Sex differences observed in a study of EEG of linguistic activity and resting-state: Exploring optimal EEG channel configurations

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***Abstract*—This study reports the differences observed in the EEG signals of linguistic activity and resting-state between male and female subjects in a population of 16 individuals (8 females and 8 males). These differences were spotted while performing two experiments: sex identification and subject identification, where the initial aim was to identify the optimal number and placement of EEG channels to obtain high accuracies in sex and subject identification. The results of the identification show that the signals analyzed contain sex-specific information and that the best features from this sex-specific information are extracted from different EEG channel locations and from different hemispheres of the brain, for either sex. The effect of the number of electrodes and electrode localization is seen with clear differences between male and female subjects. The accuracy loss for sex identification when reducing the number of channels from 14 to 1 was of only 0.03 points during resting states (Accuracies from 0.79 to 0.76). For subject identification within either male or female groups during resting states, the accuracy loss was larger when reducing the number of channels from 14 to 1 (0.96 to 0.71 for female, 0.96 to 0.81 for male subjects). One finding of this study is that Theta and Gamma bands are strongest for males in the right hemisphere during resting states, whereas during linguistic activity these bands exhibit similar strengths in the left hemisphere for both males and females. Similar specific features in brain signals may enable the design of a flexible EEG device that can be adapted to specific mental tasks and Subject settings.**

***Index Terms*—Sex identification, Subject identification, Electroencephalograms (EEG), Empirical Mode Decomposition (EMD)**

I. Introduction

Consumer wearable EEG technologies have experienced a steady growth of devices with a reduced number of EEG channels available for personal use such as meditation, relaxation training, motor imagery and control of moving objects [1]. As a result of this, today people can measure their own brain signals outside medical laboratories thanks to the proliferation of low-cost wireless headset EEG devices with a varying number and configuration of EEG channels, with dry or wet electrodes. For rigorous comparison studies between laboratories and researchers, the 10-20 international system has been proposed and adopted by the scientific community [2]. Although the ease of use and portability of emerging wireless EEG devices offer a promising alternative to conventional recording systems, reliability and quality of the measurements remains elusive since the different EEG devices are not directly comparable in the absence of a valid benchmark.

A previous validation study demonstrated that data derived from a single channel, the wireless system (NeuroSky MindWave) is comparable to EEG recorded from conventional lab-based equipment. However, critical open issues (e.g., real-time, quality of recordings) remain yet unexplored [3]. One of the unexplored aspects is the electrode placement, which in most EEG devices is fixed depending on the targeted application/s.

For real-time applications, the high-quality-high-density EEG devices will be computationally costly and the applications will be very limited. The existing wireless portable devices with fixed electrode placement will also have limitations since depending on the task, the neuro-paradigm used, age and sex of the subject, most relevant features of brain signals may be obtained at different locations of the electrodes in the scalp [4]–[7].

The openBCI device is a more flexible EEG headset in the sense that enables to add and remove electrodes within a fixed frame of positions on the scalp but it does not allow to scan the optimal position for a given task, neuro-paradigm, age or sex.

Table I lists the main features of the most popular low-cost portable devices available today in the market. The current EEG technologies are based on *wet* or *dry* fixed electrodes.

The devices presented in the table have different electrodes configurations, but in general, the electrodes are localized according to the 10-20 international system. The current trend for new EEG devices is the use of dry electrodes to avoid the use of the inconvenient gel.

In a comparison presented in [8], the authors suggest that EMOTIV EPOC may be more suitable if the neuro-paradigms are attention/meditation, and in the case of Neurosky MindWave with eye blinking. However, the conditions are not directly comparable because the first device uses wet-electrodes while the second one uses dry electrodes. It is well

TABLE I
EEG DEVICES

Name	Channels	Sample rate	Sensors
OpenBCI[1]	16	250 Hz	Dry
EMOTIV EPOC[2]	14	128 Hz	Wet
EMOTIV Insight[3]	5	128 Hz	Dry
Muse[4]	5	256 Hz	Dry
Neurosky MindWave[5]	1	512 Hz	Dry

known that wet electrodes have problems for real-time/long-term use.

Most EEG devices available in the market were tailored designed for a set of tasks and neuro-paradigms and in general, they are found to be reliable only within those tasks and neuro-paradigms. The accuracy and reliability of these systems for repeated measurements have not been well-established and as of now a rigorous comparative investigation of the different portable solutions is not available. Most importantly, it is not clear whether the limited number of channels and their fixed localization may provide sufficient data and anatomical coverage to obtain the neural signatures necessary for the given tasks. Essentially, this is because both, electrode localization and the number of electrodes, are task-dependent [1], [4], [8]. This opens the possibilities to explore the concept of *"movable electrodes and a variable number of electrodes"* [9].

The current study aims to open the discussion of this concept of *movable and task-dependent electrode localization*, and it does so by studying the differences observed in the EEG signals of male and female subjects during resting-state and linguistic activity. The effect of both, electrode localization and the number of electrodes, is explored by gradually removing electrode information until only one electrode is left. A dataset with a population of 16 individuals (8 females and 8 males) is analyzed (Age: 26-year-old on average, 8 males right-handed, 6 females right-handed and 2 females left-handed).

The results show that useful features to create a machine-learning-based model come from different channels depending on the sex of the individuals and the neuro-paradigm selected for the study (linguistic-activity/resting-state).

II. METHOD

The method used for feature extraction and classification is explained in [10] and the greedy algorithm used in [11].

In this paper, two neuro-paradigms were used, the first one is called *imagined speech* to correspond to the internal speech of words without uttering sounds and without articulating gestures [12]. The second neuro-paradigm used is named *resting-state*, that refers to the absence of goal-directed neuronal action with the integration of information from the external

[1]OpenBCI: https://openbci.com/
[2]EMOTIV EPOC: https://www.emotiv.com/epoc/
[3]EMOTIV Insight: https://www.emotiv.com/insight/
[4]Muse: http://www.choosemuse.com/
[5]Neurosky MindWave: http://neurosky.com/

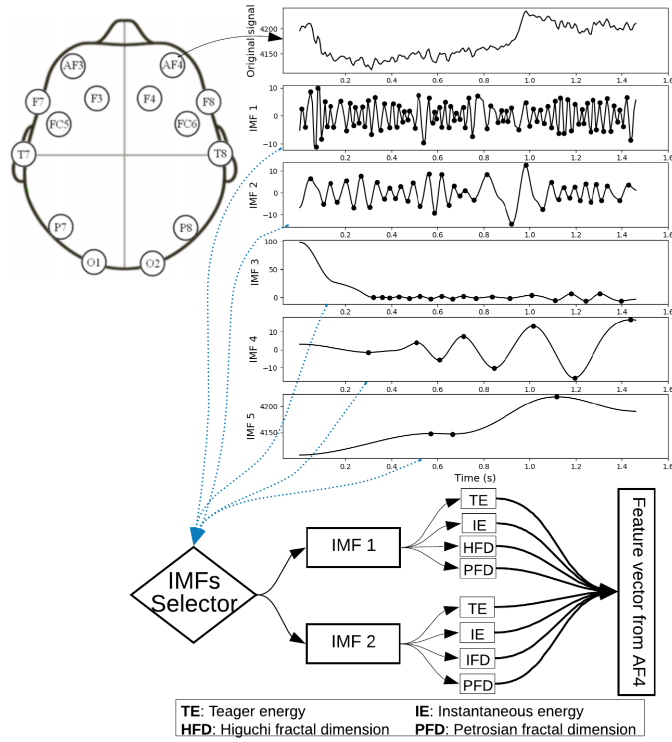

Fig. 1. Flowchart summarizing the feature extraction procedure using EMD [11].

environment and Subject internal state, this is why resting-state can be used to obtain patterns from the brain signals [13], [14].

In summary, the feature extraction stage for each electrode is based on Intrinsic Mode Functions (IMFs) from Empirical Mode Decomposition (EMD) that were selected using the Minkowski distance. Then, for each IMF 4 features were computed: The Instantaneous/Teager energy distribution and Higuchi/Petrosian Fractal Dimension. The features were concatenated to obtain a single feature vector per repetition. After that, 3 machine learning algorithms, *Support Vector Machine (SVM), naive Bayes* and *k-nearest-neighbors (k-NN)*, were used to compare them and select the best for each task. These steps are summarized in Fig. 1.

The greedy procedure to remove channels described in [11], consists on selecting the *k-combinations (k=1)* removing 1 channel to create a classifier to select the subset of channels with the highest accuracy and then repeat the step removing another channel.

A. Dataset description

The dataset used is described in detail in [15], EEG signals were obtained from EMOTIV EPOC device with a sample rate of 128 Hz and 14 channels, the electrodes were placed according to the 10-20 international system [2]. The complete dataset was obtained from 27 subjects who perform 33 repetitions of 5 imagined words in Spanish (Up, Down, Left, Right and Select) with a mean size of $\lceil 2 \rceil$ seconds, the repetitions were separated with a resting-state with a mean size of $\lceil 3 \rceil$ seconds.

The duration of each repetition of imagined speech and resting-state has different lengths between words and subjects. Because there are only 8 females in the dataset and in order to compare the results, the experiments were carried out using 16 subjects from the dataset: 8 males and 8 females and only 30 repetitions of linguistic activity and resting-state.

III. Experiments

This section presents and compares the results obtained from the experiments performed for two different tasks: Sex classification and Subject identification using two small population of males and females. For the following experiments and for simplicity, *linguistic activity* refers to the use of all words as a single class.

In the first experiment, the aim was sex identification during resting-state and during linguistic activity. In the case of sex identification during linguistic activity, the 5 different words per subject were tagged with the sex of the subject (male or female). In total, in this experiment 30 repetitions were taken into account from 5 imagined-words or resting-state from 8 males and 8 females. The setup was decided because the aim of the experiments was to show the differences between the sex of Subjects during linguistic activity and resting states, not to recognize the imagined word.

For the second and third experiment, each of 30 instances per imagined-word/resting-state was tagged with a subject id, obtaining thus 150 instances per Subject, with the aim of subject identification in a population of males and the experiment was repeated in a population of females. To understand the differences of the populations, a greedy algorithm was used to remove channels and repeat the experiments using a set of 14 channels and 4 subsets of channels (8, 4, 2 and 1 channel).

In the next Figs., the set of channels used for the experiments (14, 8, 4, 2 and 1 channel) are marked with a color box. The subset of 8 channels was marked with a blue box, the subset of 4 channels with a black box, the subset of 2 channels with a red box and finally, 1 single channel with a yellow box.

A. Sex identification during resting-state and linguistic activity

This experiment was carried out to show that brain signals from males and females are different while performing the same task. This allows us to understand the limitations of current devices with fixed electrode positions. The most favorable position of the electrodes might be different depending on the neuro-paradigm and the sex of the subjects.

In Fig. 2 the results obtained after 10-folds cross-validation using *k-NN* for sex classification, are shown. The results show that even using 1 channel, the accuracy is on the chance level for two classes (50% per class), and also that the brain signals during resting-state and linguistic activity are different between males and females. The Fig. 2 also shows that the channels T8, O2, F3, and F4 are important for sex classification during resting-state. On the other hand, the important channels used during linguistic activity were FC6, P8, F3, and T8 for sex classification.

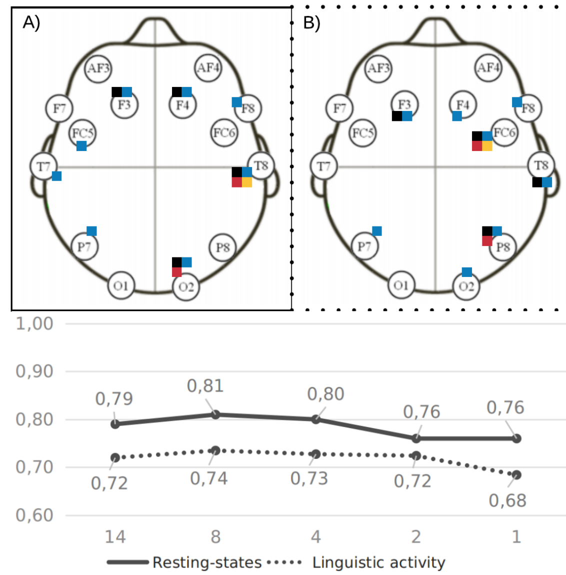

Fig. 2. Evolution of the accuracy using fewer channels for sex distinction during resting-state (Subplot **A**) and linguistic activity (Subplot **B**) using *k-NN* classifier.

The results suggest that there are specific patterns to distinguish the sex of the Subject. Possibly the classification can be done using different positions of electrodes, but if the electrode is localized according to the task, the accuracy might improve. As an example, the highest accuracy obtained for sex distinction during resting-state from 1 channel was reached using T8 channel (see subfigure **A)** from Fig. 2). In the case of Sex distinction during linguistic activity, when only 1 channel was used, the highest accuracy was reached using the FC6 channel (see subfigure **A)** from Fig. 2).

B. Subject identification during resting-state

This experiment consists of Subject identification during resting states from a female population, to compare the accuracies with a male population and to show the differences between relevant channels in these two populations. In this experiment, the results reported are with *Linear SVM* which obtained highest accuracy compared with *naive Bayes* and *k-NN* [11].

In Fig. 3 the results obtained for subject identification during resting-state, are presented. When subject identification task using 14 channels was performed using a female population, the accuracy obtained was the same compared with a male population, but when the number of channels is decreasing, the accuracy in a male population is highest. Also, the channels with more relevant information for this experiment were T8, F4, FC6 and O2 in a male population and F4, T7, FC6 and O2 in a female population. In Fig. 3, the channels for the experiment using a male population are shown in the sub-plot **A)**, and for the female population in the sub-plot **B)**.

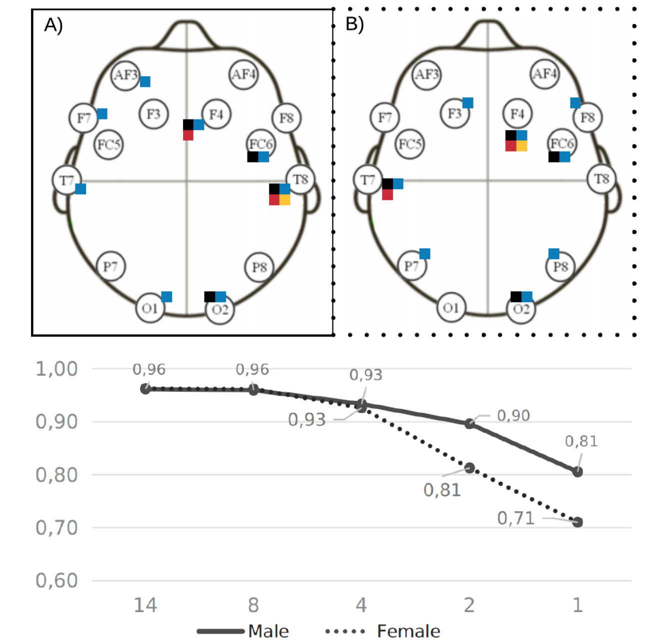

Fig. 3. Evolution of the accuracy using fewer channels for Subject identification in Male (Subplot **A**) and Female population (Subplot **B**) during resting-state using *Linear SVM*.

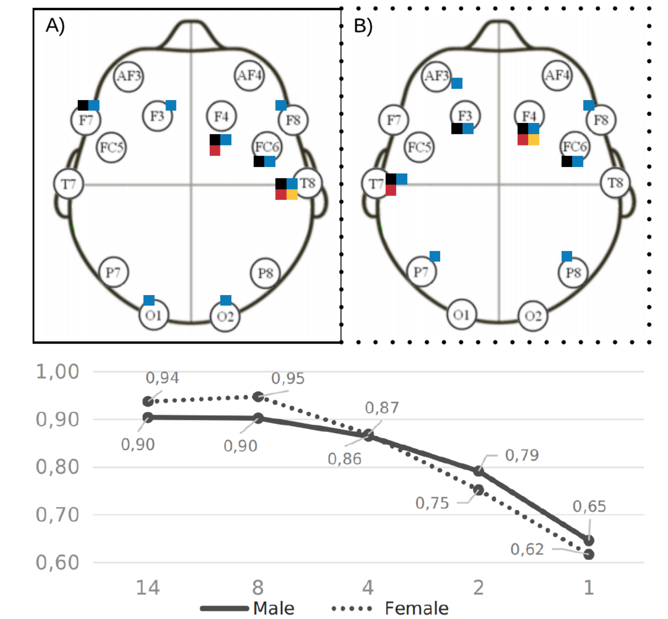

Fig. 4. Evolution of the accuracy using fewer channels for Subject identification in Male (Subplot **A**) and Female population (Subplot **B**) during linguistic activity using *Linear SVM*.

C. Subject identification during linguistic activity

The subject identification task was repeated using linguistic activity and *Linear SVM* classifier. The results obtained are shown in Fig. 4, where the last two channels used for subject identification in both populations are the same. The channels with more relevant information according to the experiments are T8, F4, FC6, and F7 when the male population was used, in the case of the female population the channels are F4, T7, FC6, and F3. In Fig. 4 the channels used in this experiment are shown and the channel removal order is marked with colors codes as explained earlier. The channels used with a male population are shown in the sub-plot **A)**, while those for the female population are shown in the sub-plot **B)**.

D. Rhythms differences during resting-state and linguistic activity

In the previous experiments (for subject identification in male and female populations, during resting-state and linguistic activity), it is shown that for the male population, the right hemisphere was more active even using only 3, 2 and 1 channel, in both; resting-state and linguistic activity. In general, higher amplitudes were observed in the right hemisphere compared with the left hemisphere for these tasks.

In Fig. 5, a comparison of the left and right hemisphere of mean amplitude from 30 instances of linguistic activity and resting-state from the male and female population, is presented.

In Fig. 5, it is shown that theta and gamma rhythms for the male (in both left and right), are highest compared to the female population during resting-state. Comparing the differences in percentage, the left hemisphere of the male population is 49%, 36% difference in average to the right hemisphere during linguistic activity and resting-state, respectively. On the other hand, for the female population, the left hemisphere is 20% different in average for both, linguistic activity and resting-state.

IV. Discussion

The experiments performed show that human brain activity is different even during the same task depending on different factors, specifically depending on the sex of the Subject and the neuro-paradigm used.

Using the method for sex classification with 14 channels, the accuracies were 0.79 and 0.72 using resting-state and linguistic activity, respectively. With sex identification during resting-state, the accuracy shows fluctuations but the difference using 14 channels and 1 channel is only 0.3 using the *k-NN* machine learning-based algorithm (from 0.79 with 14 channels to 0.76 using 1 channel), obtaining the same accuracy using 1 channel during resting-state compared with 14 channels during linguistic activity.

When the experiments for subject identification during resting-state were carried out with male and female populations, and after applying the greedy algorithm to remove channels, the accuracies obtained were drastically reduced. In the case of the female population, the accuracy using 14 channels was 0.96 and using 1 channel 0.71, while for the male population was only from 0.96 to 0.81, respectively.

In Fig. 6 is shown a comparison of configurations found for the male and female population with 4 channels (according to the Fig. 4) during resting-state. To understand the importance of the configurations, the experiments for Subject identification

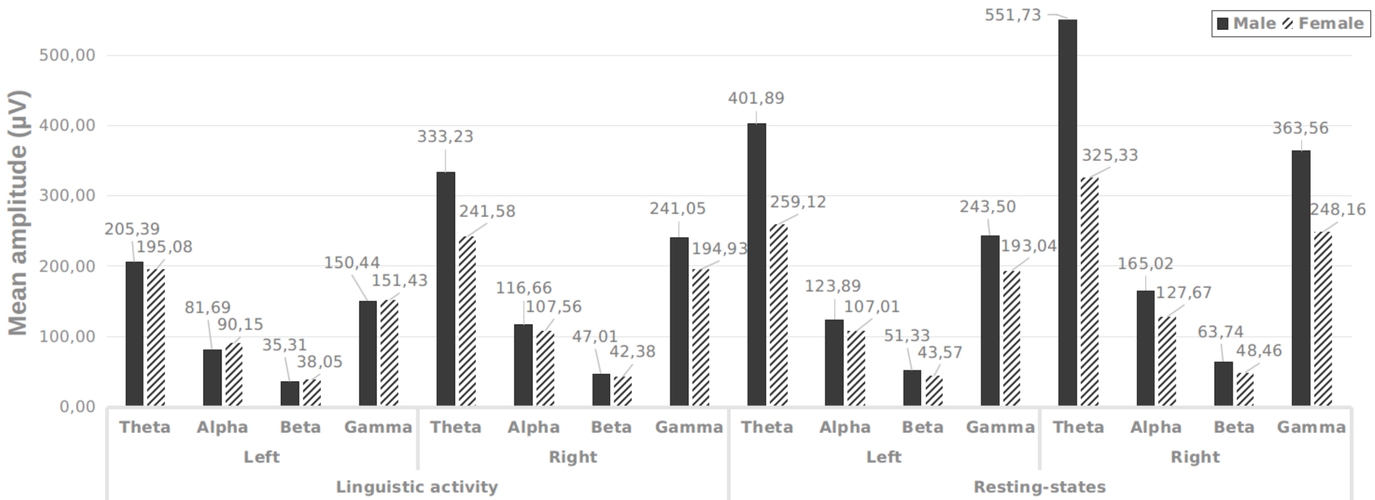

Fig. 5. Left and right hemisphere comparison of mean amplitude (Theta (4-7 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (31-60 Hz) frequency bands [16]) during linguistic activity and resting-state from the male and female population using the EEG raw signal (14 bits).

during resting-state were repeated but using both configurations in both populations.

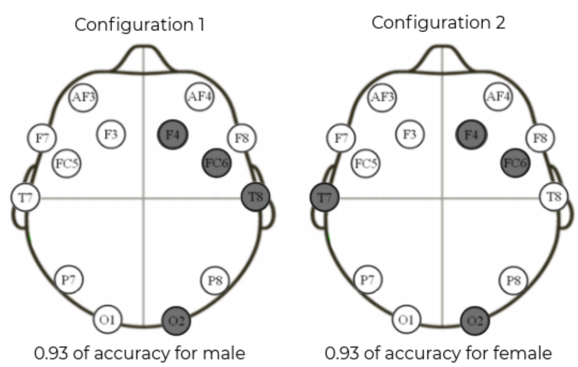

Fig. 6. A comparison of configurations using 4 channels for male and female populations during resting-state.

As it was mentioned previously, the accuracy obtained with the *configuration 1* for the male population was 0.93; however, using the same configuration for the female population the accuracy was 0.89. Using the *configuration 2* the accuracy for the female population was also 0.93, but if that configuration is used for the male population, the accuracy was 0.90. The importance of using a sex tailored configuration is shown in this experiment, since using an adapted configuration the accuracy was 0.04 and 0.03 points higher, respectively. In this case, the configurations used were during resting-state and there is only 1 channel difference, but in the case of linguistic activity, there are 2 channels difference in the subset of 4 channels.

With the results presented previously, the idea of using 5 channels mixing both configurations (T7, O2, T8, FC6, and F4) quickly come to mind. This is why the experiment for subject identification was repeated with this new configuration of 5 channels. However, the accuracy obtained was 0.93 with both populations. This means that the channel added to create that configuration does not contain useful/fruitful information for the specific characteristics of each population, and the channel only added computationally cost. Even if the populations are mixed (obtaining thus 16 Subjects for the experiment of Subject identification) the accuracy was 0.86, which obviously is lower.

To understand if the accuracies are affected by having only right-handed males and females in the population, the experiment of Subject identification was reproduced considering only 6 Subjects, since there are only 6 right-handed females in the dataset. The results obtained during resting-state (**0.97, 0.97, 0.94, 0.86 and 0.77**) and during linguistic activity (**0.93, 0.94, 0.88, 0.78 and 0.69**) respectively for 14, 8, 4, 2 and 1 channel also suggest that left and right-handed populations may hold common information in the populations and if that is taken into account, the accuracy may improve. However, to obtain more evidence about this behavior, a comparison of right-handed versus left-handed in both populations (male and female) within a larger population, will be necessary.

Comparing the previous results obtained for Subject identification with only the right-handed female population and the results from Fig. 3, the accuracy increased significantly, especially using fewer channels, i.e., during linguistic activity; using 2 channels the accuracy improves from 0.81 to 0.86 and with 1 channel from 0.71 to 0.77.

There is evidence in the state-of-the-art that suggests that male brain is more asymmetrically organized than female brain [7], [17]. Taking this into account and looking at the results in Figs. 3, 4 and 5, they appear to support the view of a more pronounced functional brain asymmetry in males than in females. This behavior becomes more evident when channels were removed using the greedy algorithm. In the male populations the location of channels is on the right hemisphere whereas, for the female population, the channels are distributed in both hemispheres, using 4 channels or fewer.

These results are supported by different applications with relatively high accuracy for subjects identification and therefore hint on the existence of unique patterns for each Subject. This means that a static EEG device design for multi-purposes and for different types of populations may not be effective even when using the same neuro-paradigm. This also points out to potential improvements in the accuracy and reliability of the acquisition system if the acquisition of brain signals is associated with the characteristics of the Subject.

Some of these characteristics are sex, age, the task to perform, culture, and even the subject intelligence level [4], [5], [18], [19]. Some studies have shown that alpha, theta and beta oscillations are associated with the sex of the Subject for certain tasks [4], [5]. In the work presented in [6], is it exposed that according to the culture, and the age of the population, the brain signals may differ. The experiments performed during resting-state show that children from Switzerland demonstrated stronger power in the Delta-band at Fz electrode, instead of the stronger Alpha-band activity of Saudi Arabian children. These observations are supported by some works where neuroplasticity was studied to explain the age variations, and the effect of intelligence on EEG signals [18]–[20].

Current EEG technology presents some limitations for real-time and for many real applications. The consumer grade EEG devices in the market are limited to Dry/Wet electrodes and often to specific tasks, for example, in the case of Neurosky MindWave the research is focused only in resting-state/concentration and eye-blink [8]. With *a-priory* understanding of Subject related characteristics, the analysis of the signals can substantially improve, and this can help to create a flexible device design for new applications.

Nonetheless, due to the high complexity of the brain, the methods/knowledge to obtain valuable information from brain data are still limited. Well-known challenges are the problem of transfer learning and patterns acquisition in real-time which require information from different sessions. The presence of artifacts associated with the devices is another challenge that affects the analysis.

To create machine-learning based models, it will be necessary to take into account the sex differences even during resting-state or in others states [21]. Nowadays, the features can be extracted using different methods, but for a certain task, it will be necessary to use more steps to add features related to the Subject in order to improve the performance.

Future efforts will be dedicated to improving the accuracy of sex classification, using the results of this paper. One of the limitations of this study is the small population used in the experiments. This is why new experiments will be designed with an enlarged population with comparable characteristics (age, right/left-handed, sexes, etc.).

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