Brain Waves for Automatic Biometric-Based User Recognition

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***Abstract*— Brain signals have been investigated within the medical field for more than a century to study brain diseases like epilepsy, spinal cord injuries, Alzheimer's, Parkinson's, schizophrenia, and stroke among others. They are also used in both brain computer and brain machine interface systems with assistance, rehabilitative, and entertainment applications. Despite the broad interest in clinical applications, the use of brain signals has been only recently investigated by the scientific community as a biometric characteristic to be used in automatic people recognition systems. However, brain signals present some peculiarities, not shared by the most commonly used biometrics, such as face, iris, and fingerprints, with reference to privacy compliance, robustness against spoofing attacks, possibility to perform continuous identification, intrinsic liveness detection, and universality. These peculiarities make the use of brain signals appealing. On the other hand, there are many challenges which need to be properly addressed. The understanding of the level of uniqueness and permanence of brain responses, the design of elicitation protocols, and the invasiveness of the acquisition process are only few of the challenges which need to be tackled. In this paper, we further speculate on those issues, which represent an obstacle toward the deployment of biometric systems based on the analysis of brain activity in real life applications and intend to provide a critical and comprehensive review of state-of-the-art methods for electroencephalogram-based automatic user recognition, also reporting neurophysiological evidences related to the performed claims.**

***Index Terms*— EEG, biometrics, brain rhythms, elicitation protocols.**

I. Introduction

In THE last decade, an always growing interest towards the use of biological signals, like electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), electrodermal response (EDR), blood pulse volume (BPV), to cite a few, for the purpose of automatic user recognition is being witnessed. Within this framework the so-called "cognitive biometrics" refer to biometric traits which are detected during cognitive and/or emotional brain states. Therefore, while conventional biometrics rely on the use of either physiological or behavioral characteristics, that is on some biological characteristics the individual "possesses" or on the "way the individual behaves" respectively, cognitive biometrics are based on the measurement of signals directly or indirectly generated by the "way the individual thinks" as a distinctive characteristic for automatic user recognition.

The study of brain activity during specific mental states has been explored by means of different methodologies in order to extract discriminating features for the purpose of user recognition. Specifically, brain activity can be recorded either by measuring the blood flow in the brain or by measuring the neurons' electrical activity. To the first category belong approaches like functional magnetic resonance imaging (fMRI), which measures the concentration of oxygenated and deoxygenated haemoglobin in response to magnetic fields; near-infrared spectroscopy (NIRS), which measures the concentration of oxygenated and deoxygenated haemoglobin by means of the reflection of infrared light by the brain cortex through the skull; positron emission tomography (PET), which measures neuron metabolism through the injection of a radioactive substance in the subject. To the second category belong approaches like magneto-encephalography (MEG), which is sensitive to the small magnetic fields induced by the electric currents in the brain, and electroencephalography (EEG), which is sensitive to the electrical field generated by the electric currents in the brain. EEG recordings are acquired with portable and relatively inexpensive devices when compared to the other brain imaging techniques. Specifically, signal amplifiers with high sensitivity and high noise rejection are used to measure the voltage fluctuations on the scalp surface, resulting from the electric field generated by the firing of collections of pyramidal neurons of the cortex. The EEG amplitude of a normal subject in the awake state, recorded with scalp electrodes, is in the range 10 – 200 μV, and a healthy human brain has its own intrinsic rhythms falling in the range of 0.5 – 40Hz. EEG based brain imaging techniques present a limited spatial resolution due to the physical dimension, in the range of several millimeters, of the surface electrodes usually employed in the acquisition setup, which limits the possible number of the electrodes covering the whole scalp. A limited spatial resolution is also due to the dispersion of the signals, generated by the sources on the cortex, within the head structures before they reach the scalp. On the contrary, EEG techniques have a high temporal resolution, in the range of milliseconds, which allows dynamic studies to understand the underlying mechanisms by means of computational methods. In fact, information concerning for instance psycho-physiological state, neurological and neuromuscular health, emotions, memory, the course of concentration, attention, lev-

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els of arousal, mental fatigue or workload during special tasks, and sensitiveness to external stimulation can be extracted from EEG inspection and manipulation [1]. Such a kind of evidence has led in last decades to use brain signals to convey conscious volition in EEG-based systems, like brain computer interface (BCI) [2], [3], and brain machine interface (BMI) [4], aiming at controlling remote devices by means of the interpretation of the brain electrical activity.

Although some isolated attempts to use EEG to discriminate people have been performed in the past [5], only recently the scientific community has started a more systematic investigation on the use of EEG signals as human distinctive traits which can be potentially used in a biometric system [6]. In fact the way the brain regions are organized and coordinated during specific cognitive functions or mental states, such as the response to audio or visual stimuli, during real or imagined body movements, imagined speech, resting states, etc., or during emotional states, can provide relevant information about the brain conditions which, in the studies conducted so far, have shown to have some discriminant capabilities among subjects [7], [8], due to both morphological and anatomical traits, and functional plasticity traits. Therefore this overview paper will focus on the level of understanding that is been achieved about the use of EEG signals as biometric identifiers so far. Specifically, we cover and discuss several issues which need to be taken into account to design an EEG based user recognition framework and to perform a fair comparison among the existing systems in terms of usability and recognition performance. A comprehensive though critical review of the methodologies dealing with EEG biometrics proposed in the existing literature is presented to effectively crystallize the state of the art, and to systematically identify the most important issues to address in the research agenda on EEG biometrics. Therefore the aim of this paper is to provide the interested researchers and practitioners with an overview of the approaches currently employed to recognize identities using EEG based cognitive biometrics as well as to establish a correlation between the recognition capabilities of the state of the art approaches and neurophysiological evidences. The different modeling approaches suitable for the several scenarios considered to elicit brain responses are reviewed and evaluated according to the specific application. In particular we compare the existing EEG based biometric systems with respect to the employed acquisition protocols in terms of cognitive task, the number of electrodes and their spatial configuration, the feature extraction algorithms, the classification algorithms and their effectiveness in clustering the observations. We will try to report, whenever possible, also a physiological interpretation of the extracted features by correlating them to the anatomical traits and functional organization of the brain structures during specific mental tasks.

The paper is organized as follows. In Section II a characterization of a generic EEG signal acquisition system is given along with a characterization of the brain rhythms. In Section III the EEG signal acquisition protocols used in biometric oriented applications are described. In Section IV the different characteristics of EEG biometrics are deeply analyzed. State-of-the-art approaches are described in Section V where an analysis on the employed protocols, the feature extraction algorithms, the classification algorithms, and the database structure is conducted. In Section VI open issues on the design of EEG based biometric systems are detailed and conclusions are finally drawn in Section VII.

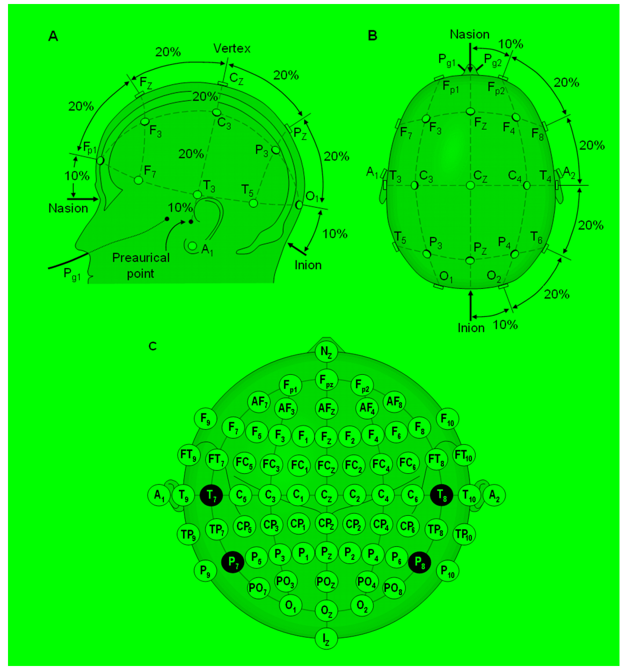

Fig. 1. The 10-20 international system seen from left (A) and above the head (B). The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes. Even numbers identify electrodes on the right hemisphere, odd numbers those on the left hemisphere, and "z" (zero) refers to electrodes placed on the midline. (C) Location and nomenclature of the intermediate 10% electrodes, as standardized by the American Electroencephalographic Society (Jaakko Malmivuo and Robert Plonsey, Bioelectromagnetism, Oxford University Press, 1995, WEB version).

II. Brain Activity Sensing: EEG Brain Rhythms

EEG signals are usually acquired using superficial scalp electrodes, placed according to the 10-20 international system depicted in Fig. 1 and recommended by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology [9]. The "10" and "20" refer to the percentage of the distance between the landmark points, namely the inion, the nasion, and the preaurical points, as shown in Fig. 1(A) and (B), used to draw the lines at which intersections the electrodes are positioned. In other words, given the landmark points, the electrodes positioning is made by considering the intersections between lines which are sagittally and coronally drawn, spaced at 10 or 20% of the distance between the landmark points.

不同频率脑电波的介绍

Since the early research on EE[illegible] observed that the regions of a hea[illegible] their own intrinsic rhythms in the range of 0.5 – 40Hz. In general, five main rhythms can be detected from an EEG recording: Delta (δ) 0.5 – 4Hz, Theta (θ) 4 – 8Hz, Alpha (α) 8 – 14Hz, Beta (β) 14 – 30Hz and Gamma (γ) over 30Hz. In Fig. 2 examples of $\delta, \theta, \alpha, \beta,$ and γ rhythms acquired through the O2 channel using a resting state with closed eyes protocol are depicted. The amount of activity in different

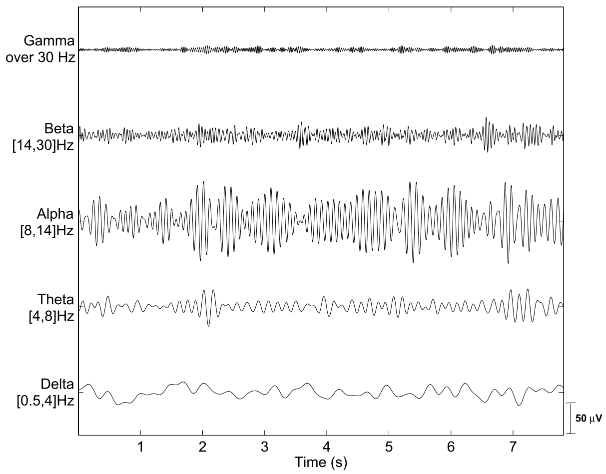

Fig. 2. Examples of Delta, Theta, Alpha, Beta, and Gamma waves acquired through the channel O2 using a "rest state with closed eyes" protocol.

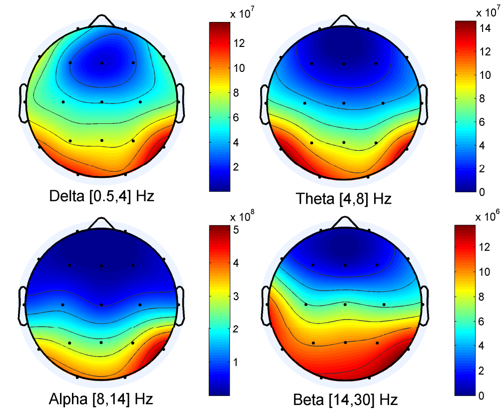

Fig. 3. Topographic maps (EEGLab toolbox [19]) of rhythms Delta, Theta, Alpha, and Beta (top view of a head). Each map shows in false colors the spatial distribution on the scalp surface of the related EEG rhythm. The mean value of the power spectral density for each frequency band is reported.

EEG frequency bands can be quantified employing spectral analysis techniques [1]. The contribution of the different rhythms to the EEG depends mainly on the level of alertness, on the age and behavioral state of the subject [10]. Moreover an EEG pattern is influenced by neuro-pathological conditions, metabolic disorders, and drug action [11]. The different brain rhythms or some combination of them significantly increase or decrease in relation to other rhythms depending on specific mental states, which can be induced by the performance of a proper acquisition protocol. Specifically, Delta and Theta frequency bands are considered to represent slow oscillating neural synchronization, or slow wave (SW) activity, while Beta and Gamma bands represent fast wave (FW) activity [1]. Brain oscillations in these frequency bands have been linked to various psychophysiological states and cognitive functions, as reported for instance in [12]. A more detailed characterization of the subbands is given in the following.

• **Delta** $0.5-4$Hz: Delta rhythm is a predominant oscillatory activity in EEGs recorded during the so called deep or slow wave sleep (SWS). In this stage, Delta waves usually have relatively large amplitudes ($75 - 200\mu V$) and show strong coherence all over the scalp. In newborns, slow Delta rhythms predominate. An increase in Delta EEG activity during the performance of a mental task has shown to be related to an increase in subjects' attention to internal processing [13].

• **Theta** $4 - 8$Hz: In human scalp EEG, changes in Theta rhythm are very difficult to detect without the help of computational methods from raw EEG traces. If EEG power in a resting condition is compared with a test condition, an increased activity in the Theta subband is observed, which is known as Theta-band power synchronization. In particular Theta-band power increases in response to memory demands, selectively reflecting the successful encoding of new information [14].

• **Alpha** $8 - 14$Hz: The oscillatory Alpha band activity is the most dominant rhythm which emerges in normal subjects, most pronounced in the parieto-occipital region. It is manifested by a peak in frequency spectrum. The Alpha brain oscillations may present amplitudes large enough to be clearly seen in raw EEG traces acquired in specific mental states (see Fig. 2). It is characteristic of a relaxed but wakeful state primarily with closed eyes and attenuates with eyes opening or mental exertion due to event-related Alpha power desynchronization. These changes in the Alpha band reflect an increased arousal caused by basic processing of visual information [15]. Moreover there is evidence that attentional and semantic memory demands lead to a selective suppression of Alpha in different subbands and that the well described effects of visual stimulation represent just a special class of sensory-semantic task demand [16]. This confirms the evidence that Theta and Alpha band power are related to each other, although in an *opposite* way.

• **Beta** $14 - 30$Hz: Phase synchrony in Beta frequency band is enhanced for consciously perceived stimuli [17], and detectable mainly from the involved cortical areas, including somatosensory, frontal, parietal and motor regions, depending on the performed task. Specifically, Beta activity is characteristic for the states of increased alertness and focused attention.

• **Gamma** over 30Hz: Neuronal synchronization in the Gamma band is considered important for the transient functional integration of neural activity across brain areas, which represent various functions involving active information processing, e.g., recognition of sensory stimuli, and the onset of voluntary movements [18]. Gamma components are difficult to record by scalp electrodes and their frequency usually does not exceed 45Hz [1]. Components up to 100Hz, or even higher, may be registered in electrocorticogram (ECoG).

In general, it can be assumed that the slowest brain rhythms are dominant during an inactive state and the fastest are typical of information processing performance. In Fig. 3 the topographic maps related to the main brain rhythms during resting with closed eyes are displayed in false colors. Specifically, the mean value of the power spectral density for each frequency band is reported.

III. Acquisition Protocols

EEG signals can be acquired through portable devices that sense the electric field generated by the brain while resting or during a variety of cognitive tasks, such as response to audio or visual stimuli, real or imagined body movements, imagined speech, etc. More specifically we refer to "event related potentials" (ERP) as to a small change in the electrical activity of the brain, time-locked to a meaningful externally (exogenous) or internally (endogenous) generated event [20]. ERP signals convey information on changes which occur when similarly oriented pyramidal neurons of both individual and different local networks fire in synchrony. For endogenous ERPs, time-locked to a mental event such as the recognition of a target stimulus, the activity of the cortex reflects functional coordination during neurocognitive information processing [21]. ERP components can be described in terms of latency time, polarity, and topography. Large individual differences exist for the ERP components, while a certain stability is observed within a subject [22]. Other largely studied brain signals are the "slow cortical potentials" (SCPs), also used as control signals in BCI context. They represent slow voltage shifts in EEG, which are involved in the modulation of the excitability level of underlying cortical regions, and in the preparatory allocation of resources for cortical processing [23]. SCPs last from 300 ms to several seconds and can be self-regulated with different purposes using immediate feedback. EEG signal analysis allows catching the relative timing of neural events during a specific task performance. The physiological phenomena underlying some brain signals have been decoded studying EEG recorded within dedicated acquisition protocols. These protocols are specially designed in order to elicit specific brain responses of interest, with the aim of studying the neural mechanisms of information processing in environmental perception as well as during complex cognitive operations. In this regard several data acquisition protocols have been proposed in the literature specifying the data acquisition conditions, the task definition, and the sensing electrodes configuration related to the neurophysiological function under analysis. In this Section we describe some acquisition protocols employed in EEG studies. Topographic information on source activation are reported depending on the performed task and guidelines for efficient scalp electrodes configurations are provided.

A. Elicitation of Brain Responses

Since the earliest applications of EEG signals, particular interest has been shown in the study of cerebral activity during a state of rest, due mainly to the simplicity of the acquisition process. Therefore, the resting state protocol, with eyes closed or open, has been widely studied for different purposes. Within this paradigm the enrolled subjects are typically seated in a comfortable chair with both arms resting, in a dimly lit or completely dark room. Generally, external sounds and noise are minimized to favor the relaxed state of the subjects. Participants are asked to perform few minutes of resting state with eyes closed or eyes open, avoiding any focusing or concentration, but staying awake and alert. Brain activity during resting state without performing any task carries interesting information as contained in EEG specific patterns [24]. Eyes closed and eyes open resting conditions are usually employed in EEG research studies for baseline estimates, although they represent different processes related to global arousal and focal activation [25]. Moreover, EEG patterns have shown significant differences, specially related to the spectral analysis, between rest and several cognitive tasks, and even between different cognitive tasks themselves, involving distinct neural systems. In order to infer about the properties of neural activation in the involved brain regions, math, logical, and spatial cognitive operations have been considered in the development of suitable acquisition protocols. Changes in neuronal activation patterns due to specific components of mental calculation tasks can be observed from the analysis of each frequency band, as they seem to be related to oscillatory activity of different neural networks. In this regard, different EEG patterns have been examined by testing healthy subjects in different conditions of mental calculation through properly designed protocols. In these protocols the mental task period is usually preceded by a rest period in order to provide a baseline. During the mental task interval, the subject is asked to solve a problem providing an answer [26]. The features of such kind of brain patterns reflect inter-individual variability due to different abilities, aptitudes, innate mechanisms of habit, brain plasticity, etc.

The most explored protocols involve the elicitation of the above mentioned ERPs. Task-related ERPs, as well as background EEG, are associated to different behavioral and cognitive traits. ERP signals can be elicited using different stimulation paradigms involving for instance sensory, cognitive or motor events. Usually, the exogenous eliciting events are repetitively modulated sensory stimuli such as a visual flicker. The so elicited evoked potentials strongly depend on the physical parameters of the stimuli. On the other hand endogenous ERPs depend on internal cognitive events reflecting the way the subject evaluates a stimulus.

A largely studied and employed brain potential is the P300 ERP, especially used in BCI context. The P300 ERP is a positive deflection of the scalp potential which occurs around 300 ms after the onset of a task-relevant stimulus, with a centro-parietal focus [27]. The most effective paradigm for inducing a P300 response is the oddball task. In this paradigm an infrequent but task-relevant stimulus is presented among frequent irrelevant stimuli [28]. Different kind of stimuli can be employed to carry out such paradigm, and the characteristics of the P300 response will change with the type of stimulation, its timing, and with the task difficulty. In Fig. 4, the topographic distribution of the brain P300 response is shown for a subject involved in an oddball paradigm, where the presented stimuli are different geometric shapes, and the subject is asked to detect just one specific shape among the others. For the particular case shown in the figure, a good brain response can be detected in central and parietal electrodes, as a much larger P300 amplitude (dotted-red line) related to target stimuli stands out from a baseline measure (blue line) obtained by averaging non-target responses. The P300 individual differences relate to amplitude, latency, waveform and scalp potential distribution [27] and reflect psychophysiological aspects of individual central nervous system reactivity. Another typically employed ERP stimulation protocol during EEG acquisitions is the elicitation of Visual Evoked Potentials (VEP), performed in order to analyze the way

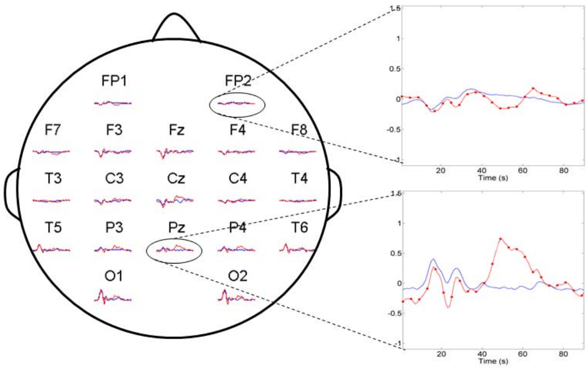

Fig. 4. Topographic distribution of P300 brain potential as elicited through an oddball paradigm (Normalized amplitude for visualization purposes). Labels which indicate the related channel are reported on each P300 waveform, obtained by averaging the EEG segments time-locked to target stimuli (dotted-red lines). Brain responses related to non-target stimuli are also reported in each subplot (blue lines).

the brain perceives and processes visual inputs, to control BCI applications and to support neurological diagnosis. VEPs are evoked potentials that occur in the visual cortex, time-locked to a repeated sensory stimulation related to a subject's visual field. Within VEP protocols no response or cognitive processing by the subject is required. The visual stimulation can consist for instance of checkerboard pattern reversal, flashing black/white images, pattern onset stimuli or photic stimulation [29]. In a typical setup to elicit VEPs a flashing stimulus is displayed either at the center of a screen or through light-emitting diodes (LEDs) in the central visual field, since it causes a greater response amplitude [30]. Some interesting evidences have been obtained from the analysis of μ [31] and β EEG rhythms recorded over sensorimotor cortex within the so-called motor imagery paradigm [32]. Typically, during each acquisition session, subjects are asked to imagine moving for instance either a hand or a foot for few seconds when the cue representing the movement instruction appears on a screen. As reported in [32] it has been observed that the patterns of μ and β rhythms desynchronization over sensorimotor cortical areas during motor imagery are similar to those during real performed movement. Moreover, in the same work principal components analysis on sample average signals has shown marked individual differences in motor-related EEG patterns, topographically and spectrally focused. More recently, EEG acquisitions have been performed during the so called "speech imagery", aiming at recognizing the neural activities associated with speech production. In some protocols, enrolled subjects are instructed to imagine continuous vowel vocalization for few seconds from the onset of a specific cue which can be an acoustic signal or a task-representative image appearing on a screen [33]. Furthermore, when using SCPs introduced above, the users' training for the SCPs voluntary control can be carried out as follows [34]. Subjects are asked to move a cursor which appears at the center or at the periphery of a screen toward a target, by modulating the SCP amplitude.

The experimental setups described above represent an overview of acquisition protocols commonly employed when investigating brain functioning with different purposes, such as the evaluation of brain activity patterns for applications like diagnosis and device control. Some of the aforementioned paradigms are also employed in biometrics for user recognition as detailed in the following, while some others have some potentials which have not been explored within the biometric framework yet.

B. Scalp Electrodes Configurations

The spatial distribution of brain activations, as reflected in scalp EEG signals, strongly depends either on the mental state of the subject or on the performed task during the acquisition session. For each designed protocol a suitable electrode configuration in terms of number of sensors, their placement on the scalp as well as their density can be identified depending on the goal of the analysis by selecting a proper subset of channels in the 10-20 extended system shown in Fig. 1.

As previously pointed out in Section II, in resting condition with eyes closed, the predominant Alpha oscillations can be detected especially in the parieto-occipital region of the scalp. They reflect the default mechanisms of cortical neurons activity synchronization [35]. Therefore a description of the ability of the central nervous system to transmit signals to and from the cerebral cortex can be carried out focusing on signals from parieto-occipital electrodes. On the other hand, a widespread reduction in activity is commonly observed turning to open eyes resting conditions, which reflect neuronal Alpha desynchronization.

Furthermore, various sensor configurations can be employed for the effective detection of different EEG activation patterns during the performance of different mental calculation tasks. Some significant differences among those tasks, related to change in power between task and rest conditions, have been observed in the Delta and Beta bands in the frontal lobe, reflecting different selective processes during focusing on relevant information [26] and depending on the complexity of the task and on the specific cognitive function involved. In the same work a general increase of Delta, Theta and Beta activity in frontal leads during subject's internal concentration has been observed. This is in accordance with the evidence that among the various functions of the human brain, the allocation of the brain resources are governed by the frontal lobe. In particular decision making, reasoning and complex calculation require the integration of multiple processes, specific of each task. This results in differences of frontal lobe activity among tasks, reflecting activation of different neural networks. Therefore frontal leads can be effectively employed for the analysis of such specific functions. More specific electrode configurations are commonly employed in the analysis of brain responses. In particular, several studies in literature addressed the effectiveness of different electrode configurations used to detect the P300 brain response. A trade off between user friendly solutions employing few electrodes and accuracy in terms of correct classification of brain responses is needed for the usability of such P300-based systems. Good results have been obtained in [36] employing only eight electrodes from the midline and the parietal region of the scalp as

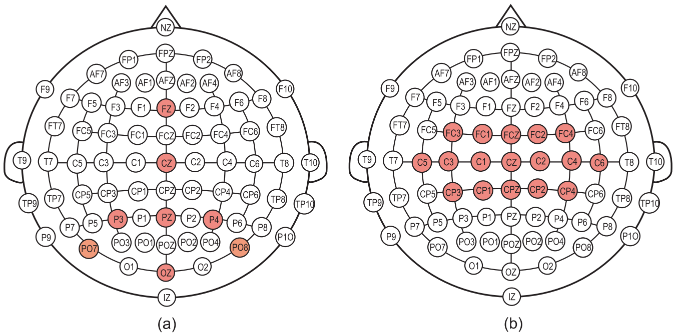

Fig. 5. Electrodes placement for a P300 based system: an example (a). Electrodes placement for a motor imagery based system: an example (b).

pictorially shown in Fig. 5 (a). Thereby accuracy improvement has been obtained by removing redundant information from contiguous time points which would reduce the generality of the analysis. A smaller subset of the electrodes montage is considered when studying VEP signals related to specific kind of visual attention stimulation as detailed in Section III-A. In these cases, EEG signals are typically recorded from electrodes located in the posterior region of the scalp, mostly over the left and right hemispheres of the primary visual cortex. Indeed, either periodic or transient brain responses to stimulation involving the visual system can be detected just considering electrodes O1 and O2 [37]. Also in the analysis of rhythms' topographies during motor imagery protocols, a subset of the extended 10-20 international system is often employed, considering sensors placed over the sensory-motor cortical area as shown in Fig. 5(b) [32]. In fact it has been repeatedly shown that both movement and motor imagery are accompanied by desynchronization in μ and β bands over the centro-lateral side of the scalp [32]. Signals from motor cortex are also employed for the performance of speech imagery protocols. It has been shown that neural activation, detected over medial sites and posterior regions, occurs during imaginary lip movement and vocalization of vowels [33] or their mental repetition. The signals acquired by the electrodes that are distant from the active regions may not carry significant information with respect to the employed elicitation protocol and therefore they can be discarded thus allowing a more reliable selection of EEG features. Moreover, effective negative and positive SCP shifts can be controlled selecting the best performing channel. In this regard, in [34] it is shown that self-regulation skills differ among subjects, but that the Cz channel could be generally used for an effective SCP feedback learning. Interestingly, in that study it was shown that many subjects generated a maximal SCP differentiation at other, often neighboring, electrodes than Cz. On the other hand, the evaluation of the most effective electrodes placement strongly depends on the task the enrolled subject is involved in. In [38] it is observed how occipital channels account strongest for the detection of mental state differences reflected in Alpha activity during a visual surveillance task and that changes of Alpha activity depend on visual processes.

The above mentioned studies have shown that, depending on the given goal, the selection of electrodes based on neurophysiological considerations can lead to more efficient systems in terms of the selection of the signals to be processed.

IV. EEG Signals as Biometric Identifiers

In [5], back in 1980, the basis for automatic people recognition using EEG signals were posed. However, only in the last decade the study of EEG based recognition systems has received a significant development. EEG signals present some peculiarities, which are not shared by the most commonly used biometrics, like face, iris, and fingerprints, and that make the investigation on the use of EEG signal as biometric identifier not a mere academic exercise but an analysis with potential dramatic effects on the design of the next generation biometric systems, namely the cognitive biometrics based systems.

Specifically, brain signals are more privacy compliant than commonly used biometrics like face, iris, and fingerprints, since they are not exposed and therefore cannot be captured at a distance. Moreover they cannot be left on a crime scene, not even a digital one, and being brain signals the result of a cerebral activity, they are less likely to be synthetically generated and fed to a sensor to spoof it, like it can happen when using gummy fingers to spoof a fingerprint sensor. This also helps in addressing the liveness detection issue. Furthermore, when using EEG based recognition systems, it is impossible for an intruder to force a user to authenticate. In fact stress signals would be present in the measured brain waves, thus resulting in a denial of access [39].

On the other hand, the use of brain signals poses new challenges. In fact, being the brain continuously and spontaneously active, there is a background electrical activity upon which the signals of interest, which come from the firing of specific collections of neurons responding accordingly to a variety of tasks, are superimposed. Part of this difficulty is the understanding of the brain areas where the response originates. These findings would drive an optimal or sub-optimal choice about the number of electrodes to use and their location. Furthermore, due to the weakness of the signal detected on the scalp while generated on the cortex, the EEG acquisition process results very sensitive to endogenous and exogenous noise, that is artifacts generated by physiological processes and by external sources respectively. Therefore, the basic mechanisms which are behind the physiological process of brain signal generation, the signal stability in time, the acquisition protocols, the optimal sensors location depending on the employed acquisition protocol, the amount of the discriminative information, as well its frequency localization, need a much deeper understanding.

In this Section the different characteristics of a biometric identifier, namely *universality*, *uniqueness*, *permanence*, *collactability*, *performance*, *acceptability*, and *circumvention*, are detailed with respect to EEG biometrics. It is worth pointing out that the analysis that follows has different depth levels for the different desired characteristics, since EEG biometrics is still in its infancy and an exhaustive analysis of the aforementioned issues is still missing in literature. Nevertheless, in the following we draw some considerations, which, in some cases, have been borrowed from physiological studies on EEG signals made for clinical applications and that can be applied to the field of EEG biometrics.

A. Universality

Each person should have that characteristic

The level of universality of brain signals is very high. In fact people with no pathological conditions affecting the brain, can make use of EEG biometrics.

B. Permanence

The characteristic should be sufficiently invariant, with respect to the matching criterion, over a period of time

The issue of the reproducibility of EEG biometrics in different acquisition sessions, in other words the intra-individual EEG stability, has been object of scientific investigation within the neurophysiology field in the past [40]–[42]. In fact, also in clinical applications, it would be desirable not to have significant variations of an individual EEG pattern when no alterations, due for example to new pathological conditions, occur. In the clinical field these studies are known as "test-retest reliability" or as "longitudinal" studies. Of course the aforementioned issue is strictly dependent on the features which are extracted to summarize the EEG and on their reliability. It is worth pointing out that a significant effort has been done for the test-retest reliability analysis of EEG in resting conditions as well as, in the recent years, when performing cognitive and sensory tasks. Some works are detailed in the following.

In [7] eight-channel recordings for a set of 47 healthy subjects under conditions of rest and perceptual stimuli were acquired. The power spectra in the range 8 – 13Hz, α subband, were evaluated and a variance analysis was done in order to determine their dispersion characteristic. The performed analysis revealed that EEG spectra are more distinctive in the eyes closed resting state with a significantly strong Alpha rhythm, while performing a task would somehow normalize the Alpha activity thus reducing the inter-individual difference. In [8] both the intra-individual and the inter-individual reproducibility of EEG parameters have been analyzed for a group of 12 healthy people, mainly women, in open eyes resting condition. Parameters related to the amplitude profiles in the different frequency bands were considered in this analysis. Results showed that for all the considered characteristics, their variance among different individuals was greater than among different measurements for the same individual over a period of two-three months. It appeared that Alpha activity is the most powerful indicator of the inter-individual differences, whereas Delta and Theta indicators have smaller inter-individual variances. In [43] eight-channel signals for a set of 26 healthy children, with an age between 10 and 13 years, under conditions of rest with closed eyes, were acquired to study test-retest reliability considering two EEG recordings 10 months apart from each other. Power spectrum related features were used and different rhythms were examined. In summary the Alpha rhythm manifested a good permanence level in the test-retest framework for the considered features, whereas the Delta band was found less permanent. In [44] test-retest reliability was investigated for a set of 19 healthy adults whose EEG was recorded using 15 electrodes, F3, F4, F8, T3, T4, T5, T6, O1, O2, P3, P4, C3, C4, and Cz, considering acquisition sessions separated by 12-16 week intervals. The employed elicitation protocol consisted in instructing the subjects to listen to randomly reproduced tones with closed eyes, and in asking them to respond to the stimulus by pressing as quickly as possible one of two switches, depending on the played tone's level, high or low. Spectral analysis was done, and peak and median Alpha frequency resulted as the most stable spectral features. It was also experimented that the electrodes montage affects the test-retest reliability. In [45] 45 healthy subjects were tested in an interval of 25-62 months in order to infer about the intra-individual variability. Features such as the absolute and relative power, the median and peak frequency, the entropy, etc. where used. It was shown that Alpha peak frequency and median frequency are stable characteristics for the period under investigation, in the sense that their intra-individual variation was less significant than the inter-individual variations. Test-retest reliability was considered also in [46], where a closed eyes protocol was used to acquire signals from a sample of 20 people during two EEG recording sessions at a mean distance of 15 months. The authors resorted to rely on power spectra which, when a closed eyes protocol is implemented, are dominated by a peak in the Alpha subband. Specifically, the amplitude and the frequency of the peak as well as the shape of the power spectra were taken into account, and a set of three electrodes, namely AFz, Cz, and Pz, from the median sites was chosen among 60. The test-retest reliability was verified by implementing a recognition system, which proved that the considered features guarantee high performance across the two considered period of time. It is worth pointing out that although a significant effort has been done mainly for the test-retest EEG reliability analysis in resting state, some attempts to analyze other tasks have been performed as well. In [47] the reliability of EEG signals recorded during cognitive tasks, specifically a working memory task and a psychomotor vigilance task, was investigated on a set of 21 healthy adults. The inter-session time was 7 days on average and the power spectra of Theta at Fz and Pz, and the slow and fast Alpha spectra at Pz were examined. Both considered tasks showed a high reliability within and among sessions. In [48] the test-retest reliability of a working memory task was analyzed using the same acquisition conditions, that is electrodes' type, time span between the two acquisition sessions, features, and validation strategy, as in [46]. The intra-individual stability was found higher with respect to the inter-individual variation, and the recognition rate comparable to that obtained in resting state with closed eyes in [46].

Despite the effort that has been done in the neurophysiology field, the repeatability issue of EEG biometrics has not received the necessary attention from researchers in the biometric scientific community. Nevertheless, its understanding is propaedeutic towards the deployment of EEG biometrics in real life. Few sporadic and non exhaustive analysis have been given in the biometric literature so far. In [49] the session-to-session variability was tested on a dataset composed of 6 subjects performing imagined speech. The entire set of 128 channels was used to extract features, and results show a decreasing performance when considering sessions temporally apart. In [50] the problem of repeatability over time of EEG biometrics, for the same user, was specifically addressed. A simple "resting state" protocol was employed to acquire a database of nine people on two different sessions separated in time from 1 week to 3 weeks, depending on the user. Although the dimension of the database employed is contained, [50] represents the first systematic analysis on the repeatability issue in EEG biometrics. Simulations were performed by considering different sets of electrodes both with respect to their positioning and number. In summary, the analysis showed that a significant degree of repeatability over the considered interval can be achieved with a proper number of electrodes, their adequate positioning, and by considering appropriate subband related to the employed acquisition protocol. However a more exhaustive analysis involving a relevant number of sessions over a significant period of time as well as different acquisition protocols is still needed.

It is also worth pointing out that EEG rhythms might depend on the time of the day as well as on the time of the year they are acquired, thus reflecting both circadian and seasonal influences respectively. However, the analysis carried out in literature (see for example [51]–[53]) focuses mainly on resting state or sustained wakefulness, which are only partially of interest in the biometric framework. In summary, although acknowledging that circadian influences might affect the acquisition of EEG signals, it is worth pointing out that no exhaustive studies have been done so far to analyze the EEG circadian dependency for the variety of elicitation protocols that can be applied to EEG based user recognition.

C. Performance

The use of the characteristic must ensure good performance

Promising recognition rates have been achieved. A detailed analysis of the recognition performance of state-of-the-art EEG-based biometric systems is given in Section V. In the presented works, performance is expressed using different figures of merit like the genuine authentication rate (GAR), the false acceptance rate (FAR), the false rejection rate (FRR), the half total error rate (HTER = (FAR+FRR)/2) and the equal error rate (EER), that is the HTER evaluated when FAR = FRR.

D. Collectability

The characteristic should be quantitatively measurable with some practical device

Collectability of EEG signals is dependent on many factors like the number of electrodes to be used, the need to use conductive paste or saline liquid to lower the skin impedance to acceptable levels, and the acquisition time needed to be able to collect relevant information for the recognition process. All these issues can limit the collectability of EEG biometrics. However, recent advances have shown that interesting performance can be achieved also limiting the number of used electrodes thus making the signal collection more user convenient as detailed in Section V. Moreover, the latest technological developments have shown that the aforementioned issues can be mitigated as clarified in Section VI.

E. Acceptability

The public should have no strong objection to the measuring/collection of the characteristic

Acquisition of EEG signals may present some drawbacks in terms of user acceptability being related to brain activity thus potentially evoking ancestral worries related to "mind reading" and emotion analysis from the data controller. This may generate a sense of discomfort in the users. Also privacy issues can be seen as an obstacle towards the acceptability of EEG based biometric applications in real life due to the potentiality to detect existing pathologies or disposition towards pathologies, as possible also for other biometrics. This could potentially lead to discrimination and undermine the human dignity. However, no specific studies on the acceptability issue of EEG biometrics have been performed yet.

F. Circumvention

The characteristic should be robust to attacks

Brain signals, as a result of cerebral activity, are not exposed biometrics like face, iris, and fingerprints. Therefore, as internal traits, they are less prone to spoofing attacks than other external biometrics [54], since they are "secret" by their nature, being impossible to capture them furtively at a distance, while this is possible for face and iris, which can be then synthetically generated. Besides, EEG biometrics cannot be acquired in absence of the user, since they are not left on objects like it might happen with fingerprints that instead can be used at a later time in order to spoof the employed acquisition sensor. This is virtually impossible with brain signals since they are the result of ionic current flows within the neurons of the brain in response to a specific task or during a specific mental state. Therefore, an attacker should be able to synthetically generate resulting EEG waveforms and feed them to a sensor to spoof it. Hence, the problem of liveness detection, which needs to be addressed when using conventional biometrics, is naturally overcome without the need to resort to specifically designed sensors.

G. Uniqueness

Any two persons should be different in terms of the characteristic

The uniqueness of EEG signals is a complex issue which has several facets to be considered and that has not captured the necessary attention within the biometric community so far. Nevertheless, some early studies in neurophysiology, see for example [7], [10], [55] have demonstrated that EEG is a highly individual characteristic. In [56] a variance analysis of Alpha waves in a closed eyes condition showed a significant level of individuality. In [57] the same conclusions were drawn for the open eyes condition. Of course, the level of individuality is also related to the specific acquisition protocol, subband analyzed, and to the extracted features. Moreover, it is worth pointing out that the uniqueness and the permanence issues can be considered as two facets of the same medal, being related to the intra-individual and inter-individual distances, and that these distances get some meaning when related to each other. Therefore, contributions that address one issue need to consider also the other one, as evident in the analysis on the *permanence* carried out in Section IV-B.

Heritability and personality factors also play an important role in characterizing an individual's EEG. In the following we focus on the dependance of EEG signals on heritability and personality factors, and report some results found in the field of neurophysiology which can help to have a better understanding of the uniqueness issue within the biometric framework. Specifically, the heritability and the personality issues are considered in detail in Sections IV-G.1 and IV-G.2 respectively.

1) Heritability of EEG Variants: In neuroscience, the influence of hereditary factors on individual differences in central nervous system functioning has been addressed by using electroencephalography as neurophysiological investigation technique among the others.

In the early seventies it emerged that some aspects of the ongoing brain activity during resting state is hereditarily determined, that is it carries genetic information [58]. Automatic classification of genetic EEG variants was first performed in [59] where spectral analysis was used. More recent studies have confirmed that both genetic factors and shared and non-shared environmental influences as well as anatomical features of the brain and of the related structures around, like for instance the skull thickness, affect important traits of neurophysiological functions. An interesting study on genetic determination of inter-individual variability of brain functioning, assessed using relative power values in different EEG frequency bands, was performed in [60] where EEG recordings acquired from a group of 213 adolescent twins in resting state with closed eyes were analyzed. Univariate genetic model fitting was used to estimate the degree of heritability of EEG power spectrum related features. In general, the results of the univariate analysis showed that ongoing activity in monozygotic twins is significantly similar for all frequency bands and areas because of the predominant genetic influence on the environmental variances. In particular, for most EEG rhythms, the variance of power related features explained by genetic factors resulted high at all brain regions, except for power features in the Delta band, where lower heritability was found at frontal regions. Moreover, multivariate modeling was used in [60] in order to estimate the contribution of genetic and environmental factors to the covariance of EEG Alpha power features related to different brain regions. From this analysis it could be concluded that there are no hemispheric differences in genetic heritability of power features, and that the same genes influences Alpha power related features at all brain regions. In [61] 1038 adolescent twins were recruited and asked to perform 4 minutes of resting state with closed eyes. Data were analyzed through multivariate genetic, still partitioning the total variance into the contributions due to additive and non-additive genetic factors and to the contribution due to non-genetic factors, including both common and non-common environmental influences, and measurement errors. Results confirmed that EEG is a high heritable trait and that common genetic factors influence all bands in both hemispheres, especially at occipital sites. Also band-specific effects were observed to be more influential at frontal sites. Authors interpreted the common factors as due to either basic structural features such as skull thickness or reflecting neural genetic properties affecting EEG features across all frequency spectrum. On the other hand, band-specific influences seem to be related to the higher functional and structural complexity of anterior regions with respect to the posterion ones, which is also confirmed by neuro-anatomical evidences.

Task performances other than resting state have been considered to investigate inheritance aspects in cognitive functions such as attention, focusing, memory or general cognitive processing. Specifically, heritability has been suggested to affect individual variations of ERPs characteristic features. In particular in [62] authors studied the genetic influences on individual differences in the amplitude and latency of P300 responses, elicited within a so-called delayed-response working memory task, where subjects are asked to remember for short time the spatial location on a screen of target stimuli briefly presented. A number of 708 siblings from 354 families were recruited for this study. The analysis aimed at distinguishing three sources of variance for P300 amplitude and latency: additive genes, shared and non-shared environmental influences. Results showed a significant influence of genetic factors on P300 amplitude, while suggesting the same influence of those factors on the latency. Findings from the application of multivariate genetic models indicated that common genes influence P300 amplitude at frontal, central, and parietal regions. From the analysis of genetic expression in frontal region P300 response, authors suggested that specific and common genetic factors influence functionally distinctive cognitive processes, not in contrast with the evidence that there are more neural generators of P300. A comparison with results of other studies on the same issue suggests that the heritability of P300 amplitude is not influenced by task difficulty, so that a low level cognitive process genetically mediated could be involved in the P300 elicitation. On the contrary, the genetically controlled processes influencing P300 latency involve speed in allocation of attentional resources for the processing of new stimuli, showing heritability only when the task is cognitively demanding. The studies cited above, among others, have provided strong evidence about the heritability of spontaneous EEG and ERPs. Moreover there is evidence that ERP amplitude is positively correlated with EEG spectral power, especially for low frequency bands, suggesting commonality of genetic factors influencing variability of spontaneous EEG rhythms and ERPs. In [63], where EEG signals from 213 pairs of twins were analyzed, authors demonstrated that genetic influences on EEG power spectrum, especially in the Delta range, also affect the determination of the P300 amplitude. It was observed that this is in accordance with the evidence that ERPs are the result of the synchronization of spontaneous EEG oscillations elicited by a kind of stimulus onsets. Moreover, the high heritability of lower frequency EEG activity is in agreement with the finding that a strong genetic correlation between ongoing EEG power measures and P300 amplitude is observed in the Delta band, suggesting variation in P300 amplitude to be the effect of heritable individual differences in EEG spectral power.

All the aspects discussed above lead to the observation that, although the EEG is influenced by psychophysiological factors and depends on the particular cognitive demand, genetic and environmental factors contribute to provide some unique features of the EEG signals acquired during a given mental state, assumed to be individual-specific.

2) EEG Personality Correlates: Roughly speaking, personality reflects the combination of emotional and attitudinal traits of an individual, which define a specific profile of each human being. Several research studies on healthy subjects have reported evidence that relationships between observed properties of brain activity and personality profiles exist. Some highlights are given in the following.

In [64] the association between arousal indices, measured through EEG, and extroversion was examined. Extroverts are expected to show more rhythmic low-arousal EEG activity than introverts. Emotional imagery was employed as experimental condition, and the related degree of brain activation was considered to reflect sensitiveness underlying personality traits. Results showed higher levels of slow activity in the Theta band for the impulsive subjects. Moreover broadly distributed Theta activity, especially in the posterior region of the head, seems to reflect low arousal levels. These evidences support the initial assumption. Affective disposition linked to extroversion and neuroticism has also been related to frontal asymmetry of cortical activation. In this regard, anterior EEG asymmetry in resting conditions was investigated considering the functional relation with the Behavioral Inhibition System (BIS) and the Behavioral Approach System (BAS), postulated in [65], which are neural systems reflecting the emotional response to positive or negative affects respectively. In [66] it was speculated that each anterior brain hemisphere is functionally involved in one of these two neural systems. Therefore individual differences of asymmetrical anterior activity were supposed to reflect different affective styles influenced by sensitivity of individual's BIS and BAS systems. Several studies on healthy subjects showed the relationship between affective style and anterior EEG asymmetry as observed in cortical activation patterns while experimenting emotions [67] or resting [68], and significant reliability and test-retest stability along time were observed.

Moreover, spatial EEG asymmetries other than anterior patterns have been investigated in literature in order to understand their connection with personality traits. In [69] some findings were given concerning the relationship linking Alpha and Theta activity gradient between frontal and posterior sites, with the sensitivity of the BIS and BAS emotion-based neural systems introduced above and responsible for behavior regulation. Some correlation between personality variables, related to extroversion and neuroticism, and individual differences of the Antero-Posterior Spectral Power Gradient (APSPG) values was observed in all frequency bands.

Individual differences in cognitive styles and dispositions were also studied through the analysis of the so called EEG microstates [70]. Such EEG patterns describe rapid spontaneous reorganization of large scale neuronal activity, resulting from the integration of incoming information. The microstate syntax allowed the interpretation of cognitive processes typical of each personality group.

V. EEG Signal Based Recognition Systems

The use of brain activity as user identifier is suggested by its general role in controlling the functioning of the whole body, the cognitive processing, and the response to external stimuli. In this regard, memory mechanisms (experience), personality correlates, and anatomo-physiological factors contribute generating individual specific traits. Some promising results have been obtained employing different EEG acquisition protocols, involving both resting conditions with closed or open eyes, response to specific stimuli, like visual stimuli, and execution of real or imagined body movements. Since the recognition performance of a biometric system in general, and of an EEG based system in particular, depends on the proper design of the acquisition protocol, on the feature selection approach, and on the classification algorithm, in this Section the aforementioned issues will be considered to compare the state of the art EEG based biometric systems. Databases structures will also be taken into account. An overview of state-of-the-art contributions of EEG based biometric systems is given in Table I and detiled hereafter.

A. Protocols

Some mental tasks are more appropriate to be performed for person recognition than others being intrinsically able to highlight distinctive traits of individuals. The analysis conducted hereafter aims at pointing out which aspects of cognitive and mental functions are worth to be further investigated to effectively recognize users.

Several studies investigate EEG traits during brain ongoing activity (Section III-A) for user recognition, which does not require any mental task at all. Specifically, in [71] a closed eyes in resting condition protocol was employed to acquire data using the O2 channel from the occipital region of the head (see Fig. 1 for electrodes positioning on the scalp). The α rhythm, predominant in the parieto-occipital region during rest as discussed in Section II, was extracted and overlapping subbands were individually considered for feature extraction. The performed tests were aimed at verifying four *authorized* users against a single class of *non-authorized* users and at their identification. The obtained classification scores in terms of genuine acceptance rate (GAR) ranged between 80% and 100% depending on the individual, the frequency band, and the test performed, while the correct recognition rate (CRR) related to the identification tests ranged between 80% and 96%. In general, different frequency bands showed to be more performant for different individuals. The same protocol was tested in [72]. A different analysis of the same rest EEG signals, briefly described in the next Section, yield to a GAR ranging from 72% to 84%. In [78] the EEG activity was

TABLE I

OVERVIEW OF STATE-OF-THE-ART CONTRIBUTIONS USING EEG SIGNALS AS BIOMETRICS

Paper	Protocol	Database	Channels	Features	Classifier	Performance	sessions
Poulos et al. [71] '99a	EC	4	1 (O2)	α spectrum	NN	GAR=80%-100% CRR=80%-95%	-
Poulos et al. [72] '99b	EC	4	1 (O2)	AR (8th-12ve)	NN	GAR=72%-84%	-
Riera et al. [73] '08	EC	51	2 (FP1, FP2)	AR (100th) & DFT MI&Coh.&CrossCorr.	Discriminant Anal.	EER=3.4%	4
Su et al. [74] '12	EC	40	1 (FP1)	PSD	k-NN	CRR=95%	2
Campisi et al. [75] '11	EC	48	3 (T7,Cz,T8)	Burg's refl. coeff.	Polynomial regression	CRR=96.98%	1
La Rocca et al. [76] '12	EC	45	2, 3, 5	Burg's refl. coeff.	Polynomial regression Fusion of bands	CRR=98.73%	1
La Rocca et al. [50] '12	EC/EO	9	3, 5	Burg's refl. coeff.	Linear classifier Fusion of bands	CRR=100%	2
Abdullah et al. [77] '10	EC/EC	10	4	AR	NN	CRR=97%	5
Paranjape et al. [78] '01	EO	40	1 (P4)	AR (3rd-21st)	DA	GAR=49%-82%	1
Das et al. [79] '09	VEP	20	20 (occipital)	LDA	KNN	CRR=94%	1
Palaniappan and Mandic [80] '07	VEP	102	61	MUSIC spectrogram	Elman NN	GAR=98.12%	1
Palaniappan [81] '04	VEP	20	61	spectral power ratio	BP NN	CRR=99.15%	1
Palaniappan [82] '08	Mental tasks	5	6 (posterior)	AR, spectral power, synchronization, entropy	Manhattan (city block) distance	FRR==1.5-0% FAR=0%	1
Marcel and Millán [83] '07	Motor Imagery	9	8 centro-parietal	GMM	MAP model adaptation	HTER=8.1%-12.3%	3
	Word generation	9	8 centro-parietal	GMM	MAP model adaptation	HTER=12.1%	1
He and Wang [84] '10	Motion tasks	7	17	AR (7th) on ICA	Naive Bayes	HTER=4.1%	1
Brigham and Vijaya Kumar [49] '10	Imagined Speech	6	128	Burg's AR (2nd)	Support Vect. Mach.	GAR=99.76%	4
	VEP	120	64	Burg's AR (4th)	Support Vect. Mach.	GAR=98.96%	4

recorded from 40 subjects while resting both with eyes open (EO) and with eyes closed (EC). Although eight sensors were employed for the acquisition, only the signals acquired using the channel P4, from the parietal region of the head, were considered in the study. An analysis was performed for user identification in the EO condition and GAR ranging from 49% to 82%, depending on the modeling parameters, was obtained. In [73] a closed eyes resting condition was used to acquire EEG signals from 51 subjects using two forehead electrodes (FP1 and FP2). Through discriminant analysis the best achieved result was an EER = 3.4%. In [74] the influence of the diet and circadian effects on the identification performance was investigated. In the considered protocol, segments of 5 minute EEG signals, acquired by an FP1 electrode, were recorded during rest with closed eyes. Signals were acquired on two separate days (sessions) in which subjects had water in one session and coffee in the other one. In each session, 6 EEG runs were recorded. A database of 40 subjects was collected. The classification accuracy achieved for subject identification was of 95%. In the same study an implementation of the Covert Warning (CW) concept to enhance the security of the EEG-based biometric system was presented. Muscle signals from clenching the teeth, shown to produce robust signals, were used to send the covert message. 24 volunteers were enrolled and performed 3 minutes of resting with closed eyes, while clenching the teeth 3 times. Authors showed that CW messages were detected perfectly, while a small decrease in the identification performance with respect to the scenario without CW was observed. In [77] signals from 10 subjects in 5 different sessions over two weeks, using 8 electrodes to obtain bipolar signals at C3, P3, C4, P4, were collected. In each session subjects performed resting state with closed eyes and open eyes, repeating each task in 5 runs of 30 seconds. Different spatial arrangements were evaluated in order to identify users using a suitable electrodes configuration. Best performance of CRR = 97% was obtained employing all 4 channels in the eyes closed condition, while configurations in the right hemisphere (C4, C4-P4) produced the highest CRR compared to the other arrangements relying on an equal number of electrodes. Such result was in accordance with the significant role of the right hemisphere, involved in processes like imagination, creativity and feeling, which are dominant during resting. This supports the idea that brain activity detected in the right hemisphere shows distinctive information during rest. Brain ongoing activity in EC condition was investigated in [75] for user identification. EEG signals were recorded from 48 subjects employing 56 scalp electrodes. An analysis on suitable scalp configurations was carried out considering different sets of symmetrically placed electrodes. Signals filtered in the range 0 – 33Hz were analyzed and a best CRR = 96.98% was obtained considering channels T7, Cz, T8. In [76] signals from 45 subjects in EC resting conditions, acquired through 56 electrodes, were analyzed. Signals were filtered in order to extract the different brain rhythms ($\delta, \theta, \alpha, \beta$), so that the different frequency bands were individually analyzed, as well as combined together. Different channel configurations were considered to perform user identification and a best CRR = 98.73% was obtained from a set of 3 parieto-occipital channels. A comparison between EC and EO condition for user identification was carried out in [50] on a smaller dataset. Longitudinal recordings allowed addressing the repeatability of EEG features, which is a very important issue for the application of biometric systems in real life scenarios. A perfect identification of users enrolled in a previous acquisition session was obtained for the EC condition considering the subband 0.5 – 30Hz and a set of 3 electrodes placed in the posterior part of the head. An extensive analysis was also performed in [50] in order to find the most appropriate set of parameters involved in the analysis.

Other studies on EEG biometrics address the analysis of brain activity recorded during the performance of different tasks, involving real or imagined motion, imagined speech, response to visual stimuli and mental calculation. In particular in [84] data were acquired from 7 subjects performing motion related tasks consisting of the interaction with a virtual environment by blocking virtual target balls rapidly approaching the subject. Each subject performed five runs in one acquisition session. Seventeen channels were employed, clustered into 5 groups according to their physical position. Specifically, the regions right fronto-polar, left fronto-polar, central, right parieto-occipital and left parieto-occipital were individually considered for feature extraction. HTER $= 4.1\%$ was achieved, averaging over all subjects and runs, and employing all acquisition channels. In [83] a person authentication system based on EEG recorded during imagination tasks, such as imagination of left and right hand movements, as well as during the generation of words beginning with the same random letter was proposed. The employed dataset was composed of 9 enrolled subjects and eight centro-parietal recording channels, specifically C3, Cz, C4, CP1, CP2, P3, Pz, and P4, most of them from the sensory-motor region of the scalp (Section III-B). Each subject performed three recording sessions on different days, and four 4-minute runs per session, where the three tasks were sequentially proposed each lasting 15 seconds. The signals were preprocessed by retaining the band 8 – 30 Hz, which contains μ, β and γ rhythms involved in the activation of the primary sensory-motor area during movement and imagination movement (Section III-B). A surface Laplacian (SL) spatial filter was also applied for a better representation of the local sources below the electrodes. HTER performance of 6.6% was achieved for left hand task considering 3 subjects and runs of the first day, while HTER ranging from 19.3% to 36.2% was obtained for the same task considering training/validation and evaluation on different days. Best results ranging from HTER $= 8.1\%$ to HTER $= 12.3\%$ were achieved for the evaluation sets of day 2 and 3, respectively, performing incremental learning. Authors showed that the left hand task was the best suited in the database under analysis for person authentication and that using training data over different days improved performance. In [49] a subject identification system relying on two different EEG datasets was proposed. One contains VEP responses to visual stimuli collected through 64 channels while showing black and white images of objects to 120 subjects with a number of trials per subject ranging from 30 to 120. The other one contains imagined speech EEG data collected using 128 channels, from 6 volunteers who imagined speaking the two syllables /ba/ and /ku/ with no semantic meaning. These latter data were recorded in separate sessions, each comprising 20 trials for each of six conditions (runs), represented by different rhythms of the covertly spoken syllable. The so obtained data were preprocessed for artifact removal. For the imagined speech data, frequency filtering was performed to remove electromyographic noise. A best GAR $= 99.76\%$ was achieved on 6 subjects for the case of imagined speech, whereas a GAR $= 98.96\%$ was obtained on 120 subjects for the VEP case. The authors also observed that the classification performance did not change much when using only one rhythm or one syllable. Also in [79] VEP data for person identification were used. EEG signals were collected from 20 subjects, by means of a 64 electrode montage, during a difficult visual perceptual task in which filtered noise was added to the visual stimuli. Face and car images were sequentially presented to users as stimuli which appeared each for 40 milliseconds, after which subjects had to identify the category of the stimulus, either car or face. 1000 trials split into runs of 200 trials were presented to each subject. A subset of 20 electrodes placed in the occipital region of the head, over the visual cortex (Section III-B) was selected after investigating statistical informative contribution in the spatial domain, which resulted in accordance with the experimental setup (Section III-A). The same analysis showed the period $120 - 200ms$ after the stimulus to be the most informative with respect to discrimination between individuals, which is consistent with the latency of the visual cortex activation in visual attention tasks. Authors used the pre-stimulus and post-stimulus EEG data to discriminate between individual's neural response, obtaining classification rates ranging from 75% to 94% for the best performant post-stimulus set, which showed VEP dynamics to play a crucial role in person identification. In [81] VEP signals for individual identification purpose were also investigated. VEP data were recorded from 20 subjects exposed to single stimuli, consisting of pictures of common objects represented through black and white line drawings, easily recognizable by all the individuals. EEG measurements were taken for 1 second from 64 electrodes. Significant differences were investigated through ANOVA tests on each channel. A high classification accuracy of CRR $= 99.06\%$ was obtained in this study employing all 61 channels. In another study [80] a similar protocol was employed, and 300 milliseconds VEP stimuli consisting in showing black and white drawings of common objects were used to collect EEG signals. Here a mental task consisting in recognizing and remembering shown objects was proposed. A database of 102 subjects was used and signals from 61 channels were recorded, for a total of 3560 VEP signals stored. EEG signals were filtered through a $25 - 56$Hz pass band filter, to retain the γ rhythm containing the dominant frequencies within the VEP signals spectrum, which are related to perception and memory evoked when visualizing a picture. A CAR spatial filter was also applied to reduce the observed intra-class variance due to scale factors of γ band energies. A GAR of 98.12% was reached using all channels. Authors argued that the high classification result over a such large dataset could have been due to the different properties of the binding process during stimulus perception and recognition for different subjects. This is in accordance with the evidence that the brain function underlying VEP generation seems to be genetically influenced [85], resulting in different levels of perception and memory between individuals. In [82] a user recognition system using mental task EEG data, collected from 5 subjects and publicly available[1] was described. The mental tasks consisted of baseline where the subject was at rest, visual counting, geometric figure rotation, mental multiplication, and mental letter composition. These tasks were chosen since they involve hemispheric brain wave asymmetry, which was exploited for individual recognition, among other traits briefly discussed in the next Section. EEG signals were recorded from the posterior part of the head on positions C3, C4, P3, P4, O1, and O2. For each mental task a run lasting 10 seconds was collected within 10 day runs for each subject. Each mental task run was segmented into 0.5 second segments to increase the sample size. EEG segments were filtered using a common average referencing (CAR) filter, which consists in subtracting the mean of the entire electrode montage (i.e.the common average) from channels of interest at any one instant, and mean value was removed from each channel. Recognition was subsequently performed for each mental task separately. The obtained FRR ranged from 1.5% to 0%, while the FAR was 0% for all 5 subjects.

The results reported above have to be thoroughly evaluated and compared also considering the features extracted, the complexity of the classification algorithms employed and specially the database structures used for training and testing the classifiers. In this regard some considerations are reported below.

B. Features

The proper selection of representative and stable features from an acquired biometric signal is a key step in a recognition problem. When dealing with EEG signals, specific features of the brain activity either during resting or specific mental tasks have shown to have different degrees of distinctiveness among people. EEG features extraction has been performed in different domains like the time domain, as well as the time-spatial or the frequency domain. Among those we can recall autoregressive (AR) coefficients, power spectrum density (PSD) function, energy of the signal, autocorrelation function, latency and area of characteristic peaks. Coefficients from AR stochastic modeling, which characterize the power spectral density function of EEG signals, are employed as features in most of the works on EEG biometrics. Some of them rely on resting state condition. The Burg's method was employed in [50], [75], and [76] to extract the reflection coefficients from the data AR model fitting. Feature vectors were obtained concatenating the coefficients extracted from different sets of electrodes. Different analysis on the extracted features *vs* the brain rhythms were performed in [75] and [76] were 6-th and 12-th model orders were selected respectively to obtain the coefficients assorting the feature vectors. The repeatability of the obtained EEG features was furthermore addressed in [76], where a 10-th model order was adopted to fit the dataset and extract reflection coefficients. In [77] AR coefficients of order ranging in the set [3÷21] were considered as features representing EO and EC resting signals, recorded with a sampling frequency of 256Hz. The best performing model order, namely $p = 21$, was empirically selected and feature vectors composed of 21 concatenated AR coefficients were obtained from single channels or their combinations. AR features were also employed in [78] where resting EEG signals where acquired. Specifically, Lattice Equivalent Model and Levinson Recursion were employed to extract AR models from EEG traces sampled at 120Hz and model orders ranging in the set [3÷21] were tested. Only coefficients from the P4 electrode were used to assort the feature vectors. Authors observed that the discriminant power of the features improved as the model order increased up to 21. Also in [73] the EEG signals recorded during EC rest were modelled through an AR model. AR coefficients as well as other features extracted from both single channel measures and synchronicity measures between the only two forehead channels used FP1, FP2 were tested for user recognition. Signal processing consisting in EEG sampling at 256Hz, filtering in the band 0.5 – 70Hz, and application of a notch filter at 50Hz was performed. Both single channel and inter-channels features were tested. Specifically, for the first category, AR coefficients of an 100 order model and discrete Fourier transform retaining the band 1 – 40Hz were considered, whereas, for the second category, features including mutual information, spectral coherence and cross-correlation measures obtained for the channel pair analyzed were used. All features were tested separately, and later merged at the decision level, as described in Section V-D. In [72] AR coefficients were extracted from the α rhythm contained in EEG signals which were recorded during EC rest, employing a bipolar measure of voltage between leads O2 and CZ. Signals sampled at 128Hz were modeled through 8 AR coefficients used as features for the authentication of four subjects. In [84] EEG data related to motion in a virtual environment were modeled through independent component analysis (ICA). The 17 acquisition channels provided signals downsampled at 125Hz clustered into 5 brain regions. ICA was performed for each scalp region separately, thus selecting the most energetic component for each region as a feature. AR modeling, with order equal to seven, was then performed on each of the selected components thus obtaining the feature vectors tested for person recognition. Different features, concatenated in a unique vector composed of 126 elements, were tested in [82] for subject recognition during thought activity. Six AR coefficients were extracted using the Burg's method from the signals acquired through the 6 employed channels, and sampled at 250Hz. Moreover, channel spectral power values in the frequency bands α, β, and γ were provided thus obtaining 18 additional features. Other 27 features were collected computing inter-hemispheric channel spectral power differences in the same spectral bands. The so called inter-hemispheric channel linear complexity, which accounts for the amount of spatial synchronization between channels, was also computed for each band providing 27 other features. Finally, six approximate entropy values for each band, quantifying non-linear complexity, were also considered to assort the total feature vectors. Principal component analysis was then used to reduce feature size in the classification problem. Other works on EEG-based biometrics consider feature vectors composed of spectral values only, to represent inter-subject variability. Some characteristics of the EEG spectrum carry genetic

[1] http://www.cs.colostate.edu/eeg/main/data/1989_Keirn_and_Aunon

information as well as personality correlates as described in Sections IV-G.1 and IV-G.2. In [71] the spectrum of the EEG signal in the α rhythm frequency band was used to obtain feature vectors. The α rhythm, extracted from single channel EEG acquired in resting conditions, was further partitioned into three 3Hz overlapping subbands, each containing 540 spectral values, which were separately considered to address the verification and identification problems. In [74] PSD values as distinctive features of single channel EEG signals acquired in resting conditions, for the implementation of a biometric-based covert warning system, were considered. PSD was computed via Burg's method, and the spectral content in the range 5 – 32Hz was retained to generate the feature vectors, thereby removing high and low frequency noise. In [83] extracted PSD values in the frequency range 8 – 30Hz from 8-channel EEG signals, acquired during task performance related to motor imagery and generation of words, were considered. Electrodes and frequency band were chosen according to evidences from BCI research on the detection of the relevant information for the mental tasks considered. PSD was estimated every 62.5ms using windows of one second, through the Welch periodogram algorithm, obtaining a resolution of 2Hz in the range 8 – 30Hz. PSD values, normalized to the total energy, computed for the 8 employed channels, were concatenated so that a 96-dimensional feature vector, 8 channels $\times$ 12 frequency components, was obtained for each one second EEG sample.

Other contributions, still using features from the power spectrum of EEG signals, propose further processing to extract distinctive traits in the frequency domain. For example in [81] the estimation of γ band spectral power ratio values from each of the 61 channels employed to record VEP signals was proposed. Values from all channels were concatenated to form the feature vector for each of the 40 VEP trials for each subject. A one-way ANOVA test was employed to infer about the significance of the differences between the features extracted from all the subjects, and significant differences were observed for all the channels. Spectral features from VEP signals, filtered in the band 25 – 56Hz, were also extracted in [80]. Multiple Signal Classification (MUSIC) algorithm was used to estimate dominant frequency and power content, based on the eigen-decomposition of the data correlation matrix. Unique descriptors of person's brain activity and dimensionality reduction were obtained from the performed MUSIC based spectral analysis of the VEP signals in the γ band. The dominant powers within the MUSIC spectrogram extracted from each of the 61 employed channel, and normalized with respect to the total power from all channels, were concatenated into a unique feature vector. The so obtained VEP biometrics were used for subject identification. A different approach was adopted in [79], where the linear discriminant analysis' (LDA) coefficients, based on the Fisher's criterion, were extracted from EEG recordings and employed to study spatio-temporal patterns encoding discriminative information in VEP signals. More in details, after the so called "Fisher-brains" analysis, employed to select the most informative electrodes location and time interval to analyze, feature extraction was performed by projecting EEG data into the space generated by the Fisher's LDA coefficient matrix. Features from the 200ms pre-stimulus and 500ms post-stimulus EEG data were tested for person identification.

C. Database Structure

As previously pointed out, for the purpose of biometric user recognition, a proper structure of the dataset under analysis is needed to evaluate the system's recognition accuracy. The dataset size, including the number of subjects and trials performed, the cross-validation framework provided and above all, the number and temporal distance of the recording sessions are key elements that must be considered in the recognition pipeline. Most of the datasets used to speculate about the use of EEG for biometric recognition are collected in different frameworks than the biometric one, mainly within the BCI context. Moreover, while some of these studies consider different acquisition sessions, performed on different days, most of them implement user recognition based on a single acquisition session for each user who performs different runs of the same experiment within the same session. The structure of the databases employed in state-of-the-art contributions are thus detailed in the following and summarized in Table II.

In [71] and [72] a dataset of 255 EEG recordings is provided. Specifically, 4 genuine subjects and 75 impostors were considered. For each of the 4 subjects, 45 EEG recordings, each lasting 3 minutes, were acquired. One EEG recording was rather acquired for each of the 75 impostors, thus obtaining a total of 255 EEG signals ($75 + 4 \times 45 = 255$). For each genuine subject 25 recordings were used for the training, while the remaining 20 for test. No cross-validation framework was provided and no information is given about recording sessions. The dataset employed in [79] was collected from 20 subjects participating in the study. For each of them, 1000 trials, split into 5 runs of 200 trials, were recorded on a single session. A 10-fold cross-validation scheme was implemented for the evaluation of the system's performance, and 10 independent cross-validation runs were performed to estimate the classification rates. The dataset used in [81] to perform individual identification contained signals from 20 subjects, with 40 VEP trials per subject recorded on a single session. Therefore, a total of 800 trials assorted the dataset under analysis. Half of them were used for training and the remaining half for testing, within 10 runs of a 10-fold cross validation scheme. A larger VEP dataset was used in [80], where 102 subjects were recruited for the study. A total of 3560 trials, from a minimum of 10 to a maximum of 50 blink free trials per subject, were collected during one session. Again a 10-fold cross-validation scheme was performed 10 times to statistically evaluate the recognition performance. Specifically, training was done using nine sets of feature vectors, while the remaining set was used for classification. This process was repeated 10 times, using each time nine different sets of feature vectors for training. For the recognition experiment proposed in [84] authors used data collected from 7 subjects performing 5 tasks. For each subject and each task, 11 trials were recorded in one acquisition session, so that a total number of $7 \times 11 = 77$ frames per task assorted the analyzed dataset.

TABLE II
DATASET CHARACTERISTICS

Paper	Subjects	Trials per subject	Acquisition sessions	Training/Classification	Cross validation
Poulos et al. [71] '99	4 genuine	45	1	25 training 20 classification	n.a.
	75 impostors	1			
Das et al. [79] '09	20	1000	1	n.a.	10 10-fold runs
Palaniappan [81] '04	20	40	1	50% training 50% classification	10 10-fold runs
Palaniappan et al.[80] '07	102	10 to 50	1	90% training 10% classification	10 10-fold runs
He et al. [84] '10	7	11 per task (5 tasks)	1	10 frames for client training 1 frame for client class. 66 frames for impostor class.	leave-one-out all combinations
Paranjape [78] '01	40	8	1	50% training 50% classification	n.a.
Campisi et al. [75] '11	48	20	1	70% training 30% classification	50 runs
La Rocca et al.[76] '12	45	77	1	2/3 training 1/3 classification	77 runs on different partitions
Su et al. [74] '12	40	6 per session	2 over two days	50% training 50% classification	100 hold-out runs
Abdullah et al. [77] '10	10	11 per session per task (5)	5 over two weeks	90% training 10% classification	10 runs on different partitions
Palaniappan et al.[82] '08	5	10	5 over 5 days	50% training 50% classification	4 4-fold runs modified
Riera et al.[73] '08	51	12	4 within 34-76 days	training/classification on different days	8 different runs for genuine/impostor tests
Marcel et al.[83] '06	6 genuine 3 impostors	4 per session per task (3)	3 over three days	training/classification on different day	n.a.
Brigham et al.[49] '10	6	20 per experiment (6)	>1 over three days	training/classification on different days 25% training 75% classification	4 runs combining sessions 4 4-fold runs
La Rocca et al.[50] '13	9	237 per session	2 over three weeks	training/classification on different days	230 runs on different partitions

A leave-one-out cross-validation approach was employed to evaluate performance. For a given subject, ten of the eleven trials were used for training and the remaining one for testing. The trials from the other 6 subjects were used to build a set of impostors' trials. EEG data collected from 40 subjects were used in [78] to study subject identification. Each subject provided about 8 trials of 8.5 seconds during one acquisition session, hence a dataset composed of 349 frames was obtained for the analysis. 50% of frames were used to train the classifier while the remaining 50% to perform identification tests. In [75] a dataset composed of 48 subjects, each of them performing one acquisition session, was collected. Each EEG signal had a 60 seconds duration and was segmented into frames of 3 seconds duration so that 20 feature vectors were extracted for each user and 50 independent cross-validation runs were performed to test identification accuracy, considering different frames for the training and for the test. A similar framework was proposed in [76] for a dataset composed of 45 subjects who underwent one acquisition session. Three second overlapping frames were extracted from 60 seconds recordings, in order to increase the sample size for training and test, thus obtaining 77 frames for each subject. Non-overlapping frames between the training (2/3 of the total number of frames) and the test (1/3 of the total number of frames) datasets were considered for the solution of the recognition problem within a cross-validation framework. 77 cross-validation runs were provided considering 77 different partitions of the dataset into subsets of subsequent training and test frames.

All the aforementioned papers do not allow to infer about repeatability and stability of EEG features which on the other hand represent properties of paramount importance for deploying an EEG-based biometric system in real life. Furthermore, although in some referred works, different acquisition sessions were performed, they were considered to assort a single dataset, where randomly selected EEG segments were used for training and testing a classification algorithm for recognition purpose. In [74] the tested dataset is composed of 40 subjects whose signals were recorded on two separate days. In each session 6 runs were performed by each user at different times. Therefore the dataset comprised 480 EEG recordings ($40 \times 2 \times 6 = 480$) in total. Within the considered cross-validation framework, half of the 12 recordings for each subject was randomly selected and used to train the classifier, while the remaining half was employed to test the recognition accuracy. This process was repeated 100 times, and the average performance was given, losing information on the different sessions. Also in [77] EEG signals from 10 subjects were recorded in 5 separated sessions over 2 weeks. In each session 5 different runs were provided for each task, and 11 trials per task were repeatedly performed, so that a dataset composed of 275 EEG frames for each user ($11 \times 5 \times 5 = 275$) was obtained. The collected dataset was randomly divided into training and testing subsets, considering 90% and 10% of the whole data respectively, shuffling signals recorded on different sessions. 10 cross-validation runs were provided for the system's performance evaluation, considering 10 different partitions. In [82] the analyzed dataset is composed of EEG signals recorded from 5 subjects performing 10 runs for each of the proposed mental tasks, each performed on different single day sessions. For each subject, 200 EEG segments (trials) were extracted from all the recordings related to each mental task. In the proposed recognition framework, for each subject, data were split into 50 randomly selected frames for training, 50 different randomly selected frames for validation, and the remaining 100 frames for recognition tests. The performance was provided within a modified 4-fold cross-validation framework times to increase the reliability of the results.

Only few works test the distinctiveness of EEG features for user recognition considering different acquisition sessions performed on different days for the training and the test stages separately. In [73] 51 subjects, who underwent 4 different recording sessions within 34-74 days, and 36 subjects recorded just once who represented the group of intruders to be revealed, were considered. A cross-validation framework was provided for the identification experiment, where for each of the 51 subjects 3 takes related to 3 different days were used for the training, while the remaining recording session was used for the test. For each take, the first or the second minute EEG segment was considered for the training. The process was repeated for all combinations of sessions and EEG segments. In [83] the analyzed dataset contains data from 9 subjects recorded during 3 different sessions over 3 days. Each session comprises 4 runs lasting 4 minutes, which were split into 3 frames, each containing a 15 second EEG segment, related to a given mental task. Hence, the entire dataset is composed of $9 \times 3 \times 4 = 108$ frames per task used to solve the classification problem. In some of the performed experiments, sessions from different days were separately considered to assort the training and the evaluation subsets. In particular in one of the experimental protocols, 3 subjects were considered as impostors and the remaining 6 as clients. Two runs from the first day were used to train the classifier on genuine users, and one different run from the same day was considered to validate the model. The last run from the first day and all runs from the second and the third days, were considered to evaluate the classification performance separately on days 1, 2 and 3. In another protocol, half of the day 1 runs and half of the day 2 runs were used for client training, the remaining runs from the same days were used to validate the model, and all runs from the day 3 session were used for performance evaluation. Finally, authors tested incremental learning employing the first run of each session for incremental client training, and considering the remaining runs for client/impostor evaluation. This allowed to evaluate the accuracy of the system while enrolling subjects during a day, and performing recognition tests on subsequent days. In this case a degradation in the recognition performance was observed by the authors, compared to cases where training and test subsets belonged to the same day. In fact, referring to the proposed framework, they claimed that data collected over only one day is not enough for training robust models. One of the datasets analyzed in [49], related to speech imagery, contains data from 6 subjects whose signals were recorded over separated sessions, each composed of 20 trials for each of the performed experiments. A total number of 3787 trials were used in the analysis, including all 6 experiments. A 4-fold cross-validation framework was provided to evaluate performance, and 10 runs were performed keeping training and test sets distinct. In one of the performed tests data recorded on 2 different days assorted the training and test datasets, and all combinations of sessions were considered: day i to train the classifier and day j to evaluate performance, with $i, j = 1, \ldots, 4$ and $i \neq j$. Considering the obtained results, authors could observe that the tested features representing speech imagery EEG data are most likely not fully stationary with respect to time. Finally, in [50] the dataset analyzed contains signals recorded during two different acquisition sessions performed on different days, from 1 week to 3 weeks apart depending on the subject. 9 subjects performing resting state were enrolled in this longitudinal study. EEG signals of duration of 60 seconds were segmented into frames of 1 second, with an overlap factor of 75%, thus obtaining a number of 237 frames for each subject and each of the two temporally separated recording sessions. Therefore, for the solution of the recognition problem, frames for the training and for the recognition datasets were obtained from two different acquisition sessions in order to infer about the repeatability of the EEG features over the considered interval, for the acquired dataset. Performance evaluation was provided within a cross-validation framework, obtained selecting for each user 75% of feature vectors related to cyclically subsequent training frames, while 75% from subsequent test frames. Moreover, within the cross-validation framework, classification results were reported separately considering the two combinations obtained training on day i and performing recognition tests on day j, with $i, j = 1, 2$ and $i \neq j$.

D. Classification Algorithms

The efficiency of the classification algorithms employed for EEG biometrics user recognition depends on the specific distribution of the observed vectors in the feature space. In fact, for a proper solution of the classification problem it is important to use a suitable classifier fitting the scattering distributions generated by the different classes to distinguish among. Different machine learning algorithms present specific capabilities in approximating different boundary surfaces among the actual decision regions in the feature space, representing the classification problem. The most commonly employed algorithms used in literature for EEG biometrics are based on Neural Networks (NNs), suitable in the classification of data not linearly separable in the feature space. Several architectures of NN based classifier have been proposed in the published studies, with different numbers of nodes for each of the considered layers, and different training functions, such as the scaled-conjugate training function [77], the back propagation algorithm [80], [81], and the Kohonen's Liner Vector Quantizer [71], [72]. Some other works rely on the use of the k-Nearest Neighbor (KNN) classifier, based on different distance measure techniques [74], [79], [80]. Also Discriminant Analysis based on different linear and non-linear discriminant functions were exploited for the solution of the recognition problem based on EEG [73], [74], [78]. In [49] a support vector machine classifier with a linear kernel to identify subjects based on EEG features was used. Other employed classification algorithms can be found in [82]–[84]. In [83] Maximum a Posteriori training was employed to adapt a generic model to a client-dependent model. In [82] the Manhattan distances between feature vectors from training and from validation datasets were computed, in order to implement a two-stage biometric authentication method. It was based on the computation of threshold values used to improve accuracy in the classification of the test dataset, in terms of reduction of FAR and FRR. Polynomial regression was employed in [75] and [76] where different expansion degree values were tested, while in [50] a linear classifier, resorting to the minimization of the mean square error as optimization criterium, was used. A naive Bayes approach was adopted in [84] to probabilistically model the observed feature vectors, assuming gaussian distribution and statistical independence of elements from the generic feature vector.

VI. Research Directions

As outlined in the previous Sections, EEG biometrics poses several new challenges to be tackled by researchers. Many issues are shared also by other biometrics, but many others are peculiar of EEG based systems. For example permanence and uniqueness are two basic requirements that need to be well analyzed for each candidate biometrics to be employed in actual systems. However, when dealing with EEG biometrics, the target brain responses need to be elicited using some specific protocols, ranging from resting state to imagined movements to speech imagery and so forth. This variety of elicitation methods has not equals within the biometric field and, with the exception of the resting state condition, which has been deeply analyzed mainly in the neurophysiology area, all the other protocols have not received the necessary attention from the biometric scientific community. Therefore, permanence and uniqueness need to be analyzed with respect to the protocol employed and also with respect to the extracted features. It is worth pointing out that, the elicitation methodology is just one aspect of the protocol definition. For example, electrodes positioning and number need to be optimized according to the employed elicitation mechanism. Despite the several advantages of EEG biometrics, already listed in the previous Sections, against conventional biometrics, the major obstacle towards the deployment of EEG based biometric systems is mainly related to the inconvenient acquisition setup for users, consisting of a number of electrodes placed on the scalp, usually employed with conductive gel to reduce skin impedance. Therefore, the minimization of the number of employed electrodes is a crucial issue that needs to be tackled in order to improve user's quality of experience. However, some EEG based products, mainly for entertainment purposes, which employ only few electrodes, have already been commercialized. Although, they are not implementing any biometric system, they can be seen as a proof of concept that the electrodes number can be reduced. Moreover, recently, dry electrodes not requiring any conductive gel have been introduced in the market. Their use would alleviate the user inconvenience with no degradation of performance but with an increasing price. Therefore, improvements in EEG signal acquisition and technological advances in sensor design, which could dramatically improve the system usability, need to be addressed by researchers in order to outline some guidelines for practical system implementation which could trigger attention from industry, and which can be a reference to lead future research towards feasible EEG biometric systems. Some developments in this regard have been presented in [86] where some prototypal contactless electrodes, that is not requiring any electric contact with the scalp, made of flexible polymeric material have been proposed. Also the reduction of the acquisition session's length as well as the definition of less constrained acquisition conditions are important research lines that need to be addressed by researchers. Specifically, EEG signals are usually acquired in dim lit rooms where no external visual or audio stimuli are present. Of course this is not a realistic condition for systems that need to operate in an unprotected environment. However, some attempts to use EEG based systems in real life conditions have been already taken into account as in [87] where single trial EEG signal collection in outdoor walking for brain computer interface purpose has been addressed, or as in [39] where a mobile based scenario, employing low cost acquisition devices, is considered for EEG based recognition systems. Public databases, collecting data using different acquisition protocols, are strongly needed. In fact, only few, collected for other purposes rather than biometric recognition, are available. The spoofing issue is an open research topic. At the present stage of research, no attempts to spoof EEG based recognition systems have been documented in literature. Therefore a thoughtful analysis on possible spoofing methodologies could help in either corroborating or criticize the statement that EEG based systems are more secure than systems based on other biometrics at least at the sensor level.

In summary, there are plenty of research opportunities to be addressed and challenges to be tackled to design a reliable, usable, performant, and secure EEG based biometric system.

VII. Conclusion

In this paper we have given an extensive and critical review on the state-of-the-art of EEG based automatic recognition systems. An overview of the neurophysiological basis, which constitute the foundations on which EEG biometric systems can be built, has been given. Employed acquisition protocols, features extraction algorithms, database structure, classification algorithm used in state-of-the-art approaches have been detailed. The major obstacles towards the deployment of EEG based recognition systems in everyday life in the near future have been presented and some challenging research lines for the interested researchers have been suggested.

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