biometrics

Although the performance of brain biometrics is improving, it still suffers problems similar to other unimodal biometric systems, such as noisy data (e.g., eye blinks, muscle movements, or defects in

Table 11. Performance of Brain Biometrics with Score- and Decision-Level Fusions

Papers	Sbjs	Chs	Protocols	Classifiers	Fusion Levels	Performance	
						Before	After
[6]	30	1	ERP	CC, DIVA, NDL, SVM	Decision (voting)	Chance acc.: 82%-92%	97%
[7]	5	14	Mental	Linear SVM	Decision (voting)	CRR: 97.69%	98.67%, 100%
[40]	109	64	RC, RO	Euclidean Mahalanobis	Score (concatenation, arithmetic mean, max, min, geometric mean, Bayes rule likelihood ratio)	EER: 4.46%-10.6% FRR@1%FAR: 2.1%-3.5%	1.42%-2.48% 1.76%-3.61%
[44]	37	4	ERP	Euclidean	Decision (SRBFNN)	CRR: 47.3%-67.57%	82.7%-91.62%
[80]	36	3	RC	LDA	Score (multiplicative inverse sum)	CRR: N/A	up to 99.69%
[81]	108	56	RC, RO	Mahalanobis	Score (multiplicative inverse sum)	CRR: up to 90.49%	up to 100%
[97]	50	19	RC, RO	Manhattan Euclidean Cosine	Score (mean) Decision (voting)	CRR: N/A	up to ~90%
[130]	25	19	ERP	Manhattan	Score (sum) Decision (voting)	CRR: 66.93%-94.8%	88.27%-99.33% 97.33%-100%
[142]	50	30	ERP	CC	Decision (voting)	CRR: 60%-86%	100%
[147]	50+20I	2	RC	LDA, D-LDA, QDA, D-QDA, TREE, COP	Score (mean, median, OR) Decision (voting)	EER: N/A	mean: 2.4% median: 3% OR: 4.8% voting: 2.59%

the capturing sensors), restricted degrees of freedom (e.g., feature similarities in systems with large user population), spoof attacks (e.g., in voice recognition, spoofing is done by recording the voice and using it to get access), and intra-class variations (e.g., user movements while being authenticated). To address those problems, multimodal biometric systems were proposed to eliminate the weakness of relying on one source of information in unimodal biometric systems [3, 15, 101, 141]. To integrate the information, fusion can be performed at the data or feature level, where the data itself or the extracted feature sets are fused; at the matching score level, where the matching scores generated by multiple classifiers are combined; or at the decision level, where the final output results of multiple classifiers are consolidated [141]. For brain biometrics, the most common fusion level is the feature level. Generally, multiple features are extracted from one or more channels and then concatenated together as a feature set for classification (as shown in Tables 6 to 10 in Section 8, which show two or more features or channels). Thus, in this section, only higher fusion levels (i.e., score and decision) are discussed. Table 11 summarizes the studies using a single EEG as a biometric trait but fusing at the score and decision levels. In score-level fusion, the scores could be integrated by operations like concatenation, arithmetic mean, maximum, minimum, geometric mean, Bayes rule, likelihood ratio, multiplicative inverse sum, sum, median, or OR [40, 80, 81, 97, 130, 147]. In decision-level fusion, the widely adopted fusion mechanism was voting [6, 7, 97, 130, 142, 147]. Besides the voting method, Gui et al. [44] proposed the frequency-based and probability-based Simplified RBF Neural Network (SRBFNN) to combine the preliminary decision-level results to improve identification accuracy. The before and after fusion performance presented in the table shows that fusion techniques could improve EEG recognition performance.

Depending on the number of traits, sensors, and feature sets, multimodal biometrics can be classified into four scenarios: (i) single biometric trait, multiple sensors; (ii) single biometric trait,

Table 12. Performance of Multiple Traits-Based Multimodal Biometric Systems

Papers	Sbjs	Chs	Protocols	Classifiers	Biometric Traits	Performance	
						EEG	Multiple Traits
[2]	31	1	eye blink, RC, ERP	LDA	EEG, eye blink	EER: 2.43%-4.4%	0.89%- 2.53%
[9]	9	61	RC	Euclidean	EEG, ECG	EER: 11.17%	2.94%
[10]	52	64	RC, RO, Mental	sum, product, weighted sum	EEG, ECG	EER: 22.97%-29.36%	0.928%-8.216%
[66]	40	4	RC	NBM	EEG, iris	EER: 4.16%	2.12%
[86]	32	8	ERP	DNN	EEG, EOG, GSR, Rb	CRR: 88%	94%
[103]	32	32	ERP	meta	EEG, EOG, GSR, Rb	CRR: 97.7%	100%
[118]	5	19	ERP	NN, LDA	EEG, ECG	CRR: 76.9%-93.5%	92.4%-99.8%
[124]	10	18	Motor	Euclidean	EEG, hand kinematic	EER: N/A	7.5%
[135]	14	N/A	Mental	mean	EEG, face	CRR: 91.4%-93.8%	100%
[157]	40	1	RC	NBM	EEG, fingerprint	EER: 4.16%	1.12%
[172]	6	19	ERP	sum, min, max	EEG, face	FAR: 0-20% GAR: ~52%-91%	0-20% ~85%-100%
[178]	15+25I	16	ERP	least square	EEG, eye blink	FAR: 6.71% FRR: 8.49%	2.71% 2.09%
[185]	6+2I	64	ERP	RNN, SVM	EEG, ID, Gait	FAR: 0 FRR: 63.16%	0 1.9%

multiple classifiers; (iii) single biometric trait, multiple units; and (iv) multiple biometric traits [141]. For brain biometrics, it is common to use multiple electrodes of the same type and that number into the hundreds, to collect EEG signals from different brain regions. Current studies have not considered the possibility of performance improvement by using different sensors for brain activity recordings. But multiple classifiers, multiple units, and multiple biometric traits have already been investigated. For example, Armstrong et al. [6] combined the results of CC, DIVA, NDL, and SVM and used multiple classifiers for the final decision-making. Sun [162] considered imagery tasks of moving left and right fingers separately; this use of multiple tasks data could help improve performance in correctly recognizing individuals compared to a single task. ECG and other types of biometric traits were also combined to seek better performance. Table 12 lists the papers which used multiple traits for authentication. EEG was combined with eye blinks [2, 178], ECG [9, 10, 118, 155], face [135, 172], iris [66], hand kinematic synergies [124], fingerprint [157], ID and gait [185], EOG, GSR, and a Respiration Belt (Rb) [86, 103], and performance improved.

9.2 Security of Brain Biometrics

Although brain biometrics have shown a high level of security in terms of signal acquisition and processing, they still share a similar identification/authentication architectural flow (i.e., sensors, feature extraction, a matching module, and a decision making module) with other biometrics such as fingerprint, face, and so on. Thus, brain biometric recognition systems are also vulnerable to modern cyber attacks. Currently, hill-climbing attacks to brain biometric recognition system were studied [93, 94], in which an attacker can access the matching scores produced by the matcher module and use them to generate synthetic EEG templates to successfully pass an authentication. The Bayesian algorithm, Nelder-Mead algorithm, Hooke-Jeeves algorithm, SPSS algorithm, and

implicit algorithm were investigated and employed to address this risk. Gui et al. [45] studied the replay attack when the replayed ERPs were created by adding Gaussian noise to the original ERPs. Residual features varied between the ERPs with or without noise. An ensemble classifier combined with a low-level noise detector based on the ERPs' statistical variations was adopted to detect the replay attacks.

Moreover, an authorized person may be coerced to pass a recognition system. Su et al. [160] proposed an EEG-based identification system with a covert warning scheme. Besides thinking as instructed in protocols for EEG data collection, the users also generate three short bursts of muscle signals by clenching their teeth to code covert warning messages along with the EEG signals. Even though the input EEG identity might pass the recognition system, the input user would still be considered as unauthorized if the covert warning message was detected.

A popular approach to securing biometric authentication systems is to establish cancelable biometric templates [125], for example through various types of revocable and noninvertible template transformations. Lin et al. [88] argued that cancelability can be achieved for brain-based biometrics by nature, in that the manipulation of visual stimulus can elicit a new ERP biometric template while preserving its intrinsic uniqueness. In other words, the change in visual stimulation can alter the ERP signal of individuals and allow a truly cancelable biometric.

9.3 Permanence of Brain Biometrics

Permanence, which represents the intra-individual stability of brain activities over a period of time, is an important characteristic and should be carefully investigated to provide sufficient evidence to support brain biometrics. Although many studies have worked on the reproducibility of intra- and inter-individual psychophysiological features [19], it is only recently that researchers examined reproducibility in the area of brain biometrics. These experiments asked participants to return to the lab for more data recording sessions after a certain amount of time following their first visit. The identification accuracy of different sessions was analyzed by setting the first session as a performance reference. Table 13 lists studies which investigated the permanence of brain biometrics. Generally, most of the permanence studies recorded two [33, 79, 84, 96, 106, 130, 143, 174, 177, 178] or three sessions [6, 32, 34, 36, 54, 97, 146]. Maiorana and Campisi [92] extended the experiment to 6 sessions. The time durations among the sessions varied from about 1 week [6, 32–34, 79, 92, 97, 106, 146, 174] to approximately 36 [92] months from the first EEG data recording date. With data from one or more sessions as a training set and data from all the sessions or other different sessions as a testing set, typically, the identification or authentication performance was maintained or degraded only slightly. These results demonstrated that EEG can be a biometric that can last for a long time.

9.4 Stability of Brain Biometrics

EEG is known to be sensitive to emotional and mental states. Therefore, Pham et al. [129] studied the stability of EEG biometrics on a publicly available emotional EEG database, DEAP. During the enrollment phase, only data of calm emotional state was selected. But for the verification phase, emotional states of calm, stress, and excited were used. The results showed that the calm state had better EER than the stress and excited states when the data length was about 1–1.5s, suggesting a good choice for antio coercion attacks. As the length increased, stress gave better performance. When the data length reached 8s, the performance of the three emotions was very close. Thus this could be an optimal data length to tolerate emotion effects in EEG-based biometric authentication.

Moreover, diet is also thought to have an impact on EEG signals. There are studies investigating the EEG signals in the resting protocols with an intake of pure water and coffee [66, 160], but

Table 13. Permanence of Brain Biometrics

Papers	Sbjs	Chs	Protocols	Sessions	Features	Classifiers	Performance		
							1st	2nd	3rd
[6]	30	1	ERP	1 (30 sbjs) 2 (15 sbjs, 5-40 days) 3 (9 sbjs, 134-188 days)	raw ERP	CC, DIVA, NDL, SVM, Meta	Chance acc.: 82%-97%	89%	93%
[32]	50	6, 17	ERP	2 (1 week) 3 (25-49 days)	raw ERP	Cosine	EER: N/A	~8%-18%	~10%-25%
[33]	40	17	ERP	2 (1 week)	raw ERP	CNN	CRR: N/A	80.65%-98.8%	
[34]	50	6, 17	ERP	2 (1 week) 3 (25-49 days)	raw ERP	DTW	EER: N/A	~7%-17%	~10%-25%
[36]	8	32	ERP	2 (3 weeks) 3 (6 weeks)	variance	kNN	GAR: N/A FAR: N/A	GAR: 92.5% FAR: 0.9%	GAR: 91.3% FAR: 1%
[54]	50	19	RO	3 (1 month)	AR	Manhattan	CRR: N/A	up to 95%	
[79]	9	3, 5	RC, RO	2 (1-3 weeks)	AR	Linear	CRR: 91.8%-100%	43.46%-100%	
[84]	4	1	RC	2 (10 days-5 months)	α frequency MP, SP	LDA	CRR: N/A	86.7%-100%	
[92]	45	19	RC, RO, Mental	2 (~1 week) 3 (~1 month) 4 (~7 months) 5 (~16 months) 6 (30 sbjs, ~36 months)	AR, MFCC, Bump modeling	HMM	EER: ~2%-6%	~1%-8%	~2%-10% (3rd) ~4%-10% (4th) ~3%-11% (5th)
[96]	30	19	RC, RO	2 (1 month)	EB, ETB, LDA, PSD	Cosine, Euclidean, Manhattan, Mahalanobis	CRR: N/A	up to 90%	
[97]	50	19	RC, RO	2 (~1 week) 3 (~34 days)	AR, COH, PSD	Manhattan Euclidean Cosine	CRR: N/A	up to ~85%	up to ~86%
[100]	9	8	Mental	12 (3 days)	PSD	GMM, MAP	HTER: 7.1%-16.1%	34.9%-45.5%	36.2%-51.5%
[106]	15+5I	2	RC	2 (5-15 days)	AR, PSD	LDA	CRR: N/A GAR: N/A HTER: N/A	67.8% 95.5% 18.2%	
[130]	25	19	ERP	2 (15 days)	AR, MFCC	Manhattan	CRR: N/A	66.93%-94.8%	
[143]	20	26	ERP	2 (48-516 days)	raw ERP	CC	CRR: 100%	100%	
[146]	30	1	ERP	1 (30 sbjs) 2 (15 sbjs, 5-40 days) 3 (9 sbjs, 134-188 days)	raw ERP	CC	CRR: 99%	93%	84%
[174]	4	128	RC	2 (1 week)	CWT	Euclidean	CRR: 78.16%-99.73%	51.09%-92.58%	
[177]	15+30I	16	ERP	2 (~30 days)	weighted average logistic regression	HDCA	FRR: 7.85%	7.27%	
[178]	15+25I	16	ERP	2 (~30 days)	raw ERP	CNN	FRR: 8.49%	7.07%	

there was no comparison result reported. In Su et al. [158], the authors analyzed circadian and diet effects. Forty subjects participated in experiments with pure water for the first period and the same amount of coffee for the second period. In each period, there were 6 sessions. After one pre-dose session that started at 9:00 am, the subjects drank water or coffee. Then five post-dose sessions were recorded every 0.5 hour after drinking (i.e., 0.5–2.5 hours). The results showed that factors like diet and time of the day could diminish the identification accuracy by almost 30%.

10 CONCLUSION

In this article, we presented a survey of brain biometrics, which possess some unique characteristics and advantages over conventional biometrics and thus have gained increasing attention in the community. We surveyed the recent literature and reviewed some background on the acquisition, processing, and analysis of brain signals. For data acquisition, we reviewed commercially available EEG devices, recording protocols, and publicly available databases for brain biometrics. To analyze the EEG data, we presented popular pre- and postprocessing methods, frequently used features and feature/channel selection techniques, dimensionality reduction methods, and classifiers. In addition, we also discussed and highlighted some of the open research areas in the field, including multimodal biometrics which have EEG as one of the biometric traits, and the security, permanence, and stability of brain biometrics. Finally, we summarized a table of terminology and abbreviations (see Table 1 of the Supplementary Online-only Material) that have been introduced and used in the literature.

Above and beyond the practical considerations we have presented, we argue that brain biometrics have theoretical advantages over other biometric credentials. Brain biometrics in general cannot be collected without a user's knowledge and consent, which makes them resistant to theft. In particular, ERP-based brain biometrics are nonvolitional, meaning that users are neither aware of nor in control of these responses. This makes them resistant to disclosure. Brain biometrics also are resistant to coercion as brain activity is altered by events that cause stress. Brain biometrics are cancelable in that they can be acquired from numerous distinct functional brain systems (e.g., the memory system, the decision-making system, the facial recognition system). The theoretical motivation for exploring brain biometrics is thus strong, and the emerging literature that we have reviewed here demonstrates that their theoretical advantages are accompanied by empirically demonstrated feasibility.

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