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Review

Electroencephalogram subject identification: A review

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ABSTRACT

This is, to the best of the authors knowledge, the first complete research on the state of the art on EEG based subject identification. As well as covering the full story of this field (from 1980 to 2013), an overview of the findings made in genetic and neurophysiology areas, from which it is based, is also provided. After a comprehensive search, 109 biometric publications were found and studied, from which 88 were finally included in this document. A categorization of papers is proposed based on the recording paradigm. The most used databases, some of them public, have been identified and named to allow the comparison of results from these and future works. The findings of this work show that, although basic questions remain to be answered, the EEG, and specially its power spectrum in the range of the alpha rhythm, contains subject specific information that can be used for classification. Moreover, approaches such as a multi-day-session training, the fusion of information from different electrodes and bands, and Support Vector Machines are recommended to maximize the system's performance. All in all, the problem of subject identification by means of their EEG is harder than initially expected, as it relies on information extracted from complex heterogeneous EEG traits which are the results of elaborated models of inheritance, which in turn makes the problem very sensitive to its variables (time, frequency, space, recording paradigm and algorithms).

1. Introduction

The genetic traits on the human electroencephalogram (EEG) have received great attention from the scientific community almost since the very beginning of the human EEG recordings by Hans Verger in 1924 (Collura, 1993). This genotype–phenotype map will make a major and inexpensive tool for understand, diagnose and early diagnose many diseases, specially those affecting the brain (Begleiter & Porjesz, 2006; Zietsch et al., 2007). Mainly because a tool based on the quantitative measure of EEG properties will be closer to gene function than the traditional interpretation of cognitive tests (Begleiter & Porjesz, 2006).

Biometric systems based on the EEG, as a non-invasive and relatively inexpensive window into the human brain, have received special attention within the scientific community. Most of these efforts have focussed on the development of diagnosis and monitoring tools for conditions such as sleep apnea, schizophrenia or epilepsy (Sabeti, Katebi, Boostani, & Price, 2011; Song & Zhang, 2013; Tagluk & Sezgin, 2011) and on the creation of Brain Machine Interfaces (BMIs) to assist disabled people (Blasco, Iez, Beda, & Azorn, 2012). Applications in other, perhaps more exotic fields, such as marketing, has also been explored (Khushaba et al., 2013).

EEG based subject identification is a relatively new biometric modality which finds its origins in the advances of such human genetics and clinical neurophysiology studies. Its relevance relies mainly in the prospects of high quality and robustness. Passwords will be harder to steal, as users do not need to perform any revealing action. Even if stolen, the system can be tuned to respond not to the passwords semantic meanings but to the subjects specific EEG patterns, which are extremely hard to reproduce, if at all possible. Furthermore, if a user is forced to enter their password, their high stress level could be detected by the system, forbidding the access. This property is referred to as "*circumvention*" within the biometry field.

On the other hand, EEG based biometric systems face their most obvious drawback in the inconvenience of the recording method. Although the sensor technology has given giant steps forward in EEG machines, users still need to have contact with them, and the preparation time is longer than other modalities and require of qualified staff. Moreover, the vast majority of these devices still rely on conductive gel to decrease the impedance between the scalp and the electrode, and obtain quality signals. All in all, EEG based biometric is a modality that promises to deliver real high security tools in the future.

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This work is a comprehensive research on the state of the art on EEG based biometric systems from its origins until the end of 2013. In particular, it aimed to answer the following questions:

- What are the subject specific traits of the EEG?
- Where are these traits in terms of space and frequency?
- Are they constant across recording paradigms and time?
- Which are the best techniques to extract and evaluate such traits?

Although there exist overviews on the field, they focussed on some of the algorithms applied over a particular approach for EEG based biometric systems (Khalifa, Salem, Roushdy, & Revett, 2012; Revett, 2010, 2012; Singh, Singh, & Ray, 2012). On contrary, this is a broad study considering all publications on the matter, and therefore fully covering all techniques and strategies as well as their relationships. In addition, it provides an overview of genetic and neurophysiology findings, so that a link between them and biometric studies can be draw. Hence, this is, to the best of the authors knowledge, the first complete research on the state of the art on EEG based biometric systems.

The remaining of this document is organized as follows. First, a detailed description of the research methodology is given in Section 2. A brief presentation of the major findings on the genetic traits of the human EEG is then given in Section 3. Section 4 enumerates the main EEG databases used in the biometric field. Section 5 provides detailed descriptions of the most important results in each of the studied approaches. An extensive discussion is provided in Section 6, where findings are put together in a global picture. Finally, the extracted conclusions are presented in Section 7.

2. Research methodology

The present study was executed in two phases. First, a search in the genetic and neurophysiology fields regarding the phenotypic features of the EEG was made. This allowed the establishment of a scientific base in the matter and provided a non-technical point of view of the problem. A search with the criterion "genetic", "EEG" and "subject specific" was carried. Here, a study of the level of the biometric field was not intended, and therefore only the most relevant publications and reviews were revised. A total of 17 of these works were included here. Of special relevance is the book "Genetics and the Electroencephalogram" by Vogel, a key figure in the genetics field, which is a comprehensive compilation of findings on the genetic, clinical and neurophysiological aspects of the EEG (Vogel, 2000).

The second phase comprised the search in the biometric field. In this case, the keywords "EEG", "brainwaves", "biometric", "subject", "identification" and "verification" combined in numerous ways were used for the search. References of found articles were also scrutinized. After a comprehensive exploration, 108 works were finally found between 1998 and 2013. This emphasizes the novelty of the method, and explains the relatively small amount of publications when compared to older research lines. Therefore, instead of filtering the outcome to keep only journals; as it is usually the case in reviews, all 108 works were considered for this study, from which 87 were finally included. Fig. 1 shows the amount of publications per year.

The following classification of the literature based on the recording paradigm is proposed:

- **REC and REO:** A big part of the articles relies on EEG data recorded while subjects were resting with eyes closed (REC) or resting with eyes open (REO).
- **ERP:** Event related potentials (ERP) have also been used to identify users. Even though until the date only visual evoked potentials (VEP) have been used for this purpose, a global category name is proposed so that it will be able to accommodate possible future works on other ERPs.
- **Multi-task:** Some works used EEG recorded under different mind tasks such as mathematical operations, writing letters and imagined movements. Usually, this works study the differences in performance obtained by different recording paradigms.
- **Indirect:** Other researchers have tried to identify users by recognizing a thought password rather than subject-specific EEG traits.
- **Others:** This category includes reviews, dissertations, reports and any other published work that is related to the subject but does not propose any system architecture or experiment.

A further differentiation is proposed based on the hardware used to record the database. This consideration was taken as both **medical** and **consumer** equipments have been used. The later represent a cheaper alternative that does not require conductive gel and is considerably easier to use. However, all these come in detriment of the quality of the signal, providing lower signal to noise ratios and sensitivity. Accordingly, it seems fair to keep in mind which hardware has been used in each case when comparing results. Conveniently, all these categories can also be used to classify genetic and neurophysiology works in the matter.

Figs. 2 and 3 show the distribution of publications across each category. Note that these figures do not represent percentage values, as some works can fall in several categories. It can be seen that the great majority of studies have focussed on REC and VEP (ERP) modalities. This is consistent with genetic and neurophysiology studies. Multi-task studies have also received special attention, as authors tried to find the best suiting paradigm for their systems. In addition, as commercial EEG hardware have just recently appeared, the proportion of studies using them is obviously lower than those using medical equipment.

To maximize the understanding of the progress made in the field, publications where tagged and clustered in teams. This also helped to identify the databases used in each publication, which was specially important as most of these databases did not have a name to refer them and tended to be difficult to track. Once they where named, it was possible to compare results reported by different works.

3. EEG genetics

The uniqueness of individuals can be greatly attributable to their genetics. Thus, if a system tries to identify a subject, it is actually trying to identify their phenotypes as well as characteristic effects of exogenous factors. Moreover, if such machine is based on information regarding an organ as complex and unknown as the human brain, findings on the genotype–phenotype map of the EEG become vital.

Identify the genetic traits of the EEG has proven to be an arduous task. These are complex heterogeneous traits, as they are the result of elaborated models of inheritance. For example, some evidences suggest that some genes have different effects at different brain areas and EEG frequencies. In addition, exogenous factors have also been proven to influence the human EEG and have to be considered when evaluating the results (Zietsch et al., 2007).

Twin studies have proven of great help on the understanding of this genotype–phenotype relationship. Davis and Davis were the first to study the EEG on twins (Davis & Davis, 1936). Evaluating a number of EEG traits; mainly based on distinguishing marks of

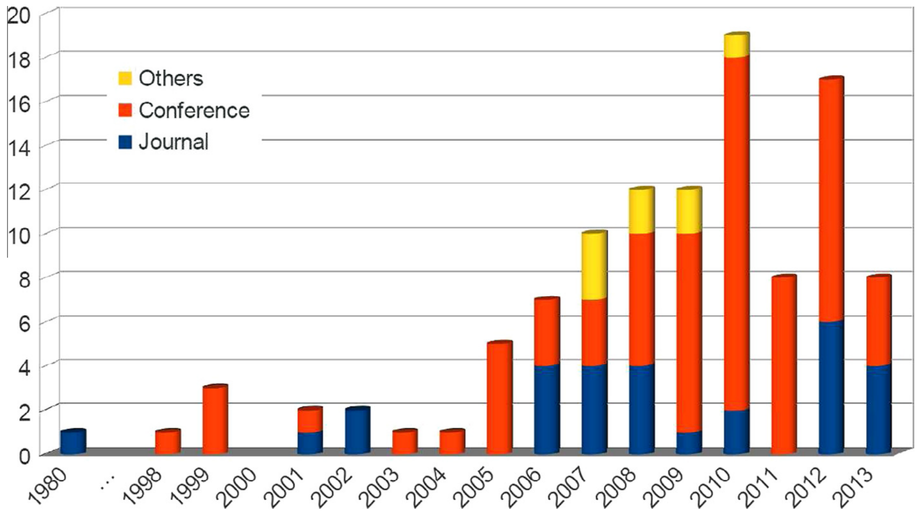

Fig. 1. Number of publications per year. Categories "conferences", "journals" and "other" are considered separately.

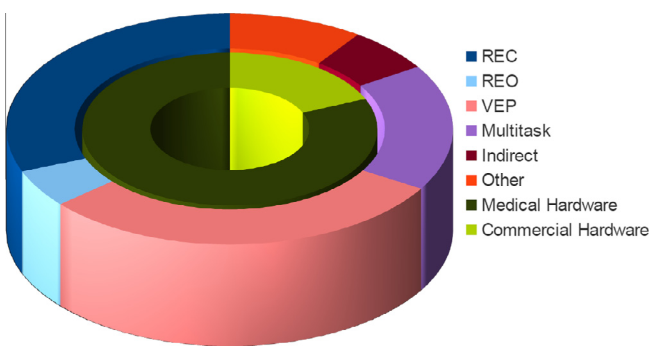

Fig. 2. Distribution of publications per category. Note that these are not percentages, as a single publication can fall in multiple categories.

the posterior rhythm, the authors concluded that the resting EEG of monozygotic (MZ) twins were identical; i.e. as similar as recordings from an individual across time (see Fig. 4). This was not the case of dizygotic (DZ) twins, which showed lower degrees of similarities on their EEG, although significantly higher than those of unrelated subjects.

These results were latter confirmed by numerous works across time, regardless of their methods of examination; visual inspection, measures on paper or computer evaluations (Vogel, 2000). Finally, the first direct connection between the morphology of the EEG and the genotype of subjects was made by Vogel (1970). In addition, some of the effects of time over the EEG also proved to be concordant across MZ twins. Interestingly, these results were also found in researches of twins reared apart, excluding the effects of exogenous factors. Similarities were also present in reaction to hyperventilation, photic stimulation and during sleep. In the latter case, the No-REM sleep EEG patters have been reported as more heritable than those of resting EEG or ERPs, specially in the range between 8 and 16 Hz (De Gennaro et al., 2008).

Family studies reasserted the findings of experiments conducted with twins. EEG traits such as the mean spectral power and frequency values of alpha and beta bands were proven highly heritable (Eischen, Luckritz, & Polich, 1995; Vogel, 2000). Moreover, some of these parameters seem to form a continuously phenotypic range rather than cluster in well defined discrete classes, so that traits of family members are more alike than those of unrelated individuals (Stassen, Bomben, & Hell, 1998).

Rather than using the resting EEG, other researches focussed on the brain response to external stimulus, ERP. Visual and auditory

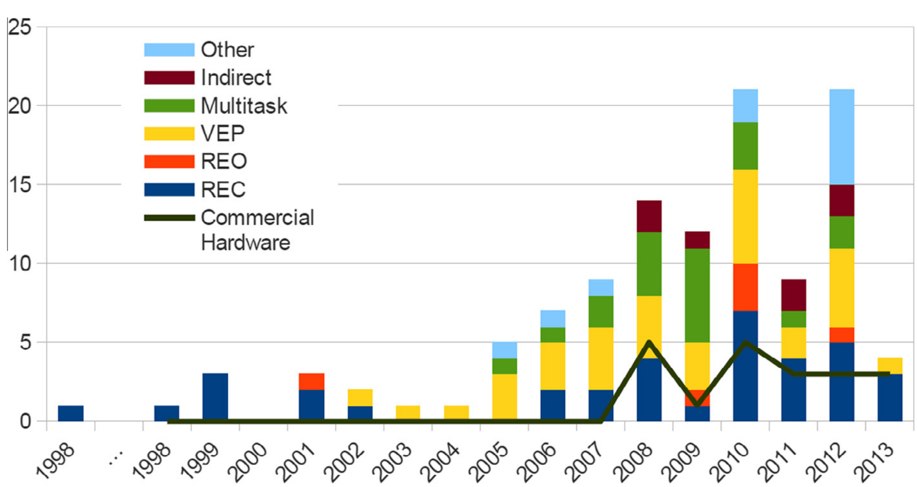

Fig. 3. Distribution of publications per category and per year. Note that these are not percentages, as a single publication can fall in multiple categories.

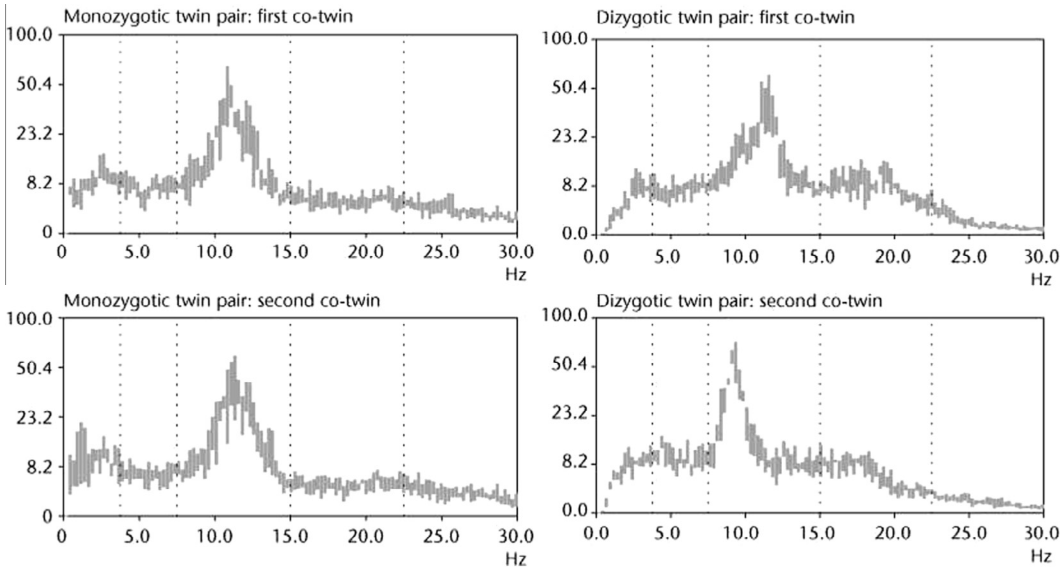

Fig. 4. EEGs of two MZ twins (left) and two DZ twins (right). Shaded areas represent variation (Stassen, 2006).

event potentials (VEPs and AEPs) were recorded again from twins and families, showing results similar to those obtained with the resting EEG (Begleiter & Porjesz, 2006; van Beijsterveldt & van Baal, 2002; Vogel, 2000; Yung, Lader, & Fenton, 1972). A result that came to no surprise given the strong relationship described by Vogel between the resting EEG and ERPs.

Computational tools produced some interesting works. Those of Stassen (1980), Stassen, Bomben, and Propping (1995) and Stassen, Lykken, Propping, and Bomben (1988) are of special relevance. In them, the authors provided quantitative evidences of such comparability between twins and family members by applying similarity measures. In fact, the first of their works (Stassen, 1980) is in deed the first published EEG biometric system. However, researchers used it as a tool for the evaluation of the inheritance of EEG traits, without much worrying about their performance as a security system in real scenarios. Other works using computational tool focussed on the classification of Vogel's proposed EEG spectral variants: alpha and beta variants (Varner, Potter, & Rohrbaugh, 1991; Vogel, 1970). These major categories were then divided into sub-classes based on finer details of the activity, such as particularly slow alpha rhythms.

To add up to the complexity of the problem, the EEG orography seems to change with maturation (van Beijsterveldt & van Baal, 2002; Vogel, 2000). Moreover, some of this changes may not be homogeneous across subjects, rhythms or brain areas. To remove this changing factor across time and subjects, normalizing methods have been proposed (Doppelmayr, Klimesch, Pachinger, & Ripper, 1998). Still, some works claimed to find a remarkable stability of EEG spectral distribution between sessions recorded more than a year apart (Näpflin, Wildi, & Sarnthein, 2007).

Overall, alpha power and peak frequency over occipital regions seem to be the frequencies presenting the strongest heritability (van Beijsterveldt & van Baal, 2002; Vogel, 2000; Zietsch et al., 2007). This laid the foundations of the first works on EEG based biometric identification. After all, having detected the phenotype traits of the EEG, it may be enough for a system to detect and differentiate such features.

4. Databases

Some databases have been extensively used on EEG based biometric experiments. However, as most of them had not been named they were difficult to track. In some cases, studies used the same database but with a different number of subjects or channels, which made the identification process even harder. Here, names to these databases are proposed to facilitate the track. Furthermore, references to find those publicly available are given so that future works can make use of them and researchers can compare the results.

Note that electrodes will be named following the international 10–20 standard system unless other way expressed. A visual overview can be seen on Table 1. Here, the column "*Categories*" tries to give a first impression of the corresponding database based on the categorization proposed on Section 2.

4.1. Poulos' DDBB

This was the database used on the first series of published works on EEG identification by Poulos et al. back on 1998, and it has been the database used by this group in any subsequent publication (hereby its proposed name). The original mean of this database is unclear, as it was never specified by the authors. In other words, it is unknown whether it was elaborated for the solely purpose of EEG based subject identification, or if, as it has been usually the case on many publications, it was part of a bigger database recollected with other aims.

This is a small database composed mainly of only 4 registered users (here referred to as *SetR*), from which 45 recordings were taken. It also contains a second subset of data (*SetX*) composed of a single recording session from 75 different subjects. This second set was used as impostors attacks.

Each session consisted on 3 min of the subject REC while the voltage difference from electrodes 02 and Cz was recorded at a sample rate of 128 Hz.

Table 1
Databases used on multiple publications.

DDBB	# subjects	Categories
Poulos' DDBB	4 users + 75 impostors	REC
Zhang's DDBB	125 (48 healthy + 77 alcoholics)	ERP, VEP
Keirn's DDBB	5	Multi-task
IIIaBCI03 DDBB	3	Multi-task
Tottori DDBB	23	Consumer EEG; REC
Lanzhou DDBB	11 users + 11 impostors	Consumer EEG; REC

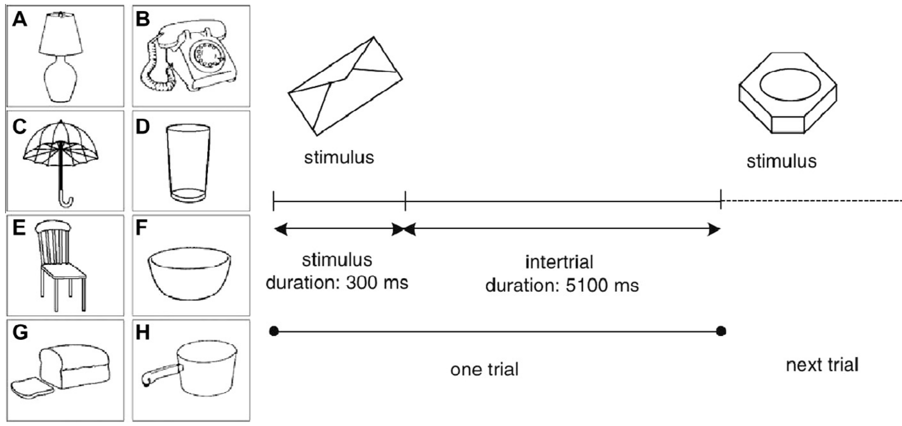

Fig. 5. Snodgrass and Vanderwart image sample (left) and a representation of the experimental paradigm of *Zhang's DDBB* (right).

4.2. Zhang's DDBB

Zhang recorded two databases for the purpose of studying the visual memory (Zhang, Begleiter, Porjesz, Wang, & Litke, 1995) and the effects of alcoholism on memory (Zhang, Begleiter, Porjesz, & Litke, 1997). It is unclear whether these studies actually used two independent databases or if the latter is an extension of the former. However, as they were recorded under the same exact conditions and their only difference resides in the number of subjects, they could be consideration the same for the practical purpose of results comparison. Thus, from here on, they will be both referred to as a single database named *Zhang's DDBB*, which is publicly available at Zhang's database (1999).

In this case, subjects were exposed to visual stimulus consisting on black and white images taken from the set of Snodgrass and Vanderwart (1980). These images represent well identified objects with defined verbal labels (see Fig. 5). The trials consisted on two stimulus; *S1* and *S2*, each lasting 300 ms and separated by 1.6 s. The subjects were asked to determine whether *S1* was the same as *S2*. In some cases, only one stimulus was presented (see Fig. 5).

40 trials were recorded from each subject, leaving 3.2 s between trials. EEG pre-stimulus data was kept as baseline from 190 ms before any stimulus was presented, and 1.44 s of EEG post-stimulus data was registered from the moment a stimulus was presented. 61 channels were used, with all channels referred to Cz. Data was sampled at 256 Hz and hardware filtered between 0.02 and 50 Hz.

This was the first database with a recording paradigm different than REC or resting with eyes open (REO) used for EEG identification. With a total of 125 subjects (48 healthy males with 25.81 ± 3.38 years old and 77 alcoholic patients with 35.83 ± 5.33 years old (Zhang et al., 1997)[1]), it also represented an important step forward on the size of the databases used for this problem at the time.

There are a number of works that may have used this extensive database to a greater or less extend (Altahat, Huang, Tran, & Sharma, 2012b; Brigham & Kumar, 2010; Nguyen, Tran, Huang, & Sharma, 2012; Palaniappan, 2004; Palaniappan & Mandic, 2005, 2007; Palaniappan & Raveendran, 2002; Palaniappan & Ravi, 2003, 2006; Ravi & Palaniappan, 2005a, 2005b, 2006, 2007; Yazdani, Roodaki, Rezatofighi, Misaghian, & Setarehdan, 2008). Some of them have even included the data recorded from the alcoholism patients, which could polemic if a statistical study discarding correlation between the features used and the normal-alcoholic condition is not provided jointly (this will be further discussed on Section 6).

It is worth it to note here that the work published by Zuquete, Quintela, and Cunha (2010b) used a database that is similar enough to allow for a direct comparison of results, as the only differences found on the paradigm was the inter-stimulus time (increased to 5.1 s) and the registered EEG (1 s post stimulus). In fact, Zuquete's database is also composed of healthy and alcoholic subjects.

[1] Zhang reported on Zhang et al. (1995) 14 males (24.3 + 3.1 years old) and 14 females (23.2 + 1.7 years old), all healthy. This was the only difference found between the databases.

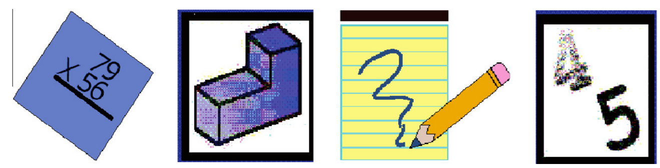

Fig. 6. Representation of tasks 2–5 (from left to right) used on the *Keirn's DDBB* (Palaniappan & Patnaik, 2007).

4.3. Keirn's DDBB

Keirn recorded EEG from subjects while they were performing different mental tasks exploring new human–machine interaction through the brain (Keirn & Aunon, 1990). Although a small database (5 subjects: 4 males and 1 female between the ages of 21 and 48) the relevance of this database resides on the multi-task recording paradigm. This allowed Palaniappan (the only author that has used it so far) to study the effects of different mental tasks on the problem of EEG based identification (Palaniappan, 2005, 2006, 2008; Palaniappan & Patnaik, 2007). The database is publicly available at Kerin's database (2012).

In particular, a total of 5 tasks were performed by subjects. Each task was repeated 5 times and recorder under both REC and REO on every session. 2 sessions were recorded from each subject in a time span of 2 weeks. The tasks were:

T1 *Base line measurements*. This task was taken as a baseline for comparison. In this case, subjects were only asked to relax.
T2 *Complex problem solving*. Subjects were asked to mentally solve non-trivial multiplication problems.
T3 *Geometric figure rotation*. Subjects were presented with an image of a 3 dimensional complex object before being asked to mentally rotate it.
T4 *Mental letter composition*. Subjects had to mentally write a letter to a friend or a family member.

T5 *Visual counting*. Subjects were asked to visualize numbers being written on a blackboard sequentially. With the previous number being erased before a new number is written (see Fig. 6).

Only the EEG signals from electrodes 01, 02, P3, P4, C3 and C4 were used on these experiments. Data was hardware filtered between 0.1 and 100 Hz and sampled at 205 Hz. The EEG signal was recorded during 10 s of each task.

4.4. IIIaBCI03 DDBB

This is another multi-task database that have been used for EEG based identification on different works (Bao, Wang, & Hu, 2009; Hu, 2009a, 2009b; Jiang & Hu, 2009; Nguyen et al., 2012; Xiao & Hu, 2010). In particular, this is the dataset IIIa of the BCI competition of 2003 (BCI, 2003), provided by the Laboratory of Brain–Computer Interfaces (BCI-Lab) of the Graz University of Technology (Gert Pfurtscheller, Alois Schologl).

In this case, the database is composed of only 3 subjects performing the following 4 different tasks:

T1: Imaging the movement of the left hand.
T2: Imaging the movement of the right hand.
T3: Imaging the movement of the foot.
T4: Imaging the movement of the tongue.

Each subject performed each task 60 times. The EEG was recorded by 60 electrodes (+4 references) at a sampling rate of 250 Hz. The signal was hardware filtered between 0.5 and 100 Hz and a 50 Hz with a notch filter.

4.5. Tottori DDBB

This was the first database recorded with a non-medical or commercial equipment and used for the problem of EEG based identification. It was collected in the Tottori University (Japan) by Miyamoto et al. and used on several studies on the practical application of EEG based identification (Baba, Miyamoto, & Nakanishi, 2008; Miyamoto, Baba, & Nakanishi, 2008; Nakanishi, Baba, & Miyamoto, 2009; Nakanishi, Ozaki, & Li, 2012).

The equipment used recorded data between 1 and 24 Hz at a sample rate of 128 Hz. It had a minimum and maximum voltage range sensibility of 5 and 80 uVpp respectively and it only contained the frontal electrodes Fp1 and Fp2. Moreover, as it was a consumer equipment, it could be used by any user without need of qualified staff or long times of preparation.

The recording sessions was kept simple, in order to make the EEG identification process more practical. 10 sessions were registered from 23 subjects while they were REC. The last minute of a 3 min recording was used for the experiments. On the other hand, all sessions where recorded during the same day, which does not match with real life applications.

4.6. Lanzhou DDBB

The Lanzhou University (China) database was also recorded with a consumer EEG. In this case, the EEG used was the Nexus-4, a wireless device connected through bluetooth with a sample rate of 256 Hz. In a bid to simplify the process for practical applications, only electrodes Cz and A2 were used on the EEG identification experiments (Hu, Liu, Zhao, Qi, & Peng, 2011; Hu, Mao, et al., 2011; Zhao, Peng, Hu, Li, et al., 2010; Zhao, Peng, Hu, Liu, et al., 2010).

Again, EEG was recorded while subjects were REC. In this case, the database contains 11 registered users; 6 males and 5 females between 20 and 24 years old, and 11 intruders. 5 recording sessions distributed in a few days were taken for both users and intruders. However, one more recording session was recorded from users around 6 months latter.

5. Experiments and results

This section provides a detailed review of the experiments and results in the state of the art on EEG based identification following the proposed categorization. For the sake of clarity and in order to easy the tracking of events, authors have been clustered in *groups*.[2]

5.1. REC and REO

As noted before, the first publication available on automatic EEG based identification is dated in 1980 by Stassen. He experimented with EEG recorded by two posterior electrodes from a group of 82 subjects from 4 different psychiatric diagnostic groups. By building a region, delimited by the maximum and minimum Power Spectral Density (PSD) of each subject, he evaluated the level of similarity between subjects to build an answer. He finally reported a classification rate of around 90%.

However, Stassen's was an isolated work meant to build a tool for future genetic and neurophysiology studies. The first series of related works started on September 1998 by Poulos, Rangoussi, and Kafetzopoulos (1998). Their work was based precisely on the findings about the inheritance of EEG traits, which mainly stated that the posterior rhythm is the most genetically determined trait of the resting EEG. Thus, in order to facilitate the arousal of such rhythm, a database with a REC paradigm was used. The proposed system relied on the Absolute Spectral Power (ASP) of the alpha rhythm (7–12.5 Hz) recorded by the O2 channel and classified by a Computational Geometry (CG) algorithm. When tested on 4 subjects of Poulos' DDBB *SetR*, the implementation reached a success rate of 95% on classification. In addition, a 96.2% of impostors rejection rate was reported when the *SetX* was used for testing.

These results encouraged Poulos' group to keep investigating the usage of EEG as a biometric modality for subject identification. In the forthcoming years, they published a set of experiments interchanging coefficients of the PSD and Auto Regressive (AR) models as feature extractors and CG and Neural Networks (NN) as classifiers (Poulos, Rangoussi, Alexandris, 1999; Poulos, Rangoussi, Alexandris, & Evangelou, 2001; Poulos, Rangoussi, Chrissikopoulos, & Evangelou, 1999a, Poulos, Rangoussi, Chrissikopoulos, & Evangelou, 1999b). The systems were always applied over the alpha rhythm and tested using Poulos' DDBB. In these works, they also explored for the first time the differences between sub-bands of the alpha rhythm, concluding that the middle section of such rhythm provides the most discriminative information.

In a future work, Poulos et al. used an spectrum range that included for the first time all the main brain waves (i.e. delta, theta, alpha and beta), but failed to evaluate each band individually (Poulos, Rangoussi, Alexandris, & Evangelou, 2002).

A review of such experiments and the obtained accuracies can be seen in Tables 2 and 3. Although results cannot be compared directly; different experimental procedures were used on each publication, they seem to suggest that PSD provides better accuracies than coefficients of AR models. Nevertheless, both methods would prove to be the main features used by many authors.

[2] The name of the institution to which the first author belongs at the moment of their first publication.

Table 2
Structure of the systems tested with the *Poulos' DDBB*.

Sys.	Freq. [Hz]	Features	Classification	Ref.
Pou1	[7–12.5]; 0.3 Hz wide sub-bands	PSD	CG	Poulos et al. (1998)
Pou2	[7–10]		LVQ-NN	Poulos, Rangoussi, Alexandris (1999, 2001)
Pou3	[8–11]			
Pou4	[9–12]			
Pou5	[7.5–12.5]	AR		Poulos et al. (1999a)
Pou6	[7.5–12.5]; 5 sub-bands of 1 Hz width		CG	Poulos et al. (1999b)
Pou7	[1–30]		LVQ-NN	Poulos et al. (2002)
Pou8		Bilinear-AR		

Table 3
Results obtained by the systems listed in Table 2 when evaluated with the *Poulos' DDBB* on classification and verification mode. The percentage of training samples (Tr. samples) is presented as: *SetR*% | *SetX*% (see Section 4.1). For works (Poulos, Rangoussi, Alexandris, 1999; Poulos et al., 2001) only the best results are shown. Mean success rates are presented for both classification and verification experiments.

Sys.	Classification		Verification	
	Tr. samples%	Success rate (%)	Tr. samples%	Success rate (%)
Pou1	55.56 | 40	95.00	Not tested	
Pou6	22.23 | 0	47.91		
Pou2	55.56 | 0	83.75	55.56 | 33.34	87.50
Pou3		86.25		**89.28**
Pou4		86.25		87.85
Pou2	44.45 | 0	91.00	Not tested	
Pou3		94.00		
Pou4		**95.00**		
Pou7		68.00	44.45 | 40	79.28
Pou8		78.00		80.00
Pou5	Not implemented			79.28

However, the fact that Poulos' DDBB contained only 4 subjects prevented the establishment of any strong conclusion. On 2001, Paranjape et al. published a study tested with a 40 subjects database of REO and REC (Paranjape, Mahovsky, Benedicenti, & Koles, 2001). The system used AR coefficients as features and a Discriminant Function Analysis for classification. The authors noted that an increase in the order of the AR model was necessary to bear with the rise in the number of registered users. Using order 15 they achieved an 85% of success rate. This result finally proved the hypothesis that the identification of subjects by means of their EEG was indeed possible. In fact, a fairly acceptable performance was obtained using a single channel.

Paranjape et al. suggested in their work that better performance was to be expected for a system to use more than one channel. On 2006, Mohammadi et al. explored this Mohammadi, Shoushtari, Ardekani, and Shamsollahi (2006). AR coefficients and NN were again used on a 10 subjects database, reporting accuracies between 80% and 95% (depending on the order of the AR model) when one posterior channel was used, and between 85% and 100% by fusing two or more channels with a 10 subjects REC DDBB. In addition, they noted by visual examination that electrodes from the back of the scalp provided better performances than electrodes from anterior regions, an assertion that was latter proved empirically by several works (Campisi et al., 2011; La Rocca, Campisi, & Scarano, 2012) and was in line with the fact that the alpha rhythm is more prominent in occipital areas.

On 2009, Tangkraingkij et al. published the first detailed study of which channels provide the most discriminant information (Tangkraingkij, Lursinsap, Sanguansintukul, & Desudchit, 2009). In this case, the EEG was recorded while subjects were REO. Their system applied Independent Component Analysis (ICA) directly over the raw EEG for feature extraction and relied on an NN for classification. When the JADEop ICA algorithm was employed, the system achieved 100% of accuracy for a 20 subjects database using all the available 16 channels. Moreover, when testing different channels combinations, they managed to retain perfect classification using only 3 channels. From this comprehensive study, the authors concluded that the most discriminative channels under REO conditions are Fp1, P3 and C4.

On the other hand, a year latter Abdullah et al. reported a significant drop in performance when moving from central to parietal electrodes under a REO condition, but not on a REC scenario (Abdullah, Subari, Loong, & Ahmad, 2010a). They concluded that the P3 electrode should be dropped on a REO problem. The authors also studied the existing difference on performance between left and right hemispheres, which turned out to be not statistically significant. It is also important to note that in this experiment the REC condition outperformed the REO in general terms. Nevertheless, on a second work using different processing techniques, their results do not reflect all of these findings so clear, specially on the left versus right hemispheres and the REC versus REO matters (Abdullah, Subari, Loong, & Ahmad, 2010b).

In 2011, Campisi et al. also examined the contribution of different brain areas and different frequencies to the discrimination of subjects on a REC paradigm (Campisi et al., 2011). The results showed again a decrease in performance when moving from posterior to anterior areas. This decrease was more pronounced when high frequency rhythms were removed from the EEG signals. In particular, the best result was obtained with the temporal triplet T7-Cz-T8 and a cut-off frequency of 33.33 Hz (96.08% of accuracy over a 48 subjects database). Note also that this study used the reflection coefficients of an AR model, which increased the performance between 4 and 9 points when compared to the commonly used AR coefficients.

A year latter, similar conclusions in terms of location were obtained by Campisi's team, reproducing the drop on accuracy when moving from occipital to frontal electrodes (La Rocca et al., 2012). Furthermore, the results showed that alpha and delta rhythms where the best performers, followed by the theta rhythm and finally the gamma rhythm. When the selective filter was set to include more than one rhythm, the performance of the system increased. In particular, the best outcome was obtained when all 4 rhythms were included and electrodes O1–POz–O2 were used.

5.2. ERPs

On 2002 Palaniappan et al. used for the first time EEG VEPs for biometric identification (Palaniappan & Raveendran, 2002). This work aimed to extract discriminant information from higher brain functions like perception and memory. In particular, the system extracted the ASP of the gamma band. These ASP features were extracted from 61 electrodes and classifier by a NN, achieving on average a 90.95% of accuracy on 10 subjects of Zhang's DDBB.

Given the encouraged results, Palaniappan's group focussed on polishing their VEPs based system trying different algorithms and architectures. They experimented with Principal Component

Table 4
Structure of systems tested with the *Zhang's DDBB*, along with those presented on Table 5.

Sys.	Band [Hz]	Features	Classifier	Ref.
Zha01	[32–48]	ASP	FA-NN	Palaniappan and Raveendran (2002)
Zha02			RB-ENN	Palaniappan and Mandic (2007)
Zha03			Manh. kNN	
Zha04	[30–50] Butterworth	ASP	SFA-NN	Palaniappan and Ravi (2006) and Ravi and Palaniappan (2005b)
Zha05			Euc. kNN	Palaniappan and Ravi (2006)
Zha06			Manh. kNN	Palaniappan and Ravi (2006) and Ravi and Palaniappan (2005b)
Zha07			LDC	Palaniappan and Ravi (2006)
Zha08		Norm.ASP	BP-NN	Palaniappan (2004) and Palaniappan and Mandic (2005, 2007)
Zha09			SFA-NN	Palaniappan and Ravi (2006)
Zha10			RB-ENN	Palaniappan and Mandic (2007)
Zha11			Euc. kNN	Palaniappan and Ravi (2006)
Zha12			Manh. kNN	Palaniappan and Ravi (2006) and Palaniappan and Mandic (2007)
Zha13			LDC	Palaniappan and Ravi (2006)
Zha14		PCA-NR; ASP	SFA-NN	Palaniappan and Ravi (2003, 2006)
Zha15			Euc. kNN	Palaniappan and Ravi (2006)
Zha16			Manh. kNN	
Zha17			LDC	
Zha18		PCA-NR; Norm.ASP	BP-NN	Ravi and Palaniappan (2006)
Zha19			SFA-NN	Ravi and Palaniappan (2005b, 2006) and Palaniappan and Ravi (2006)
Zha20			Euc. kNN	Palaniappan and Ravi (2006)
Zha21			Manh. kNN	Ravi and Palaniappan (2005b) and Palaniappan and Ravi (2006)
Zha22			LDC	Palaniappan and Ravi (2006)

Table 5
Structure of the systems tested with the *Zhang's DDBB*, along with those presented on Table 4.

Sys.	Band [Hz]	Features	Classifier	Ref.
Zha23	[30–50] Elliptic	Norm.ASP	BP-ENN	Ravi and Palaniappan (2005a)
Zha24			LDC	Ravi and Palaniappan (2007)
Zha25		Norm.ASP; 13 ch. by GA		
Zha26		Norm.ASP; 23 ch. by GA		
Zha27		Norm.ASP; 40 ch. by GA		
Zha28	[20–50]	ARM; Norm.ASP; 1 ch. by DBI	RB-ENN	Palaniappan and Mandic (2007)
Zha29	Elliptic	ARM; Norm.ASP; 35 ch. by DBI		
Zha30		ARM; Norm.ASP; 50 ch. by DBI		
Zha31	[30–70] Elliptic	Norm.and whitened ASP; PCA		Palaniappan and Mandic (2005)
Zha32	[26–56]	ARM; ASP of dominant frequency by MUSIC		Palaniappan and Mandic (2007)
Zha33	SD-FIR		Manh. kNN	
Zha34	[30–50]	AR model of order 14 + Peak value of PSD; LDC	Euc. kNN	Yazdani et al. (2008)
Zha35	Full range	AR model of order 4		Brigham and Kumar (2010)
Zha36			lSVM	
Zha37		From channels C3, Cz, C4, P3, Pz, P4, O1, O2: MFCC + spectral features + ASP + pitch + zero crossing rate + probability of voicing + jitter and shimmer and their statistics; Correlation-based Floating Forward feature selection		Nguyen et al. (2012)

Analysis (PCA) both as a preprocessing step for noise reduction (PCA-NR) (Palaniappan & Ravi, 2003) and as a feature reduction technique (Palaniappan & Mandic, 2005). They tested different band widths such as that of the late gamma band; between 30 and 50 Hz (Ravi & Palaniappan, 2006), and numerous filters (Ravi & Palaniappan, 2005a). They also tried to increase the system's performance normalizing the features (Palaniappan, 2004) and applying different classification techniques. Two of their works offer the results of an interesting set of experiments combining and directly comparing several of these methods (Palaniappan & Ravi, 2006; Ravi & Palaniappan, 2005b). Information about all these systems and others tested over *Zhang's DDBB* are summarized on Tables 4–8.

In a bid to reduce the volume of data processed by the classifier, on 2007 Palaniappan's group applied the Multiple Signal Classification (MUSIC) algorithm to select features from a vector composed of the PSD coefficients of the dominant frequencies between 25 and 56 Hz (Palaniappan & Mandic, 2007). A NN was used for classification. This scheme achieved a 97.61% of accuracy on average for 102 subjects of Zhang's DDBB. However, as this pool of users include both healthy and alcoholic subjects (see Section 4.2), this result; and for that matter the results of all experiments with this characteristics, should be carefully interpreted (see Section 6 for a discussion).

In 2006, landmarks of VEPs, APS and AR coefficients were directly compared on an interesting study by Power, Lalor, and Reilly (2006). A Lineal Discriminant Classifier (LDC) and a 13 subjects DDBB were used. Results showed that relative amplitudes of P100 and N75 are more relevant than N135.[3] When fused, these landmarks obtained 82% of classification. On the other hand, the ASP ratio of the beta band reached 59.6% of accuracy, outperforming that of the alpha band considerably, and the AR coefficients managed a

[3] The terms P100, N75 and N135 refer to peaks on an ERP, so that P100 is a positive peak 100 ms post-stimulus and N75 and N135 are a negative peak 75 and 135 ms post-stimulus respectively.

Table 6
Results obtained by systems presented on Tables 4 and 5 when evaluated with 20 subjects of the *Zhang's DDBB* on a classification experiment. Mean success rates are provided. For those systems with configurable parameters, the range of classification rates is also given. On each case, the way the training and testing sets were computed is specified by the percentages of training samples (Tr. samples) or by the name of a cross-validation method.

Sys.	Tr. samples	Mean success (%)	Min–Max success
Using 20 subjects from the Zhang's DDBB			
Zha08	50% of DDBB	99.06	98.98–99.15
Zha14		94.18	93.50–97.75
Zha37*	66.67% of DDBB	92.80	–
Zha04	Leave-One-Out	71.14	70.50–73.00
Zha05		66.12	63.13–67.63
Zha06		70.88	67.38–72.38
Zha07		84.00	–
Zha09		66.26	65.38–69.88
Zha11		62.48	59.88–63.63
Zha12		65.64	63.25–67.00
Zha13		85.75	–
Zha14		91.93	91.63–93.25
Zha15		91.54	90.75–92.25
Zha16		94.18	93.75–95.25
Zha17		84.25	–
Zha19		92.84	92.25–95.25
Zha20		89.32	87.88–90.38
Zha21		92.04	89.50–93.13
Zha22		96.50	–
Zha34		**100**	–

Zhan37*: In this case, even though only 20 subjects of the *Zhang's DDBB* were used, the pool contained 10 healthy subjects and 10 alcoholics.

Table 7
Results obtained by systems presented on Tables 4 and 5 when evaluated with 40 subjects of the *Zhang's DDBB* on a classification experiment. Mean success rates are provided. For those systems with configurable parameters, the range of classification rates is also given. On each case, the way the training and testing sets were computed is specified by the percentages of training samples (Tr. samples) or by the name of a cross-validation method.

Sys.	Tr. samples	Mean success (%)	Min–Max success
Using 40 subjects from Zhang's DDBB			
Zha08	50% of DDBB	95.69	95.37–96.13
Zha18		95.40	89.83–97.33
Zha19		82.44	81.54–85.59
Zha23		95.42	95.00–96.63
Zha31		**99.08**	98.75–99.62
Zha08	Leave-One-Out	93.08	91.38–94.00
Zha28		13.63	–
Zha29		98.29	98.06–98.56
Zha30		**99.00**	–
Zha24	50% for GA; 50% for Leave-One-Out	72.25	55.00–90.00
Zha25		44.65	35.00–65.00
Zha26		73.95	53.00–86.00
Zha27		**82.00**	75.00–95.00

63.5% of success rate. All these best results correspond to occipital channels, which improved those of more anterior regions.

A year later, Singhal and RamKumar proposed a system that processed VEPs measured by a single occipital electrode (Oz) (Singhal & RamKumar, 2007). The algorithm was based on VEPs wave landmarks (phases, amplitudes and latencies) and relied on a similarity measure with a 2 dimensional Gaussian kernel classifier. The architecture achieved 78% of classification accuracy on a 10 subjects database.

In 2009, Das et al. produced another interesting work where they studied the spatio-temporal pattern responsible for encoding personal discriminant data (Das, Zhang, Giesbrecht, & Eckstein, 2009). They achieved this by computing what they called the

Table 8
Results obtained by the systems listed in 4 and 5 when evaluated with the *Zhang's DDBB*. The experiments were performed on classification mode, from which mean success rates are reported. For those systems with configurable parameters, the range of mean classification rate is also given. On each case, the way the training and testing sets were computed is specified by the percentages of training samples (Tr. samples) or by the name of a cross-validation method. Note also that the table is divided according to the number of subjects used from the whole database.

Sys.	Tr. samples	Mean success (%)	Min–Max success
Using 10 subjects from Zhang's DDBB			
Zha01	50% of DDBB	90.95	88.00–95.00
Using 102 subjects from Zhang's DDBB			
Zha02	10k-folds	96.43	95.09–96.64
Zha03		90.70	89.75–92.87
Zha10		96.01	94.63–96.58
Zha12		89.85	88.48–91.94
Zha32		**97.61**	96.77–98.12
Zha33		95.85	95.00–96.13
Using 120 subjects from Zhang's DDBB			
Zha35	4k-folds	95.02	93.24–96.34
Zha36		98.86	–
Using 122 subjects from Zhang's DDBB			
Zha37	66.67% of DDBB	61.70	–

"*fisherbrains*", the coefficients of the Lineal Discriminant Analysis (LDA) (see Fig. 7). In the temporal domain, they concluded that the most informative signal arises between 120 and 200 ms after the stimulus was presented, presumably an elapse time used to process the visual information. On the other hand, pre-stimulus signal led to really poor results. In the spatial aspect, occipital regions proved again to be more critical for subject identification. When EEG was classified by an Linear Support Vector Machine (lSVM), the system achieved performances between 90% and 95% on a 20 subjects database.

Ferreira et al. proposed in 2010 a system based solely on a Support Vector Machine (SVM) (Ferreira, Almeida, Georgieva, Tome, & Silva, 2010; Ferreira, Almeida, Georgieva, & Tome, 2010). The relevance of this works relies on the fact that SVM was combined for the first time in the field of EEG based biometric identification with a non-lineal Gaussian kernel, the Radias Basis Function kernel (RBF-SVM), a configuration widely used on other biometric areas. Their best effort achieved an 84.33% on a 13 subjects database. Although worst than those of the state of the art, this result was remarkably high considering that it relied entirely on the RBF-SVM (no feature extraction technique was applied). Their experiments also showed that RBF-SVM outperforms lSVM.

Finally, on 2012 Nguyen et al. borrowed techniques from the voice-processing field (Nguyen et al., 2012). In particular, the system relied on a feature vector composed by Mel-Frequency Cepstral Coefficients (MFCC), spectral features, energy and pitch measurements, zero crossing rate, probability of voicing and jitter and shimmer plus their statistics functionals. The feature dimensions was then reduced by a correlation-based feature selection with sequential floating forward selection, and classified by a lSVM. The model achieved 92.80% and 61.70% of classification accuracies on 20 and 122 subjects of Zhang's DDBB respectively (in both cases, healthy and alcoholic users where included on the subjects pool).

5.3. Multi-task

In a bid to explore the possibilities of new paradigms, at the end of 2005 Palaniappan published the first work using EEG recordings from different mental tasks (Palaniappan, 2005). As a first approach, he tested a simple system extensively used in the field; AR coefficients and an LDC. 4 subjects of Keirn's DDBB were used

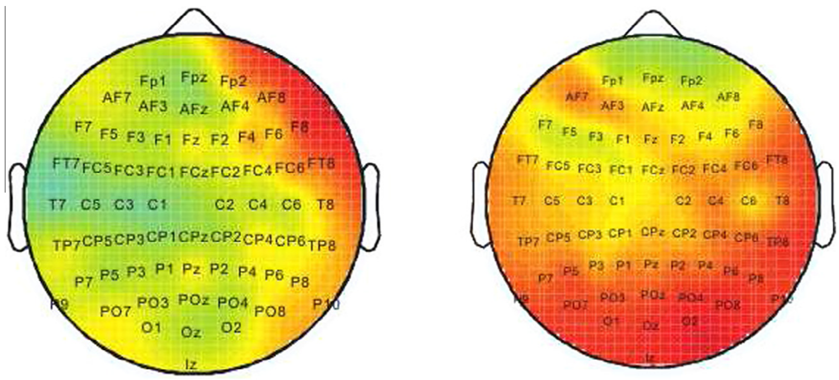

Fig. 7. Fisherbrains from a VEP database at 170 ms post-stimulus for 2 subjects presented with a face image (Das et al., 2009).

Table 9
Structure of systems tested with the *Keirn's DDBB*. Note that all these systems share a common preprocessing stage where EEG is high-pass filtered at 0.2 Hz using an elliptic filter. In addition, the data is windowed in 20 segments of 0.5 s each.

Ref.	Features	Classification	Ref.
Kei1	6 order AR	LDC	Palaniappan (2005)
Kei2	Kei1's features + SP and IH-SP of [8–13] Hz, [14–20] Hz and [21–50] Hz bands; PCA	LDC	Palaniappan (2006)
Kei3	Kei2's features + inter-hemispheric channel linear complexity + non-linear complexity	2 stage Manh. distance OCC	Palaniappan (2008)
Kei4	Kei3's features; PCA		

Table 10
Results obtained by the systems summarized in Table 9 when evaluated over the *Keirn's DDBB*. Mean success rates and Equal Error Rates (EERs) are reported for classification and verification respectively. In both cases, 50% of the database was used for training and 50% for testing on a cross-validation method. Results when testing with EEG from individual tasks is presented as well as results when fusing two tasks.

	Classification		Verification	
Sys.: Task/s	Kei1* (%) Mean success	Kei2 (%)	Kei3 (%) Mean EER	Kei4 (%)
Task 1	92.45	97.77	0.15	0.20
Task 2	97.40	96.88	0.07	0.07
Task 3	94.30	97.84	0.00	0.00
Task 4	92.45	98.64	0.10	0.12
Task 5	95.30	98.40	0.00	0.02
Tasks 1 & 2	98.98	99.60		
Tasks 1 & 3	98.15	99.52		
Tasks 1 & 4	98.50	99.60		
Tasks 1 & 5	98.50	99.60		
Tasks 2 & 3	98.85	99.24		
Tasks 2 & 4	99.05	99.76		
Tasks 2 & 5	98.90	99.32		
Tasks 3 & 4	98.60	99.56		
Tasks 3 & 5	98.35	99.40		
Tasks 4 & 5	98.75	99.60		

Kei1*: In this case, only 4 of the 5 subjects from *Keirn's DDBB* were used.

for testing. The results proved that different mental tasks do provide significant different outcomes. The worst accuracy; 92.45%, was obtained by tasks 1 and 4, while the best result; 97.40%, was obtained by task 2. Recalling from Section 4.3, tasks 1 and 4 correspond to relax and letter composition tasks respectively, while task 2 corresponds to solving complex mathematical problems.

In addition, Palaniappan also experimented with the fusion of feature vectors from two tasks. This resulted in a remarkable increase in performance, obtaining 99.05% of rightness when tasks 2 and 4 were fused and 98.95% when tasks 2 and 1 were fused, which in turn were the best overall results. Curiously, these best combinations included both the best and one of the worst performing tasks when they were evaluated individually.

Palaniappan's team produced three more works tested over Keirn's DDBB, reasserting that the fusion of different tasks' features increases the system's performance significantly (Palaniappan, 2006, 2008; Palaniappan & Patnaik, 2007). However, with contradicting results conclusions regarding the differences between recording paradigms are difficult to make. For example, some experiments reported tasks 2 and 4 being the best and worst respectively, turning around the conclusions of Palaniappan's first work. On the other hand, when trios were evaluated, tasks 1, 2 and 4 appeared again in the best combinations. A full review of all these systems and their results can be seen on Tables 9–11.

On 2007, Marcel and Millan published the first work that actually studied the effect of time over an EEG based identification system (Marcel & Millan, 2007). They did so over a DDBB including the imagined tasks of moving the left hand, moving the right hand and producing words. The system used for testing was based on normalized PSD features and a Gaussian Mixture Model (GMM) classifier. The experiments showed that the performance decays when data from a single session is used for training and data from different day sessions are used for testing. Moreover, the authors noted that this droop can be circumvented by using a multi-day-session training approach. Finally, a best performance of 6.60% of Equal Error Rate (EER) was obtained with the left hand movement task.

At the end of that year, Sun proposed a multi-task learning (MTL) approach where an NN was trained with features extracted from multiple tasks EEGs (Sun, 2008). In this case, the 9 subjects database used contained only two task: imagine left and right hand movements. An increase of around 4 points was observed when the MTL approach was used, obtaining 95.60% and 94.81% of classification on each task respectively.

Such scenario of left outperforming right hand imaging movements was also studied by other authors. For example, Bao's et al. works in 2009 contradicted this Bao et al. (2009) and Hu (2009b). Their experiments on IIIaBCI03 DDBB reported a scenario where no significant differences were found between left and right hand tasks. Their results also showed that tongue movement

Table 11
Results obtained by the *Kei2* system; described on Table 9, when evaluated over the *Keirn's DDBB* when 3 or more tasks were fused. Mean success rates are reported from classification experiments. A cross-validation procedure using 50% of the database for training and 50% for testing was applied.

Sys. Kei2	
Task/s	Mean success (%)
Tasks 1, 2 & 3	99.84
Tasks 1, 2 & 4	99.88
Tasks 1, 2 & 5	99.68
Tasks 1, 3 & 4	99.84
Tasks 1, 3 & 5	99.60
Tasks 1, 4 & 5	99.82
Tasks 2, 3 & 4	99.98
Tasks 2, 3 & 5	99.74
Tasks 2, 4 & 5	99.78
Tasks 3, 4 & 5	99.60
Tasks 1, 2, 3 & 4	100
Tasks 1, 2, 3 & 5	99.80
Tasks 1, 2, 4 & 5	99.80
Tasks 1, 3, 4 & 5	99.98
Tasks 2, 3, 4 & 5	99.78
Tasks 1, 2, 3, 4 & 5	100

imagery produced significant better results compared to hand tasks; around 10 points better, and that higher frequencies provided more discriminant information. Nevertheless, these results; and to that matter any result obtained with IIIaBCI03 DDBB (see Tables 12–14), must be taken carefully, as the database only contains 3 subjects. In fact, on a latter work from the same group, their results did show a superiority of left hand imagery task over right hand (Xiao & Hu, 2010).

In 2012, Yang and Deravi published an interesting work comparing motor imagery tasks and actual movements (Yang & Deravi, 2012). In particular, the database used contained two tasks performed under real movement and imagery conditions (*BCI2000* database (Schalk, Mcfarl, Hinterberger, Birbaumer, & Wolpaw, 2004)). The outcome was different for each task. One task gave better results when the actual movement was done while the other performed better under the imagery condition. When the authors studied the spatial information, they concluded that parietal and occipital channels P7, P8 and Oz, the pair Cz–Oz, the trios Cz–Oz–P7 or Cz–Oz–P8 and the quadruple Cz–Oz–P7–P8 contained the most discriminant information.

Finally, some works that used multi-task databases focussed merely on achieving high performances and did not report an individual study for each task. For example, He et al. applied Multivariate AR (mAR) coefficients and Naive Bayes classification (He, 2010; He, Lv, & Wang, 2009). When tested on verification over a 4 subjects database with 5 motion related tasks and recorded by 16 electrodes disposed around the scalp, the system obtained a Half Total Error Rate (HTER) of 6.70%. Soon after, He's group improved the system applying ICA as a spatial filtering tool and then using a simple 7 order AR model to characterize the brain activity (He & Wang, 2009). This improvement obtained an HTER of 2.20% on an expanded version of the database which contained 7 subjects.

Nguyen's et. al. study, introduced on Section 5.2, also tested several multi-task databases on their work (Nguyen et al., 2012). Their system obtained a 99.00% of classification on the IIIaBCI03 DDBB, a 46.24% on a 9 subjects database similar to the previous and a 80.80% database on another 9 subjects database with left and right hand imagery movement tasks.

Also in 2012, Yang and Deravi published an work comparing real versus imagined movements (Yang & Deravi, 2012). To do so, they relied on the BCI2000 DDBB (Schalk et al., 2004). The system used was based on statistics of the Discrete Wavelet Transform (DWT) coefficients as features and SVM and k-Nearest Neighbour (kNN) classifiers. They discovered differences in performance between real and imagined tasks, although these depended on the task. In addition, they reported that parietal electrodes near temporal areas gave the best results.

5.4. Consumer EEG

Once the validity of identifying subjects using their EEG was consolidated, researchers started to realize about its possibilities as a high security system (Thorpe & van Oorschot, 2005). However, for this to became a reality, the hardware side of it had to be reviewed. Medical EEG apparatuses are expensive and need qualified staff, conductive gel and at least 15 min of preparation. Some authors already tried to easy this process by using less electrodes. In fact, the first work on the field used only one occipital channel (Section 5.1). However, thanks to the advances made on the sensors' field, easy to use electrodes and commercial EEG caps started to be used for subject identification in 2008.

Riera et al. presented the first true viability test of a real EEG verification system (Riera, Soria-Frisch, Caparrini, Grau, & Ruffini, 2008). On doing so, they used a database composed of 51 registered users and 36 intruders, with REC sessions recorded in a time frame of 34 ± 74 days for each subject, thus including the effect of time on their experiment. The system used only two dry electrodes: FP1 and FP2. The proposed scheme applied five different feature extractors simultaneously: AR and PSD coefficients and 3 statistical measures. These features were then classified using 4 variants of the LDC technique, giving a total of 28 different subsystems. The best 5 combinations were selected for each registered subject and used for their corresponding record. Using no fully disjointed training and test sets, authors reported a classification accuracy of 98.10% on the mentioned database. Then, the best 15

Table 12
Structure of the systems tested with the *IIIaBCI03 DDBB*. Note that systems 1–6 use only channels C3, C4, P3, P4, O1 and O2.

Sys.	Band [Hz]	Features	Classifier	Ref.
IIIa1	[0.5–100]	AR + Linear Complexity + PSD + Phase Locking Value	BP-NN	Bao et al. (2009)
IIIa2	[8–13]			
IIIa3	[14–20]			
IIIa4	[21–30]			
IIIa5	[2–40]	IIIa1's features + Energy Entropy + Mutual Information + Cross-correlation		Hu (2009a)
IIIa6	[2–40]	ARMA model		Hu (2009b)
IIIa7	[8–30]	DWT		Jiang and Hu (2009)
IIIa8	[8–13]			
IIIa9	[14–20]			
IIIa10	[21–30]			
IIIa11	Full	SCBI-NR; 10 highest coeffs of LDC		Xiao and Hu (2010)
IIIa12	Same as Zha37 on Table 5			Nguyen et al. (2012)

Table 13
Results obtained by the systems described on Table 12 when evaluated over the *IIIaBCI03 DDBB*. These systems were applied to each recorded task individually. A cross-validation method which uses 50% of the database for training and the other 50% for testing was applied. Mean success rates and mean EERs for each task are reported for classification and verification experiments respectively.

Sys.	Task1 (%)	Task2 (%)	Task3 (%)	Task4 (%)
Classification				
IIIa1	81.20	82.10	82.80	90.60
IIIa2	∼61	∼62	∼68	∼68
IIIa3	∼56	∼57	∼54	∼55
IIIa4	∼81	∼72	∼76	∼88
IIIa6	76.70	77.90	80.90	92.20
IIIa11	82.40	79.10	81.70	88.10
Verification				
IIIa6	80.80	80.50	81.30	92.80

Table 14
Results obtained by the systems described on Table 12 when evaluated over the *IIIaBCI03 DDBB*. These systems were based on MTL, and therefore used EEG from all the recorded paradigms to calculate a final answer. A cross-validation method which uses 50% of the database for training and the other 50% for testing was applied. Mean success rates are reported for classification experiments and mean EERs for verification experiments.

Sys.	Mean success (%)
Classification experiment	
IIIa7	84.07
IIIa8	∼74
IIIa9	∼65
IIIa10	∼85
IIIa12	99.00
Sys.	EER (%)
Verification experiment	
IIIa5	∼13

classifiers were fused on a single verification system, achieving an EER of 3.4%.

By the same time, Miyamoto et al. published two works using Tottori DDBB (Baba et al., 2008; Miyamoto et al., 2008) (see Table 15). Aiming to build a practical system, the authors proposed really simple designs based on spectral features and similarity measures. These models achieved errors of around 20% in verification. A year latter, they managed to lowered this to 11.00% using the concavity and convexity of the spectral distribution from the alpha band (Nakanishi et al., 2009).

Kennet provided a deep statistical study of multiple features extracted from EEG recorded at different tasks (Kennet, 2008). His 12 subjects database was composed of relaxation, counting, read a text and thinking on a color, on rotating a mouse, on a password, on music and on words starting with the letter "M". Several features were computed. The results showed that the power of high frequencies; between 20 and 50 Hz, were the more promising based on their *std*/*mean* rate, while the mean of the phase angle obtained the worst score. In addition, features from the mid-range frequencies were the most normal, i.e. the more stable. In this case, no relation between features and tasks was found on a Manhattan distance based analysis.

In 2010 Su et al. presented an interesting work on the effects of the diet and/or circadian rhythms on these systems (Su, Xia, Cai, Wu, & Ma, 2010). With this aim, they taped a 40 users database with the consumer EEG "HXD-I" while subjects were REC. The database included sessions captured after the intake of coffee and at different times of the day. Using AR coefficients and PSD from 5 to 32 Hz as features, the system achieved 97.5% of accuracy when classifying with a combination of LDC and kNN, 81.90% when classifying with an NN, and 79.60% when classifying with an SVM. The results also showed a decrease in accuracy of around 10 points when coffee was drunk and a rise when the length of the testing EEG signal increased. Latter, a deeper study demonstrated that these differences on performance were in fact statistically significant, and that diet and coffee affect the system reliability (Su, Xia, Cai, Ma, 2010).

Finally, Zhao et al. published a number of works on Lanzhou DDBB (Hu, Liu, et al., 2011; Hu, Mao, et al., 2011; Zhao, Peng, Hu, Li, et al., 2010; Zhao, Peng, Hu, Liu, et al., 2010) (see Tables 16 and 17). The latter of these works was the first to deeply study the influence of time over long periods (around 6 months) on a commercial EEG (Hu, Liu, et al., 2011). The results reiterated the conclusions previously found by Marcel and Millan (2007). Moreover, their system was fully implemented so that EEG could be recorded from a mobile device and sent to a server for its processing. Other fully implemented systems have also been published recently (Klonovs, Petersen, Olesen, & Hammershoj, 2013; Mohanchandra, Lingaraju, Kambli, & Krishnamurthy, 2013).

5.5. Other approaches

All the works introduced so far tried to implement security systems identifying or verifying the users' identity directly from their EEG activity. However, other works applied an indirect approach based on information other than the subject's identity that will ultimately help to identify them.

Palaniappan's group has been specially interested in such approach. After studying the P300 wave under target and non-target visual stimulus (Gupta, Palaniappan, & Paramesran, 2012; Gupta, Palaniappan, & Swaminathan, 2008), they proposed a system to introduce a password mentally. The system flashed letters (Gupta, Khan, Palaniappan, & Sepulveda, 2009) or numbers (Palaniappan, Gosalia, Revett, & Samraj, 2011) to users on a screen. When the target (that matching with the following password digit) was flashed, the subjects brain produced a P300 response which was then detected by the system. In this process, the password is built internally and then verified. The method achieved relatively high performances on small databases composed of only 4 subjects.

Table 15
Verification experiments run over the *Tottori DDBB*. System structures and EERs are reported. All the experiments run a cross-validation procedure using 50% of the database for training and 50% for testing.

Sys.	Band [Hz]	Features	Classifier	EER (%)	Ref.
Tot1	[7.8–13.3]	Non-dominant region of the power spectrum	Similarity measures	30	Miyamoto et al. (2008)
Tot2		Variance of spectral power		30	
Tot3		Fusion of Tot1 and Tot2		21	
Tot4	Full range	N maximum spectral values and their frequencies		30	Baba et al. (2008)
Tot5		Sum of frequency values over a threshold		31	
Tot6	[8–13]	Concavity of spectral distribution, variance, convexity of spectral distribution		11	Nakanishi et al. (2009)
Tot7	Score fusion of Tot4 and Tot5			28	Baba et al. (2008)

Table 16
Structure of the systems tested with the *Lanzhou DDBB*.

Sys.	Band [Hz]	Features	Classifier	Ref.
Lan1	Full range	6 order AR	kNN	Zhao, Peng, Hu, Li, et al. (2010)
Lan2		ApEn + C_0-complexity + The correlation dimension D_2 + The largest Laypunov Exponent		
Lan3	[0–40]	FastICA; Center freq + max power + average peak-to-peak value + power ratio		Zhao, Peng, Hu, Liu, et al. (2010)
Lan4	[4–7]			Zhao, Peng, Hu, Li, et al. (2010)
Lan5	[8–13]			
Lan6	[12–15]			
Lan7	DWT noise reduction	(PSD by adapatative AR model): Lan7's features + activity, mobility and complexity Hjorth parameters		Hu, Liu, et al. (2011)
Lan8	DWT noise reduction; [8–13], [14–30] and [4–7] Hz	(PSD by AR model) Maximum PSD and its frequency + PE of each rhythm	Naive Bayes Classifier	Hu, Mao, et al. (2011)

Table 17
Results obtained by the systems described in Table 16 when evaluated over the *Lanzhou DDBB*. Classification and verification experiments are differentiated. The experimentation procedure is detailed in each case and success rates are provided.

Sys.	Notes	Success (%)
Classification experiments		
Lan3	3k-folds over 3 registered users	99.23
	3k-folds over 4 registered users	~98.50
	3k-folds over 5 registered users	~97.75
	3k-folds over 6 registered users	~97.60
	3k-folds over 7 registered users	~97.25
	3k-folds over 8 registered users	~97.20
	3k-folds over 9 registered users	~96.90
	3k-folds over 10 registered users	96.77
Lan1		83.78
Lan2		<25
Lan4		97.29
Lan5		94.59
Lan6		94.59
Lan8	Using 4 s of EEG	~65
	Using 60 s of EEG	~100
Verification experiments		
Lan7	11 registered users + 11 intruders	~66
	Same day test	94.60 TAR
	1 week latter test	83.64 TAR
	6 months latter test	78.20 TAR

Another interesting work was presented by Yeom, Suk, and Lee (2011, 2012). They used the differences between VEPs elicited by self and non-self images to verify users (see Fig. 8). When tested on a verification experiment, the model achieved an 86.10% of accuracy on a 5 subjects database. In addition, the authors noted that frontal, central and parietal regions provided the most discriminant data.

6. Discussion

At this point, one can affirm that the problem of subject identification by means of EEG is sensitive to several factors, such as the spatial location of electrodes, frequencies, time span, recording paradigm, subject condition and the system's architecture. This section draws a global picture of the findings located in the state of the art, discussing everyone of the mentioned factors individually.

Previously, it is important to discuss the usage of EEG recorded from unhealthy subjects for the evaluation of EEG based identification systems. This has been the case of several works (Brigham & Kumar, 2010; Altahat, Huang, Tran, & Sharma, 2012a; Nguyen et al., 2012; Palaniappan & Mandic, 2007; Zuquete, Quintela, & Cunha, 2010a, 2010b), which used data from healthy and alcoholic users. The problem with this practice is that alcohol has been proven to affect various aspects of the EEG (Begleiter & Porjesz, 2006; Zietsch et al., 2007), including the so much used alpha rhythm (Vogel, 2000). Therefore, it is likely that such datasets were biased, overrating the systems' performances. In order to clarify this, a statistical study probing that the parameters used are not affect by the disorder, i.e. assuring they are uncorrelated, must be adjoined.

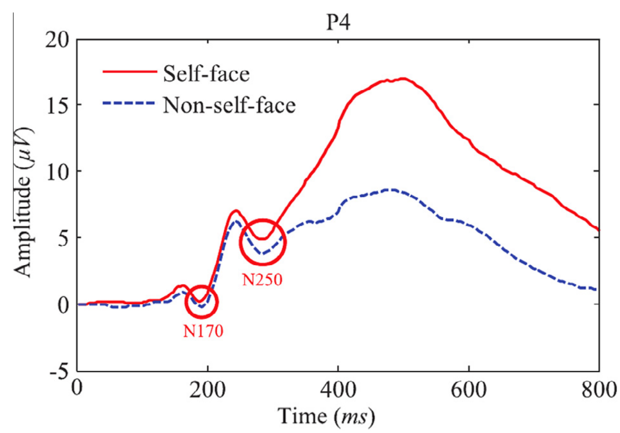

Fig. 8. VEPs elicited by self and non-self face images (Yeom et al., 2012).

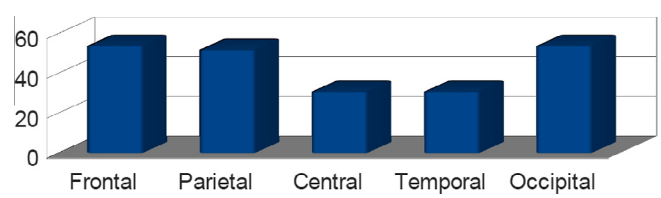

Fig. 9. Number of publications using channels from a specific brain area.

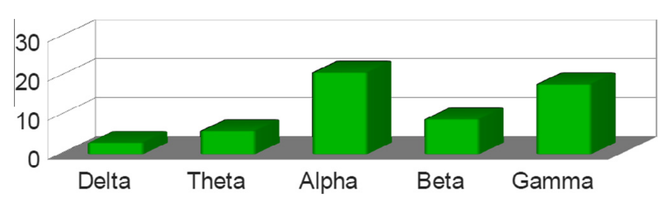

Fig. 10. Number of publications using a specific brain rhythm. Publications using bandwidths including more than a single rhythm were not included in this representation. The number of publications in the gamma band is mainly due to the amount of publication based on VEPs.

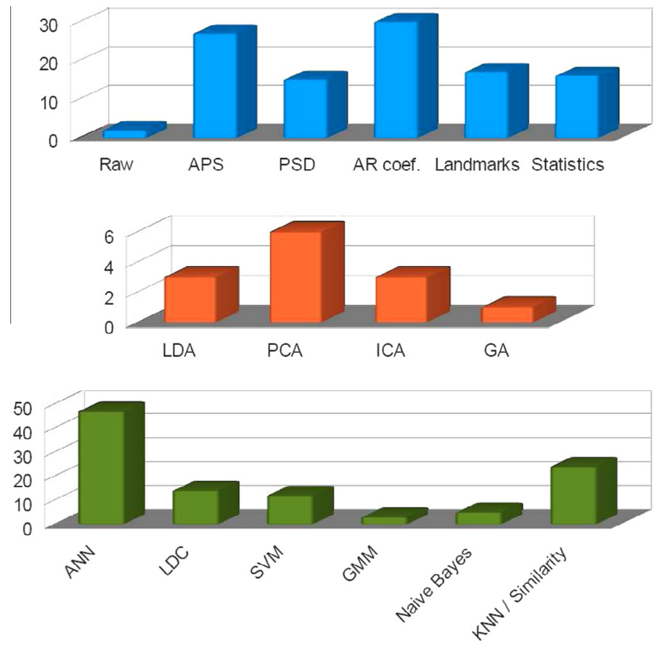

Fig. 11. Number of publications using a specific algorithm for description, feature selection and classification respectively from top to bottom.

6.1. Which are the subject specific traits of the EEG?

The works referenced above confirm that EEG subject traits are present within the frequency domain. Which exactly these traits are is, at the moment, less clear. Genetic and physiology studies affirm that the power and peak frequency of the alpha band present the strongest heritability relationship, followed by the beta band (van Beijsterveldt & van Baal, 2002; Eischen et al., 1995). Nevertheless, they proved to be insufficient to obtain high accuracy rates on biometric systems, forcing researchers to explore the usage of different characteristics. The results suggest that other frequencies may carry substantial discriminant information as well. Unfortunately, such efforts have been aimed exclusively to increase performances, without paying attention to the extend and the significance of the features used. The lack of an extensive study prevents drawing any further conclusions.

6.2. Where are these traits in terms of space and frequency?

Space and frequency are probably the two most determining factors of the actual problem. The location of the most informative source in terms of space and frequency is closely related to the trait evaluated as discriminant; as different brain regions and waves have been linked to different mind processes.

6.2.1. Differences in channel locations

Given that the posterior rhythm was described as highly genetically determined by genetics and neurophysiology, results reporting occipital, temporal and parietal areas as the ones providing the most discriminant information under REC condition could be expected (Campisi et al., 2011; La Rocca et al., 2012; Mohammadi et al., 2006). On contrary, the opposite scenario was observed under REO, exhibiting the implication of more anterior brain areas during further interpretations of the scene (*visual pathway* (Bear, Connors, & Paradiso, 2006)) (Abdullah et al., 2010a, 2010b; Tangkraingkij et al., 2009; Tangkraingkij, Lursinsap, Sanguansintukul, & Desudchit, 2010).

Apparently, the valance tilts again towards the occipital region on VEP experiments (Das et al., 2009). Although this effect is less reported, if finally true, it could be explained by the usage of systems tuned to analyze ERPs; more easily detected on the occipital lobe, rather than general traits of the EEG. On the other hand, Yeom's et al. studies showed that when the experimental procedure implies personality and self-representation thinking, as in VEPs elicited by self images, frontal brain areas take the baton of the most discriminant (Yeom et al., 2011, 2012). This may be again a consequence of the visual pathway.

The spatial factor has been less studied on multi-task databases. To the point that Yang's et. al. study is the only one to explore it, and they did so with small (only 3 subjects) IIIaBCI03 DDBB (Yang & Deravi, 2012). Their results suggest that parietal areas near the temporal lobes carry the most discriminant information.

Differences between hemispheres are even less clear. Some studies, including some neurophysiology, concluded that there is no significant hemisphere effects (Abdullah et al., 2010a; van Beijsterveldt, Molenaar, de Geus, & Boomsma, 1998; Tangkraingkij et al., 2009, 2010). However, others have reported that such difference does exist (Abdullah et al., 2010b; Palaniappan & Mandic, 2007; Xiao & Hu, 2010). In the latter case, they all described a scenario where the right hemisphere outperformed the left (see Fig. 9).

6.2.2. Differences in frequency bands

The frequency factor has received much less attention. Mainly because authors already aimed to information localized on a specific part of the spectrum, based on previous studies or on their own experience.

On the REC paradigm, neurophysiology as well as biometric studies concluded that alpha and delta rhythms are the most

Table 18
List of acronyms, along with Table 19.

AEP	Auditory Evoked Potentials	ANN	Artificial Neural Networks
APS	Absolute Power Spectrum	AR	Auto-regressive
BMI	Brain Machine Interface	BP-*	Back Propagation on ANN
CG	Computational Geometry based classifier	CLC	Channel Lineal Complexity
CNN	Competitive ANN	COP	Copula-Based Classifier
$D\text{-}_*$	Diagonal covariance matrix computations	DBI	Davies Bouldin Index
DZ	Dizygotic	EEG	Electroencephalogram
EER	Equal Error Rate	ERP	Even Related Potential
Eucl.	Euclidean metric	FA-NN	Fuzy ARTMAP ANN
FF-NN	Feed-forward ANN	FFT	Fast Fourier Transform
FJLT	Fast Jonson-Lindenstrauss Transform	GA	Genetic Algorithms
GLM	Gaussian Linear Model	GMM	Gaussian Mixture Model
GSMC	Gaussian kernel SMC	HTER	Half Total Error Rate
ICA	Independent Component Analysis	$IH\text{-}_*$	Inter-hemispheric computations
kNN	k-Nearest Neighbour	LDA	Linear Discriminant Analysis
LDC	Linear Discriminant Classifier	lSVM	Linear SVM

Table 19
List of acronyms, along with Table 18.

LVQ-NN	Linear Vector Quantization ANN	Manh.	Manhattan metric
mAR	Multivariate AR	MFCC	Mel-Frequency Cepstral Coefficients
MTL	Multi Task Learning	MUSIC	Multiple Signal Classification
MZ	Monozygotic	NBC	Naive Bayes Classifier
Norm.	Normalized	PCA	Principal Component Analysis
⁎-NR	Applied for noise reduction	PSD	Power Spectrum Density
QDA	Quadratic Discriminant Analysis	REC	Resting with eyes closed
REO	Resting with eyes open	RB-ENN	Resilient BP-ENN
RBF-SVM	Radial Basis Function kernel SVM	SCBI	Second Order Blind Separation
SD-FIR	Sum Difference FIR filter	SFA-NN	Simplified FA-NN
SLSF	Surface Laplacian Spatial Filtering	SMC	Similarity Measure Classifier
SNR	Signal to Noise Ratio	STL	Single Task Learning
SVM	Support Vector Machine	SVDD	Support Vector Data Description
VEP	Visual Evoked Potential	WPD	Wavelet Package Decomposition

discriminant, followed by the theta and the beta rhythm (Eischen et al., 1995; La Rocca et al., 2012; van Beijsterveldt et al., 1998; van Beijsterveldt & van Baal, 2002). Within the alpha rhythm, the middle section have outperformed the first and last portions in some experiments (Poulos, Rangoussi, Alexandris, 1999; Poulos et al., 2001). However, this has not been always the case, and the theta rhythm has been reported to be the most discriminant (Zhao, Peng, Hu, Li, et al., 2010).

On other paradigms, it has been usually the case were higher frequencies produce better classification rates (Bao et al., 2009; Jiang & Hu, 2009; Kennet, 2008; Nakanishi et al., 2012) (see Fig. 10).

6.3. Are they constant across recording paradigms and time?

6.3.1. Effects of recording paradigms

Performance differences on multi-task databases have been reported since the very first moment; except for Kennet's statistical work (Kennet, 2008). The first results by Palaniappan suggested that the most mind demanding tasks could provide the best discriminant information (Palaniappan, 2005). However, this was soon diluted by a second work of him, where the ranking was fully inverted (Palaniappan, 2006).

The lack of homogeneity on results, even on those obtained by the seam research group, makes them hard to interpret. Even in a comparison between left and right hand movement imagery tasks, there are several works reporting that the left outperforms the right (Marcel & Millan, 2007; Sun, 2008; Xiao & Hu, 2010; Zuquete et al., 2010a), while others states something different (Bao et al., 2009; Hu, 2009b).

What seems to be more clear is that the systems extracted some task dependant discriminant information, and that such information are partially disjoint between tasks. This is pointed out by the fact that Palaniappan's works found the best combination of tasks to be the best and the worst individually performing tasks. In other words, tasks with the less discriminant data contained some useful information not included, or not accessible, on the best performing tasks. These hypothesis seems to be in line with Sun's results on MTL (Sun, 2008).

Regarding the indirect methods studied by Palaniappan's work, listed in Section 5.5, it is important to note that this system does not measure any EEG subject specific traits. On contrary, they constitute BMIs to enter passwords. As a consequence, the circumvention quality of the EEG based biometric systems is lost.

6.3.2. Effects of time

Genetic and neurophysiology studies have described changes on the human EEG across maturation, some of which are related to the heritable traits. Even though these must be considered in genetic studies, one can decide not to contemplate them in a security system, as they are long span effects specially present in early ages (until 19–20 years old) (Vogel, 2000).

Is in the short time span scenario where complications arise. Genetic and neurophysiology works have observed a great stability of the EEG PSD between sessions recorded even one year apart (Näpflin et al., 2007). However, except for Nakanishi et al. visual inspection (Nakanishi et al., 2009), all biometric researches have contradicted this.

Marcel's and Milla's first statements about the drop in performance when the training and test sessions get further apart and about how this can be circumvented by a multi-day-session training approach (Marcel & Millan, 2007) got later reinforced by several works (Brigham & Kumar, 2010; Hu, Liu, et al., 2011; Kostílek & Šťastný, 2012). Moreover, studies on diet and circadian effects revealed how sensitive a system could be to changes of the EEG elicited by common events, such as the intake of coffee or daily physiological changes (Su, Xia, Cai, Ma, 2010; Su, Xia, Cai, Wu, et al., 2010; Su, Zhou, Feng, & Ma, 2012).

6.4. Which are the best techniques to extract and evaluate such traits?

Explored features can be divided in two big groups: "general focus features" and "specific landmarks/descriptors". The majority of the publications fall in the former group, which refers to features that describe EEG signals extensively, in a way that the discriminant information is not directly presented, but hidden within the whole picture. Some examples are coefficients of AR models and PSD. Thus, in these cases, it is the responsibility of the classifier; or of the applied feature selection technique, to find/access the right data.

The latter group refers to specific measures, such as the peak APS and its corresponding frequency. In these cases, the discriminant information targeted by the authors is directly given to the classifier, facilitating its task. These have been the *de facto* features used on consumer EEG databases, mainly because their low processing complexity and speed. Although they have achieved lower accuracies compared to general focus features, they have proven to boost the system performance when added to the general focus features. For example, Palaniappan improved his system on a multi-task database by adding ASP measures from each sub-band to AR coefficients (Palaniappan, 2008), even if the AR coefficients already had such information; in fact ASP values were computed from the AR coefficients.

Fig. 11 show the amount of publications using each technique.

7. Conclusions

This work has presented an extensive research of the state of the art on EEG based identification systems. Based on the results exposed, it seems clear that the EEG, and in particular its spectral distribution, contains subject specific information that can be used in an identification system. Moreover, researches suggest that this is specially true for data contained in the alpha rhythm.

Perhaps, one of the most striking facts of the reported results is the low level of agreement between them. However, this is just the representation of the complexity of the heritable model underlying EEG traits, along with the amount of variables in the problem. On top of that, these variables are not independent from one another, but a change in one of them affect the location of the optimal point on others. This is, therefore, a problem of great complexity, from which only the surface have been scratched so far.

Nevertheless, several characteristic behaviors of these biometric systems can be extracted. Some of these aspects may be expected, such as the fact that the usage of data from multiple electrodes, rhythms and tasks increases the system's performance. Others, however, contradict the results of genetic and neurophysiology studies, such as the observed worsening in the system's ability to discern between subjects when the training and the test sets get further apart in time; although this can be easily overcome by assuming a multi-day-session training approach and/or a continuous learning method.

Other features are less clear. Consumer EEG devices may give worst results than medical equipment, presumably because of the quality of the recorded signal. On the other hand, if the traits used are robust enough to noise, this may not be the case. A specific experiment where the same database is recorded with both equipments is necessary to make a final statement. In addition, tools such as PCA-NR, LDA for feature reduction and LDC and SVM seem to provide higher performances, although this depends, again, on all the other problem variables.

In order to shed light on these questions and those discussed in Section 6, an extensive study remains to be done. First, an exploration of the spectral domain of databases of different nature may clarify where, in terms of location and frequency, the discriminant information is, and how it is affected by factors such as time and recording paradigms. More importantly, this research should be done having into account the physiological implications of whatever findings. It is important to note that, even though genetic studies have already explained some of this, they did not have the exact same aim as biometric studies, and therefore the experimental conditions were not the same.

It is just after this fundamental research that high accuracy levels in terms of biometric systems should be pursued. In this case, well controlled experiments and configuration grids will allow to build a ranking of the best combinations of EEG traits and algorithms.

Appendix A. Acronyms

Tables 18 and 19 provide the list of acronyms used along the text.

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