Event-related potential from EEG for a two-step Identity Authentication System

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***Abstract*—Current problems related to high-level security access are increasing, leaving organizations and persons unsafe. A recent good candidate to create a robust identity authentication system is based on brain signals recorded with electroencephalograms (EEG). In this paper, EEG-based brain signals of 56 channels, from event-related potentials (ERPs), are used for Subject identification. The ERPs are from positive or negative feedback-related responses of a P300-speller system. The feature extraction part was done with empirical mode decomposition (EMD) extracting 2 intrinsic mode functions (IMFs) per channel, that were selected based on the Minkowski distance. After that, 4 features are computed per IMF; 2 energy features (instantaneous and teager energy) and 2 fractal features (Higuchi and Petrosian fractal dimension). *Support vector machine (SVM)* was used for the classification stage with an accuracy index computed using 10-folds cross-validation for evaluating the classifier's performance. Since high-density EEG information was available, the well-known backward-elimination and forward-addition greedy algorithms were used to reduce or increase the number of channels, step by step. Using the proposed method for subject identification from a positive or negative feedback-related response and then identify the subject will add a layer to improve the security system. The results obtained show that subject identification is feasible even using a low number of channels: E.g., 0.89 of accuracy using 5 channels with a mixed population and 0.93 with a male-only population.**

***Index Terms*—biometrics, security, identity authentication system, subject identification, electroencephalograms (EEG), empirical mode decomposition (EMD)**

I. Introduction

Security systems are important for business and personal purposes, to protect places and information where privileges are required, and different measures have been proposed. Traditional security systems use metrics ranging from security-guards, smart-cards, fingerprint and recently face-recognition, depending on whether the protection is for an organization or for a low-cost portable device [1], [2]. Systems based on image processing or fingerprint techniques, were accepted in the industry very fast. However, the vulnerabilities of authentication/authorization process of current security systems are growing, since authentications systems cannot discriminate between an authorized user and an intruder who fraudulently obtains the access privileges. Due to this, the interest in exploring new biometric measures is growing steadily [2].

Recently, the interest in using brain signals to create a biometric marker analyzing different neuro-paradigms has emerged as a good candidate to replace traditional security systems overcoming the vulnerabilities mentioned previously [3], [4]. Brain signals can be used as a measure to create a security system since they satisfy the requirements of *universality, permanence, collectability, performance, acceptability, and circumvention* [1].

Electroencephalography (EEG) is a popular non-invasive technique to record bio-electrical brain activity from a given neurological mechanism or neuro-paradigm, which can be adopted by Brain Computer Interfaces (BCI) for varied objectives [5]. Since brain signals are typically used to analyze problems relative to the subject internal state of mind, this suggests the existence of unique patterns in the subject. Additionally, EEG recordings will not be possible to replicate or duplicate since the brain is highly individual, even in the same task at the same time [6].

Event-related potentials (ERPs) are very small voltages that appear on the scalp of human brain as a response to specific events or stimuli that are time- and phase-locked. These have been used to evaluate the brain functioning and response to stimuli. ERPs produce several well-known patterns and one of the most studied is the P300 peak, that occurs approximately 300 ms after the stimulus onset. The P300-speller paradigm is developed with the initial aim to restore communication in locked-in state patients [7] and it normally consists of a NxN matrix of characters that are presented to the subject in random sequences of intensified column and row (flashed). This constitute an oddball paradigm [7], [8].

Using machine-learning techniques it's possible to create models to categorize different sets of features. In the case of the EEG signals it's not computationally effective to use all the data generated by the human brain as a response to a specific event. For that purpose, a feature extraction stage is used to obtain strong descriptors or characteristics that can increase the classifier performance. The empirical mode decomposition (EMD) has been successfully employed to analyze brain signals and extract information through the *shifting process* and it has shown to be robust decomposing non-stationary and non-linear data.

Once a set of features is extracted, it's possible to create machine learning based models to use it in real-time. Another important point is the channel placement, which in this paper is explored gradually by increasing or removing the number of used channels. There are some relevant approaches in the state-of-the-art, which are presented in next section.

II. Related work

Previous research works report the use of different configurations of neural networks, for example, authors in [9] presented an approach called global spatial and local temporal filter (GSLT) for the well-known convolutional neural network (GSLT-CNN) without feature extraction. They used visual evoked potentials from high-density EEG channels (28, 32, 64, and 256). They argue that using the neural network they obtained the highest accuracy compared with the use of *support vector machine (SVM)* (0.96 vs 0.93). In the case of *SVM* they used power spectral density (PSD) to extract features.

Authors in [10] presented and approach using 1D convolutional long short-term memory neural network (1D-Convolutional LSTM) validating the method with a dataset of 119 subjects and 64 channels. They report an accuracy of 0.92 using only 4 channels, the validation was made using only 3-folds cross-validation. However they used 12 seconds of the EEG signals per instance, which is impractical for a real-time system.

Recently, the EMD algorithm has been successfully applied to decompose raw EEG signals, extracting thus the intrinsic mode functions (IMFs) [3], [4]. The methods used for subject identification have been tested using *imagined speech* [4], [11] and *resting-state* [3]. Another approach for feature extraction using resting-state as neuro-paradigm, is the well-known power spectral density (PSD), reported in [12] considering 18 channels and obtaining an accuracy around 0.97 in the best case.

In [11], the discrete wavelet transform (DWT) was used to extract 4 levels of decomposition from the raw EEG data, and extracting instantaneous and teager energy from each level of decomposition. In that work, the approach was to investigate the feasibility of using imagined speech for subject recognition using a dataset of 27 subjects and EEG data from 14 channels of the Emotiv Epoc device. Additionally, the EMD method has been compared with the DWT, and it has been shown that EMD performs better when using a low number of channels and a low number of instances [3].

Because resting-state do not need any special or prior training, it has been shown to be a good candidate for this task [3], [12]. Event-related and visual-evoked potentials have also been successfully used for subject identification [13].

In summary, the state-of-the-art reports different approaches for subject identification. There are some proposals for feature extraction [4], [9], for classification [3], [4], [9], [10] and others using different neuro-paradigms [4], [11]–[14]. In addition, more aspects of the subject can be exploited to improve the performances of the proposals. Some works have shown that using male-only population or female-only population, the accuracy and the localization of the channels may differ [15]. In this work, a comprehensive set of experimental results are provided to support this case.

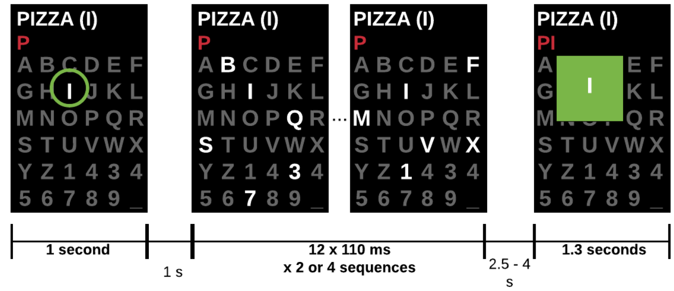

Fig. 1: Protocol design using P300-speller paradigm for recording positive or negative feedback-related responses [16].

In the next sections, the dataset and methods used are described to then present a set of experiments to evaluate the proposal.

III. Materials and methods

This section describes the process used with the aim of subjects identification. First, the dataset used is described briefly, then the methods for feature extraction and classification are presented. After that, the channel selection criteria, as well as the elbow point technique to find an approximation to the best combination between the lowest number of channels and the highest accuracy, are described.

A. Dataset

The complete dataset consists of EEG signals from 26 subjects (24 right-handed, 2 left-handed; 13 Females, 13 Males; Average age of 29.2 $\pm$ 5.5, age range 20-40) from 56 passive EEG electrodes placed following the extended 10-20 international system. The data is down-sampled at 200 Hz [16].

The protocol followed to record EEG signals is presented in Fig. 1. In summary, the protocol used to record the EEG signals from each subject is as follow: The target letter (The letter to be presented) was indicated by a green circle for 1 second. After that, letters and numbers (6X6 items, 36 possible items displayed on a matrix) are flashed by groups of 6 characters. Next, there are no changes in the display during a period of random delay/resting-state of 2.5 to 4 seconds. During the random delay (2.5 to 4 seconds) the subjects remember the letter displayed. Then, the letter chosen by the implemented P300 classifier is displayed during 1.3 seconds. If the presented letter is the one that was presented before, the subject sends a positive feedback, otherwise the subject sends a negative feedback [16].

Fig. 1 also shows an example of positive feedback-related response corresponding to the target letter *i* presented during 1 second and the feedback during 1.3 seconds.

For this study, only 24 subjects were taken into account, since there are 2 subjects (one female and one male) that are left-handed and to provide more information about left-handed population a higher number of subjects will be necessary.

B. Feature extraction

The EMD algorithm, has been effective in decomposing non-linear and non-stationary signals into a finite number of IMFs by applying the *sifting process* [17].

The method used for feature extraction was presented in [4]. In summary, the method is based on the EMD algorithm for which the first 2 more relevant IMFs were chosen based on the Minkowski distance. Then, for each IMF, 4 features were computed: *instantaneous and teager energy distribution*, and *Higuchi and Petrosian fractal dimension*.

This process is repeated for each channel to extract 8 features for each channel and then all the features are concatenated to obtain a feature vector that represents the EEG signal for each instance.

C. Classification

Because of the high computational cost required by most classifiers based on neural networks, and since our purpose is real-time classification using large datasets, *SVM* is used in this paper.

A key feature of *SVM* is that the classification complexity does not depend on the dimensionality of the features space and that the sensitivity to the number of features is relatively low. Therefore, it can learn a larger set of descriptors and also might be able to scale the number of features and classes in a better way than neural networks [18], [19]. To evaluate the performance of the classifiers created, an accuracy index using 10-folds cross-validation is used.

From the computational cost point of view, the necessary time to create a machine-learning model using *SVM* is $\mathcal{O}(N^3)$, where N is the length of the feature vector. To predict the class of a new instance using the created model needs $\mathcal{O}(1)+\mathcal{O}(N)$ [20].

D. Channel reduction criteria

The logic of the first method for channel reduction is based on a *greedy* algorithm described in details in [3]. The idea is to obtain all the possible combinations removing 1 channel at a time (k-combinations: $k = 1$), perform the feature extraction considering only the subset and then perform the classification stage. This process is repeated with each subset and the subset with the highest accuracy (local maximum) is selected. Then, the procedure to delete another channel is repeated with the subset obtained while the length of the subset is still higher than 1 channel.

The second method used for channel reduction is opposite to the previous one. The idea is to create a classifier for each channel and select the one with the highest accuracy, then repeat the process trying to add another channel and select the subset of two channels with the highest accuracy. The process is repeated adding another channel and it is completed when all the channel are added to the subset. This method provides an idea of the channels with more useful information for the classification stage.

These methods are also known in combinatorial optimization and artificial intelligence as forward-addition and backward-elimination algorithms and have been used in feature subset selection [21]–[23].

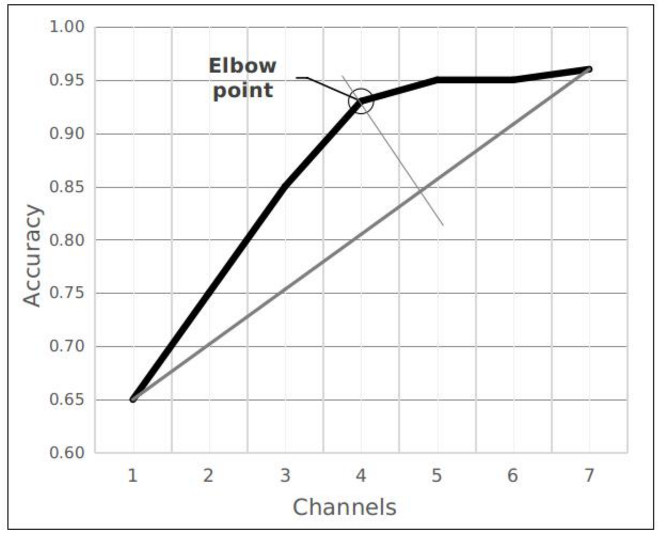

Fig. 2: An illustrative example of the *elbow method* for selecting the "optimal" number of channels.

Both methods provide an optimal solution at each step, but also none of them is able to predict complex iterations between channels or features that might affect the accuracy of the classification, that is why it is not considered as a global solution. To provide an idea of how many channels are necessary, it's also required to automatically select the "optimal" number of channels, considering that it must be low for a real-life implementation.

E. Elbow method for computing the optimal number of EEG channels

A well-known method for automatic selection of the optimal number of clusters in the *k-means* algorithm is named *elbow method*.

The *elbow method* uses within-cluster sum of errors (wcss) that is the sum of each clusters distance between that specific clusters to each point against the cluster centroid [24]. Drawing a straight line from point 1 to *N*, where *N* is the max number of clusters, and calculating the distance from each point (corresponding to the number of clusters used) to this line, the point with the largest distance is the optimal *k* for *k-means* algorithm.

The previous idea can be used to select automatically the "optimal" number of EEG channels calculating the maximum distance from the line created between the first accuracy and the last one. This "optimal" number will be a relationship between the highest accuracy reached and the lower amount of EEG channels used. In Fig. 2, an example of this concept is shown.

IV. Experiments

In the following subsections, we present the experiments performed using feedback-related potential from EEG signals to identify subjects. For each subject in the experiment, EEG signals from 5 different sessions and 60 instances per session were used, therefore 100 instances per subject. For the classification stage we use *SVM*, because of the good results obtained for EEG signals classification in different tasks [3].

A. Subject identification reducing or increasing the number of EEG channels

For this experiment, 24 subjects were used to create the classifiers. In Fig. 3, the accuracies obtained with *SVM* using 10-folds cross-validation are presented. The experiment was repeated by removing and adding channels, and during positive or negative feedback-related responses. In Fig. 3, the point when the maximum accuracy was reached in all the cases and the channels used for each case are shown 4.

Using the accuracies from one channel to the number of channels when the highest accuracy is reached, it is possible to calculate the "optimal" number of channels using the *elbow method*.

Fig. 4 also shows with a black label if the channel used to obtain the highest accuracy is used when removing or when adding channels following the method described previously, in both cases, using positive and negative feedback-related potentials.

The accuracies reached using positive feedback-related response are 4% higher than using negative feedback-related response. This is true for both cases, when reducing or increasing the number of channels. In the case of positive feedback, the highest accuracy is reached with only 19 channels, which is still high, but if the *elbow method* is applied the number of channels selected is 4, with an accuracy of 0.89.

After the maximum accuracy is reached, using more channels shows only some fluctuations, without providing useful information to improve/increase the accuracy.

Another interesting result of this experiment is shown in Fig. 4, where it is shown that channels from both hemispheres are used in all the cases and as it is expected from nature of the neuro-paradigm, most of the useful channels found following the methods are around the occipital lobe.

B. Subject identification in a male-only population

To figure out if the accuracy is affected by only taking into account a male population, the experiment was repeated but considering only the 12 right-handed males subjects in the dataset. Fig. 5 shows the accuracies reached and the corresponding channels in Fig. 6.

In the case of positive feedback-related response and comparing the results from Fig. 3 and 5, the maximum accuracy (0.99) reached was using 18 channels but if only the males population is used, the maximum accuracy (0.99) is reached only with 9 channels. Fig. 6 shows another important difference using only the male population: the number of channels used in the case of the positive feedback-related potential is lower (both cases, reducing or increasing the number of channels) than the case of subject identification with the negative feedback-related response.

Fig. 6 shows also clear differences using positive feedback-related responses, and the channels found using both methods are around the occipital lobe and from both brain hemispheres as well. In the case of the negative feedback-related responses, the number of channels to reach the highest accuracy is relatively high, but using around 6 channels the accuracy reached is 0.94, only 2% lower than the highest one.

C. Subject identification in a female-only population

The previous experiment was repeated but considering only the 12 right-handed females subjects in the dataset, with the aim of comparing the accuracies in both populations and the results from the first experiment. Fig. 5 shows the accuracies reached and the corresponding channels in Fig. 6.

The channel distribution in the female population is similar to the experiment mixing both populations (the first experiment presented in sec IV-A), in the sense that channels are distributed around the entire head.

Using only a female population the maximum accuracy reached during positive feedback-related is with 8 and 10 channels respectively for both channel reduction methods (forward-addition and backward-elimination). For negative feedback-related response the maximum accuracy reached is 0.98 using 18 channels, compared with the experiment 1 where the maximum accuracy reached was 0.95.

D. A fixed EEG channel configuration

After analyzing the previous experiments, it's possible to find a common channel configuration used in all the experiments, for both positive and negative feedback-related responses, which are: *Pz, O1, POz, O2, FP2, PO7, P7*. Using this subset of channels and taken into account that high accuracies were reached using around 9 channels in all the previous experiments, the following new experiment is proposed.

The idea is to provide experimental results when using an EEG device with 9 fixed channels. With this 9 fixed channel configuration, the subject identification experiments were reproduced for the mixed population, the female- only population and the male-only population, during positive and negative feedback-related responses. Fig. 9 shows the accuracies reached using both the backward-elimination and Fig. 10 the forward-addition algorithms.

Figs. 9 and 10, show that in most of the cases, using only 4 channels, a close accuracy (average: 0.90 ± 0.04) to the highest one (average: 0.92 ± 0.04), is reached. These channels are *O1, POz, Pz, O2*. It must be noted that most of the time, reducing or increasing the number of channels in the different plots in the experiment, the channel subset is different. In average, comparing the accuracy reached using 4 channels and 7 channels increases only 3% but the feature vector size increases 57%.

V. Summary and Discussion

The experiments carried out in this paper have shown that ERPs can be used to create a biometric security system since

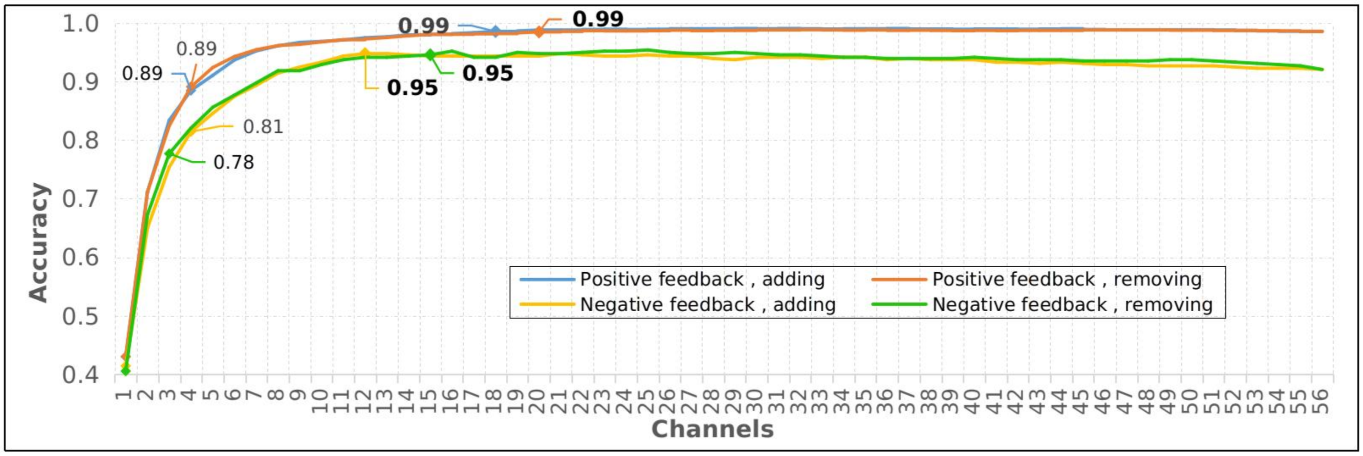

Fig. 3: Accuracies obtained removing or adding EEG channels for subject identification, during positive or negative feedback-related potential.

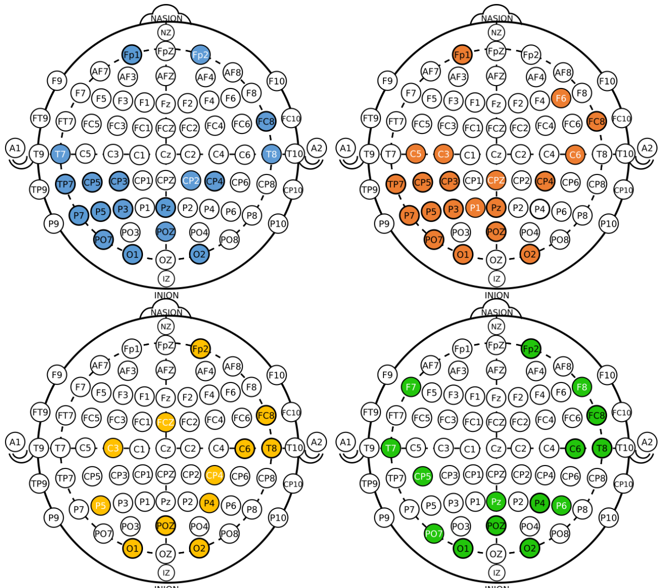

Fig. 4: Channels used to obtain the highest accuracy for subject identification, according to Fig. 3.

the classification accuracy to classify 24 subject was 0.97 using 9 channels. Reducing the number of channels with forward-addition and backward-elimination algorithms, the accuracy decreases to 0.91 when only 5 channels are used.

The above results, and the high accuracies reached in Error-Related Potential (ErrP) classification as reported in [25], indicate the potential for creating a two-step biometric recognition system based on low density EEG. Such subject identification system would record EEG signals during a short time period (1-2 seconds) and use them to detect if it corresponds to a positive or negative feedback-related responses; where the positive or negative response will correspond to a valid password for that user (from a set of passwords). This last check will add a second layer to the process of authentication for providing access. The previous idea may improve the false rejection rate and false acceptance rate, which will be tested in future steps.

At this point, it will be possible to create a headset with a fixed array of electrodes, but as it was shown in the experiments, if a female-only or male-only population is taken into account, the best channel configuration for each one, will be different. Also, if the same configuration is used for all the population, the accuracy decreases around 4%, compared with a tailored configuration for each population. The lower accuracy reached is more evident in the case of the female-only population (see Fig. 9 and 10).

Recently reported research discusses experiment results showing that female and male brains are different, taking into account not only the sex but also age, culture, IQ and the performed tasks [15], [26]–[29]. These assumptions will further highlight the importance of channel placement for the creation of a new EEG device based on the low density concept.

According to the protocol followed to record the brain signals, the 1.3 seconds used in this paper is presented to the subject to check if the letter shown is the last of a word, which include several cognitive processes highly related to the subject's internal mechanism of associating and remembering the word [30], [31]. Also, in a real-life biometric recognition system the process of remembering is not an exact repetition of the past event. Instead, it is a process mixing the subject internal state and the constructive episodic simulation hypothesis, creating thus a very unique subject-related characteristic to distinguish one subject from the rest [32], [33].

Nevertheless, there exist some assumptions about the methods for channel selection, and some techniques are based on multi-objective functions and using different soft computing techniques. The methods are limited by the analysis of some instances and some subjects and without the analysis of previous characteristics mentioned. But if the amount of instances, channels or the population changes, the result of the algorithms might also change, since some complex combinations between channels depends on the subject internal state and the recordings quality. This is true also because the paradigm involves a

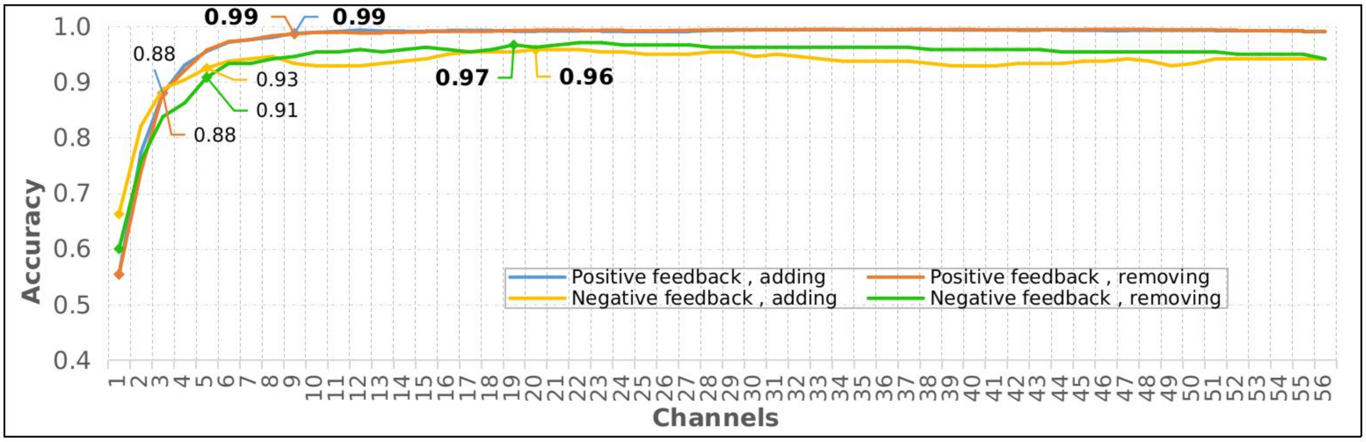

Fig. 5: Accuracies obtained removing or adding EEG channels for subject identification in a male-only population, during positive or negative feedback-related potentials.

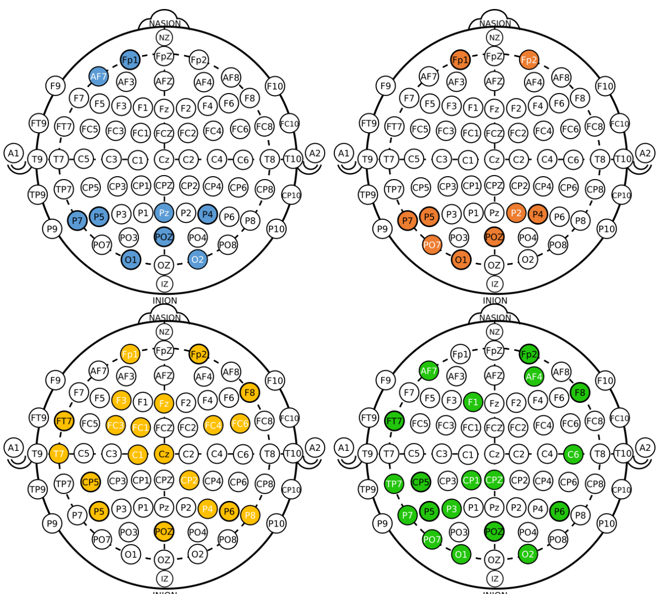

Fig. 6: Channels used to obtain the highest accuracy for subject identification in a male-only population, according to Fig. 5.

lot of subject information and because of brain plasticity. With these assumptions, a low-density EEG device will not have a unique or fixed channel configuration.

In a low-density device, the multi-objective channel selection approach will be possible to use to modify the channel's position or at least the active sensors in real time and thus increase the classification accuracy, according to the ideas discussed in [3], [34]. But in a high-density EEG device the channel selection is not possible for real-time applications, even using greedy algorithms.

There exist, different feature extraction techniques, methods and different neuro-paradigms used for the subject identification task. However, the exploration of channel reduction techniques for a real implementation is necessary [3], [4]. Considering the advances in feature extraction techniques and the high classification accuracies obtained using different machine/deep learning algorithms, the channel placement has not yet been explored. Up to now, the purpose of most low-density EEG devices is just to reduce the computational time to process the data and most of the cases for off-line testing. In addition, the available low-density EEG devices are designed to suit specific neuro-paradigms and tasks. With a 3D printer it will be easy to create an EEG device suitable for a specific task, in this case for subject identification using a channel configuration based on the results of this paper.

In the first 3 experiments, the elbow point was marked to show that if an algorithm is used to select the best combination between the lowest number of channels and the highest accuracy reached, it is possible to increase substantially adding only 1 or 2 channels and also shows that removing another channel, the accuracy can decrease drastically. Our future work will be dedicated to comparing different methods for channel selection and creating a new multi-criteria optimization strategy [35]. In this, we will take into account that the resulting strategy must be a greedy algorithm or a similar one to select the optimal number of channels in real-time.

As an example, comparing the method proposed in this paper and the one presented in [10], the accuracy reached using 16 channels is quite similar, but additionally, in this paper, the accuracy is reached with a lower number of channels. Considering the computational cost of the neural networks, the proposed method shown that can be a good candidate with a lower cost. However, as in most of the cases, the experiments are not directly comparable, and additional tests must be performed to compare the different approaches.

VI. Conclusion and Future work

In this paper, low-density EEG-based brain signals from ERPs of positive and negative feedback-related responses of a P300-speller system were successfully used for subject identification. The experimental results indicate that a low-density EEG concept is feasible and practical for a two-step identity authentication system based on ERPs.

Further efforts will also be directed to use/test Riemannian geometry classifiers since they are considered the current state-

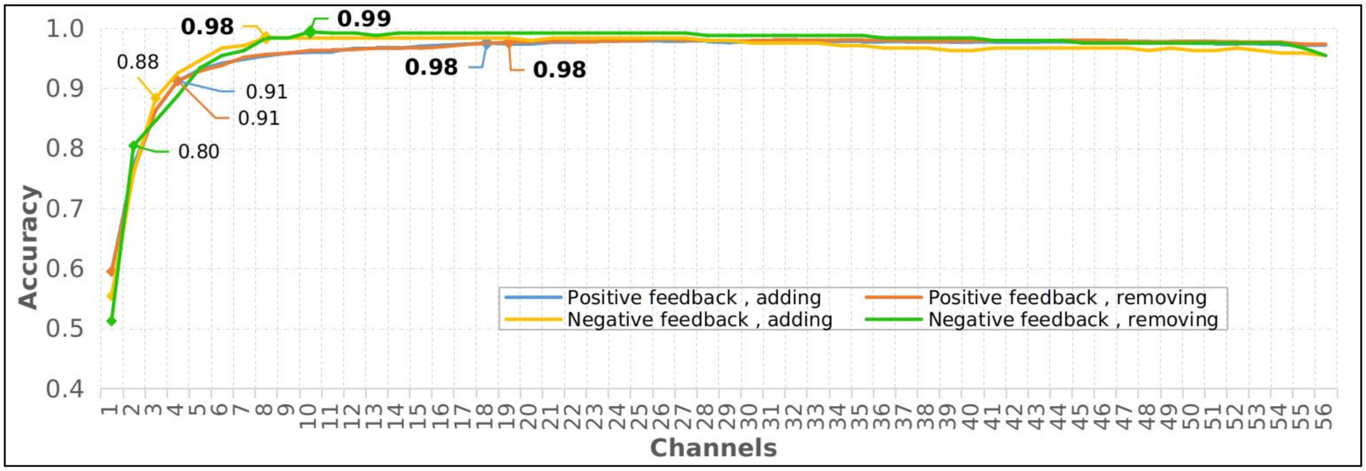

Fig. 7: Accuracies obtained removing or adding EEG channels for subject identification in a female-only population, during positive or negative feedback-related potential.

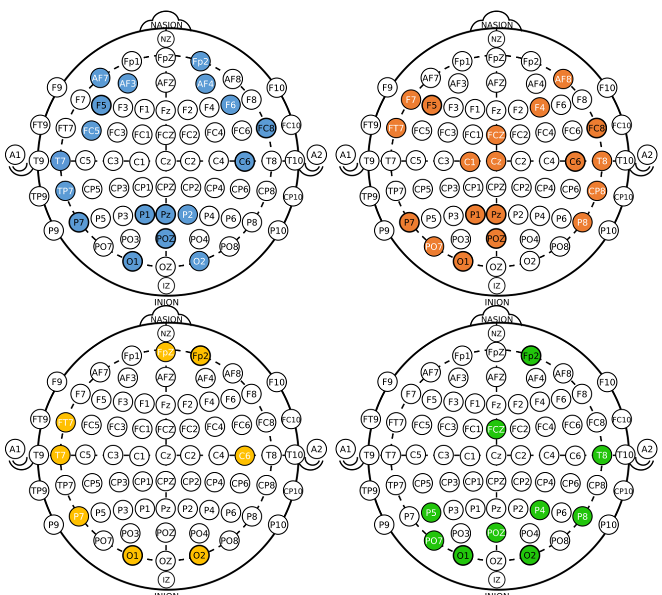

Fig. 8: Channels used to obtain the highest accuracy for subject identification in a female-only population, according to Fig. 7.

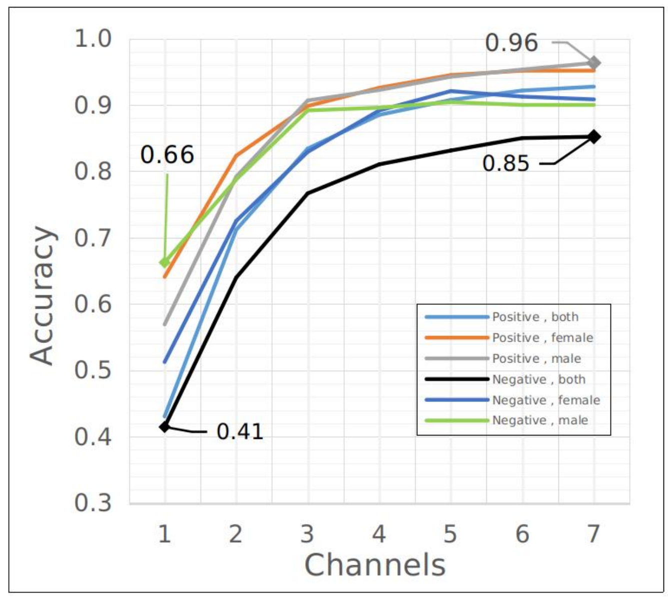

Fig. 9: Subject identification with positive and negative feedback-related potentials using the forward-addition algorithm.

of-the-art for multiple BCI problems [25]. The next step to provide more results, taking into account the methods studied and the results in this paper, will be a real implementation of the low density EEG concept. The implementation will use *ensemble learning*, to allow or deny the authorization process. In a real-life implementation, it is necessary to provide experimental results considering the real-life noise and test the proposed methods for feature extraction and classification in a noisy environment, but first testing by adding artificial noise.

A low-density EEG device with wireless dry non-invasive active electrodes will take less time to install, will be highly portable and will consume less power. Such EEG concept can become competitive over classical authentication systems for industrial level security access.

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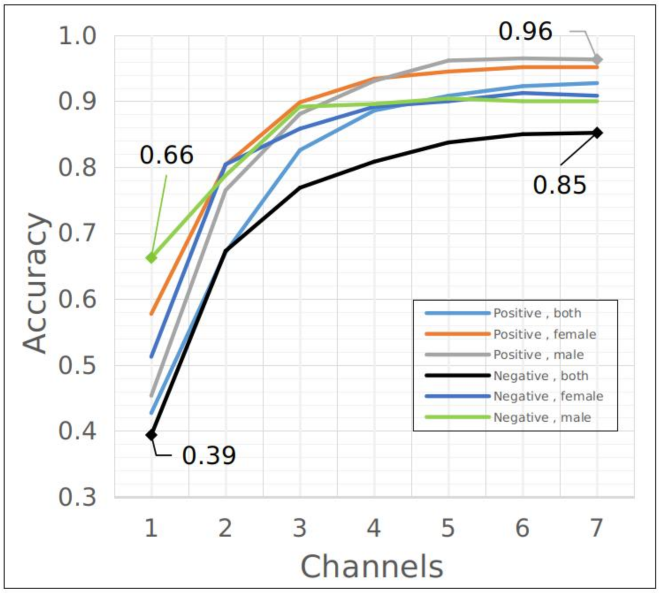

Fig. 10: Subject identification with positive and negative feedback-related potentials using the backward-elimination algorithm.

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