Wrapper method based on Soft Computing for Channel Selection in Brain Computer Interfaces

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Abstract. Brain-computer interfaces (BCI) tries to provide to a subject, in specific to his/her brain, of a non-muscular channel to interact with electro-mechanic devices. In this work, we present a channel selection method to be applied in BCI based on electroencephalography (EEG). Specifically, BCIs whose electrophysiological sources are imagined speech (sometimes referred to as internal or unspoken speech) and motor imagery. In the first case, we used a dataset composed of EEG signals, belonging to twenty seven subjects, recorded during imagined speech with a protocol based on markers. Markers delimit the EEG signal segments of interest with aim to know a priori in what part a subject imagines the pronunciation of an specific word. Each segment of interest was filtered using common spatial reference (CAR). After that, discrete wavelet transform (DWT) and relative wavelet energy (RWE) were applied to extract features, and finally random forest (RF) was used to classify unspoken words. Our method outperforms previous works. However, in order to improve more the classification performance, we have observed the need to find a good combination of channels to identify better an specific unspoken word.

Key words: Electroencephalograms (EEG), Brain-Computer Interfaces (BCI), channel selection, imagined speech

1 Introduction

Electroencephalography (EEG) is a non-invasive, simple and relatively cheap technique to measure brain activity. These features are of special interest to the brain computer interface (BCI) research community. According to Wolpaw et al. [1], a BCI system tries to provide a new channel to the brain to transmit messages and commands to the external world. In general, BCI can be seen as a pattern recognition system where EEG is used as the primary source of raw information, and machine-learning algorithms are used to learn an inference function from EEG signals. The final goals of BCI research are to help handicapped persons and improve human-computer interaction (for example, in video game control).

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Electrophysiological sources are the neurological mechanisms or processes employed by the BCI user to generate the control signals [2,1]. Among these, the most widely used are: slow cortical potentials (SCP), P300 potentials, motor imagery (sensorimotor rhythms mu and beta) and, visual evoked potentials (VEP). In recent years, unspoken speech (sometimes referred to as imagined speech) has been used as an electrophysiological source in BCI research (see the works described in [3,4,5,6]). According to Wester [7], unspoken speech is referred to as imagined pronunciation of a word without emitting a sound or articulating a facial movement.

Imaginary movements, like actual movements of different body parts, can produce attenuation of mu and beta rhythms at corresponding cortex locations. This circumscribed attenuation is called event-related desynchronization (ERD). Meanwhile, at other locations, an enhancement of both rhythms can be observed, called event-related synchronization (ERS) [8,9,10]. Briefly, different body parts are related to different locations in the motor and somatosensori cortex [11]. For example, movement or imagened movement of the left hand will cause ERD in the right motor cortex and ERS in the left motor cortex, and vice versa (see Figure 1) [12]. In general, the mu rhythm has a frequency band of 8–12 Hz and beta rhythm 18–25 Hz, but these frequency bands can vary depending upon the subjects and their mental states [13,14].

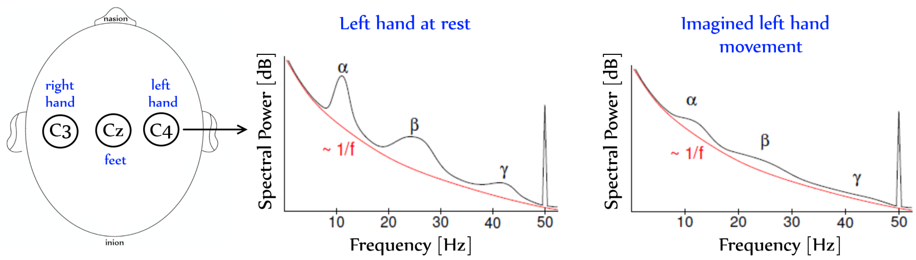

Fig. 1. Evidence of event-related desynchronization (ERD) and event-related synchronization (ERS) phenomena at channel C4 before and after onset imagined movement from the left hand (adapted from [15])

Our research is focused on motor imagery and unspoken speech because currently, BCIs based on motor imagery are the most widely used and unspoken speech is a relatively novel and interesting electrophysiological source to help prove a more natural communication channel without the need for translation [2]. BCI based on motor imagery is an independent system with high accuracy, and with the binary classification average of motor imagery tasks of the right and left hands above 90% [16].

However, both electrophysiological sources are not used in real-life applications. An important issue is that several algorithms available are focused on analyzing and processing information of multi-channel EEG. In BCI based on motor imagery, two approaches have been explored to tackle this problem: feature selection/dimensionality reduction and channel selection. In the first approach, principal component analysis (PCA) and independent component analysis (ICA) have been used. The second approach is relatively recent and looks for a more interpretable form to reduce the number of needed channels to achieve the same accuracy as a full channel configuration. The main difference between channel selection and feature selection is that information belonging to a channel is treated as a unique entity, with the main advantage that it results in a more interpretable dataset than feature selection. As with feature selection, channel selection can be divided in filter and wrapper methods, to our knowledge embedded methods have not been explored.

2 Previous works

To the best of our knowledge, an automatic channel selection method to unspoken speech has not been presented. Furthermore, at this time it is not clear what channels and brain regions are the most relevant for recognizing unspoken words from EEG signals. This last point has motivated the present research.

On the other hand, channel selection methods to motor imagery have been explored in several works, described as follows in the next subsections.

2.1 Channel selection based on filter methods

Lal et al. [17] adapted a feature extraction method known as recursive feature elimination to apply it in the channel selection context. Lal et al. [17] concluded that the number of channels used for classification can be reduced significantly without increasing the classification error. Another filter method was proposed in [18]. This work used mutual information (MI) maximization. EEG channels were ranked based on MI between the selected channel and a class label. Finally, Wang et al. [16] proposed a novel approach to select channels by common spatial patterns (CSP). Their work was applied to binary classification and their channel selection criterion was to use the first and the last columns in the resultant matrix of spatial patterns.

2.2 Channel selection based on wrapper methods

In [19], a channel selection method was proposed based on genetic algorithms and artificial neural networks (ANN). This work was applied to a binary classification problem, with three layers, and assessed by accuracy. Another work, described in [20], proposed a channel selection method based on genetic algorithms and linear support vector machine (LSVM). This method was only assessed by accuracy and was applied in a binary classification problem. Finally, [21] presented a method in which Binary Particle Swarm Optimization (BPSO) and CSP were utilized. This method aggregates a trade-off coefficient to modify the objective function. This coefficient was varied and the accuracy evaluated for each case.

The last works in channel selection based on wrapper methods have considered the possibility of simultaneously optimizing the number of selected channels and accuracy. In this case the optimization problem is multi-objective. Examples of kinds of methods were presented in [22,23]. Both methods were proposed for the same research group and were used to select channels in binary classification problems. The objectives were accuracy and number of selected channels.

2.3 Discussion

In our research, wrapper methods are of special interest because they are more accurate than filters. This is possible because wrappers use the same machine learning to assess the selected channels and to classify in the classification stage. The first works on wrapper methods only used accuracy as an objective. However, in real-life applications it is more important to process and analyze fewer channels. To our knowledge, previous works in multi-objective optimization have not attacked multiclass problems and they considered channels with artifacts in their space search. The works described in [21,16] are limited for binary nature of CSP method. These methods cannot be extended to multiclass problems. Furthermore, our work will use the same objectives proposed by Hasan et al. [23]: number of selected channels and error rate.

3 Research objective

To develop a channel selection method based on evolutionary multi-objective optimization whose accuracy and the number of selected channels will be comparable to previous works. This method will be robust against multiclass problems.

4 Methodology

The methodology is composed of the following stages: Collect data for experiments, pre-processing, feature extraction, artifacts removal, channel selection, design a classification model, and evaluation.

- **Collect data for experiments.** To realize our experiments we have collected BCI Competition Datasets. These datasets are characterized for multiclass and binary problems. Furthermore, we will use EEG datasets characterized for unspoken speech that were recorded in [24].
- **Pre-processing.** This stage will search to prepare the signals, improve the signal/noise ratio and, reject frequencies related with electromiographic signals.
- **Artifacts removal.** This stage searches to remove channels affected by artifacts such as blinking eyes, muscular movements and heartbeats. This part is very important because it reduces the search space for channel-selection stage.

- **Design classification model.** In this stage a classification strategy or model will be designed to use with multiclass problems.
- **Channel selection.** This stage will use a wrapper method and will explore different soft computing techniques (such as particle swarm optimization, ant colony optimization, genetic algorithms, memetic algorithms, among others) to experiment with on a multi-objective optimization problem and identify the best one for channel selection.
- **Evaluation.** In this stage, we will conduct statistical tests to compare the results of our method with previous works. The measures to compare are: accuracy and number of selected channels.

5 Experiments and preliminary results

We have analyzed datasets from unspoken speech used in [24]. This dataset is composed of EEG signals belonging to 27 native-Spanish-speaking subjects. EEG signals were recorded with an EMOTIV acquisition kit which has 14 channels and two reference electrodes (channel names in the 10-20 International System: AF3, AF4, F3, F4, F7, F8, FC5, FC6,P7, P8, T7, T8, O1, O2. References: P3/CMS, P4/DRL). This dataset was recorded using a basic protocol to acquire EEG signals from each subject. This protocol consists in placing a subject restfully sit with open eyes and with his/her right hand over a computer mouse. Subject delimits, by clicking a mouse to mark the EEG signals, both the start and the end of the imagined pronunciation of each of the words belonging to a reduced vocabulary composed of five Spanish words: "arriba," "abajo," "izquierda," "derecha," and "seleccionar". The aim behind of the adquisition protocol is to know a priori in what part of the EEG signal, it is necessary to search the associated patterns with the imagined pronunciation of an indicated word.

The interest segments of the EEG signals are those between the start and end markers, these segments are called epochs. Each epoch has variable duration like in spoken speech. Furthermore, each word was internally pronounced thirty three times consecutively. Before this, it was indicated to the subject what word had to internally pronounce. All blocks of words belonging to a same subject were recorded in a single session (same day). All sessions were recorded in a laboratory far from audible and visual noise.

It is important to mentione that before that the EEG signal recording is started, it was indicated to the subject to avoid blinking and any corporal movements while imagining the pronunciation of the word in turn. After each end marker the subject can take a short break to do these movements in case he/she needs to move. Moreover, to avoid the subjects distraction by counting the repetitions of imagined words or how many of them were still left, they did not know how many times the words would be repeated. For this, a control assistant, inside the recording room, internally counts the repetitions and indicates when the session should be concluded.

On the other hand, in [24], the researchers processed a subset of four EEG channels (F7-FC5-P7-T7) with their method. They assumed this combination is a good selection because these channels are the nearest to the Broca and Wernicke brain areas. But they did not explore other combinations. More recent works have suggested, however, that other brain regions can be involved with imagined speech [25]. Therefore, it is interesting to study whether EEG channels over these brain regions can be selected using a search process.

We have designed a novel method to process EEG signals. This method applies common average reference (CAR) over the EEG channels previously delimited with markers. With this, the average voltage of each sample in time from all channels is subtracted of each channel. After that, to each marked segment of each of the channels, discrete wavelet transform (DWT) is applied using a Daubechies-2 as the mother wavelet and with five decomposition levels (D1-D5 and A5 levels). Then, with each obtained DWT, relative wavelet energy (RWE) is computed to normalize the coefficients. With this, each marked segment of each EEG channel is represented with 6 coefficients, but the first coefficient corresponding with the frequencies between 32-64 is discarded. With this, each marked segment of each EEG channel is represented with the five coefficients remaining (RWE from D2-D5 and A5 levels). After that, simultaneous coefficients were concatenated to form a feature vector. Last, a random forest (RF) is trained with many feature vectors to classify each EEG marked segment in its corresponding class (any of five Spanish words). Figure 2 shows the novel method used to process EEG signals.

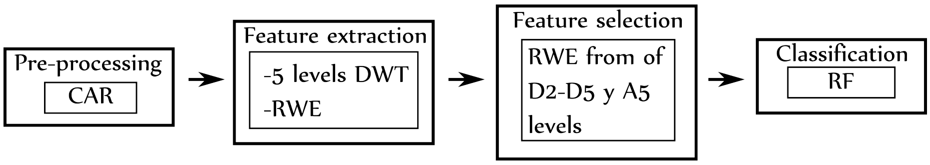

Fig. 2. Method used to process EEG signals recorded while a subject imagines word pronunciation

5.1 Experiments and results using the nearest four channels to the brain's linguistic areas

Our first experiment consisted of assessing the accuracy of our method compared with the method used in [24]. For this, we processed only four EEG channels of each subject. The channels are F7, FC5, P7 and T7, i.e., the same channels used in [24]. Figure 3 shows the percent of accuracy obtained by both methods, applying 10-fold cross validation, and using only four channels. In general, our method outperformed to the method used in [24]. Subjects S5, S7, S11, S13, S18 and S22 were not processed in [24] due to assumptions on their method as: subjects left-handed (S13 and S18) have their lenguage areas on right hemisphere of the brain (the four channels are not on this brain side), and subjects (S5, S7, S11 and S22) with many EEG marked segments whose size is more than 256 time samples were discarded.

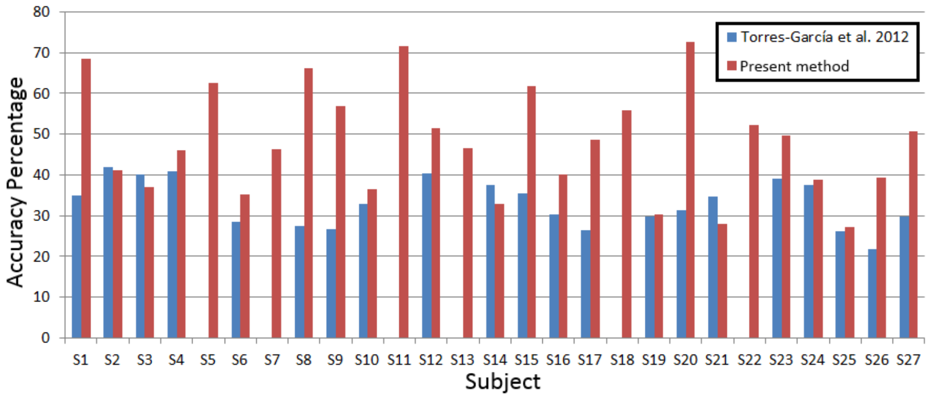

Fig. 3. Accuracy percentages obtained by both Torres-García et al. [24] and the present methods. Remarking that subjects S5, S7, S11, S13, S18 and S22 were not processed in [24]

5.2 Experiments and results using all channels

The second experiment consisted of assessing whether the use of others channels, out of the brain's linguistic areas, could contribute to improve the accuracy obtained using four channels (F7-FC5-T7-P7). At the same time, this could give evidence about how good it was the idea to use them taking into account that those channels are the nearest to the Broca and Wernicke areas. To this, the EEG signals were processed with our method, in which the classifier was trained and tested using the EEG signals with two distinct channels configurations: four (F7-FC5-T7-P7) and all (fourteen) channels. The results can be seen in Table 1. In general, the accuracies obtained using 14 channels are better than using four. It is important to mention that even though four channels (F7-FC5-T7-P7) result in a contribution coefficient greater than 0.5 for all subjects (that is, accuracy of four channels was 50-percent or more of 14 channels), this is not sufficient to conclude that only these channels contain information associated with the imagined pronunciation of words. These results are in sintony with the works mentioning that other brain regions can be involved in the imagined speech process. Furthermore, these results motivate the search for a more accurate minimal subset of channels than the 14-channels configuration.

Table 1. Accuracy percentages obtained using 4 channels and 14 channels. Column "contribution coefficient" is achieved by dividing the results of using 4 channels into the results achieved with 14 channels

	accuracy percentage		contribution
Subject	4 channels	14 channels	coefficient
S1	68.48	**80**	0.86
S2	41.21	**49.09**	0.84
S3	36.96	**63.03**	0.59
S4	46.06	**58.18**	0.79
S5	62.42	**67.87**	0.92
S6	35.15	**43.03**	0.82
S7	46.34	**64.02**	0.72
S8	66.06	**86.06**	0.77
S9	56.96	**62.42**	0.91
S10	36.36	**61.21**	0.59
S11	71.51	**83.63**	0.86
S12	51.51	**60.6**	0.85
S13	46.66	**65.45**	0.71
S14	32.72	**43.03**	0.76
S15	**61.81**	60.6	1.02
S16	40	**50.9**	0.79
S17	48.48	**67.27**	0.72
S18	55.75	**72.12**	0.77
S19	30.3	**51.51**	0.59
S20	72.72	**76.36**	0.95
S21	27.87	**36.96**	0.75
S22	52.12	**65.45**	0.8
S23	49.69	**53.93**	0.92
S24	38.78	**45.45**	0.85
S25	27.27	**43.63**	0.63
S26	39.39	**52.72**	0.75
S27	50.6	**59.14**	0.86

6 State of the research

We have studied the present EEG channel selection methods to delimit the scope of our research. Furthermore, we will begin to explore feature extraction methods, specifically, discrete wavelet transform and relative wavelet energy. We have defined two objectives for minimizing the number of selected channels and error rate (complement of accuracy).

7 Conclusions

We have proposed a novel approach for channel selection that uses a preliminary reduction of the number of channels by removing channels containing artifacts.

Furthermore, this allows a reduction in search space. The multi-objective optimization will help to find better solutions than mono-objective optimization because accuracy is not an exclusive measure in real-life applications.

On the other hand, we have proven the importance of channel selection in unspoken speech datasets. Our research only compares four and 14 channels, with 14 proving best. However, processing 14 channels is more costly than using fewer channels. The next step in our research is to determine which, and how many, channels are the best configuration for this task.

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