A Preliminary Study on Automatic Detection and Filtering of Artifacts from EEG Signals *

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***Abstract*—One of the biggest problems in EEG recordings is the contamination of the signal caused by artifacts because these interferences hinder the analysis of real neural information. Thus, their elimination while preserving as much brain data as possible is a key procedure before the study of the EEG. To address the automatic removal of craniofacial artifacts, this paper proposes a two-stages procedure: the former one is the detection stage -where both a MLP neural network and a dynamic threshold method are applied to detect the contaminated areas of the EEG-, while the latter is the removal stage -combining CCA and EEMD algorithms to remove the artifact data only. Experimental results show that both detection methods are comparable, but with the dynamic threshold detection slightly outperforming the MLP. Also, the combined technique can completely remove those artifacts scattered in all the EEG channels. This study will be extended to ocular artifacts, where more complex models would be required.**

***Index Terms*—Epilepsy, EEG, artifact detection, artifact removal**

I. Introduction

This study presents a research included in a project to train photo-sensitivity epilepsy patients to identify scenarios for which real onset risk exists, so they can transfer this knowledge to everyday life. To do so, Augmented Reality is proposed to generate scenarios of everyday life including some of them where the risk of suffering an onset gets increased. A passive Electroencephalogram (EEG) recording will provide information to the system to modulate the intensity of the experience to avoid risks and also to extract some relevant information concerning with the patient's file. On-line analysis the EEG signal is, then, crucial and, to do so, the channels should be cleaned from artefacts. This study focuses on automatically identifying artefacts by means of auto-fixed thresholds or by means of neural networks classifiers.

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EEG recordings are usually contaminated with artifacts, from muscle contraction of muscles of the head and face -Electrocardiogram (EMG) artifacts-, eyelid closing and ocular movements, EKG signal and body muscles. This interferences obscure the EEG recordings and difficult the electroencephalographers task of identifying and put in contexts the findings observed [1].

This preliminary work shows a methodology for the removal of craniofacial myogenic artifact detection (AD). A two stages procedure is proposed, firstly by detecting the AD and then by effectively removing them. For the former stage two techniques are compared -using thresholds and Multi Layer Perceptron (MLP)-. The method using thresholds have been provided with a heuristic to automatically calculate the threshold for each case. The latter stage combines Canonical Correlation Analysis (CCA) and Ensembled Empirical Mode Decompositivon (EEMD) algorithms to remove the artifact data only.

The structure of this work is as follows. Firstly, the next section focuses on the related work on craniofacial myogenic artefacts detection and elimination. Section III deals with the methods for the automatic identification of these artefacts, while Section IV details the experimentation and results, followed by a discussion on the obtained results. Finally, the conclusions are drawn.

II. Related work

Due to the presence of artifacts contaminating EEG signals and making it difficult to analyze them, it's necessary to apply methods that are capable of detecting these artifacts, eliminating them and preserving as much brain information as possible. The simplest method includes detecting the areas of the raw EEG signal where an artifact appears by visual inspection and directly removing those samples [2] or even the complete trial [3].

However, a different strategy is needed whenever an online evaluation of the EEG signal is required: techniques to reduce the effect of artifacts without eliminating the neural information hidden within them. Recently, [4] made a compilation of the most widely applied methods for removing the artifacts in EEG signals literature, the signal decomposition method among them. These methods simplify the original signal into a set of components representing the EEG signal plus a residual that, ideally, represents the non-relevant information.

On the one hand, there are those procedures that decompose the signal into a set of frequency components. The Discrete Wavelet Transform (DTW) algorithm applies pairs of high-pass and band-pass filters successively and separates different frequency bands [3], [5]. The Empirical Mode Decomposition (EMD) divides the initial signal into components known as Intrinsic Mode Functions (IMFs) using the upper and lower envelopes. There is a variation of this method that is more robust to noise called EEMD and it's capable of computing the IMFs more precisely.

On the other hand, Blind Source Separation (BSS) techniques estimate the set of source signals whose linear combination sums the original signal [6]. The simplest BSS algorithm is Principal Component Analysis (PCA), though the most cited one in Time Series decomposition is Independent Analysis Component (ICA). This algorithm computes the source signals in a way that they are statistically independent. In [7] ICA is employed to improve the results of their experiment. Another method of this group is the CCA. Unlike ICA, CCA calculates the components from uncorrelated sources with the advantage of a lower computational cost [8].

In recent years mixed methods have become very popular. These methods apply BSS algorithms together with frequency decomposition methods in order to separate the sources and reduce the amount of brain information eliminated removing only the artifact data. Different combinations of these algorithms have been proposed, e.g., DWT+ICA in [9], EEMD+CCA in [10], [11] or generic combinations of BSS and EMD variations in [12].

In addition to the previous algorithms, filtering methods make up another large group used for artifact removal tasks. Among them is the Wiener filter: a linear filter that estimates the clean signal from a noisy measure [13]–[15]. In [16], a combination of filtering and ICA is used for craniofacial myogenic artifact removal.

Artifacts removal techniques have been mentioned above, but before using them it's necessary to detect the artifacts within the signal. The artifacts can be defined as data with strange behavior, i.e., patterns in data different from those expected under normal conditions. Using this definition, it can be stated that an artifact is an anomaly and the same detection techniques can be used.

The anomaly detection systems use the concept of similarity: given two signals, a similarity metric is used to represent how similar they are. The most commonly used similarity metric is a distance metric: the higher is the distance between two signals, the lower is their similarity.

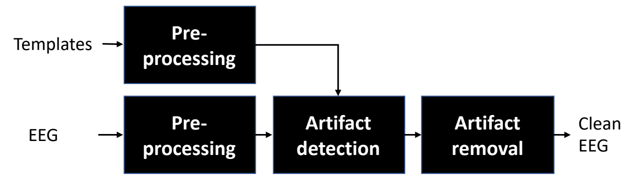


Fig. 1: Stages of the applied method.

An anomaly detection procedure based on thresholding was proposed in [17]. Firstly, a template of what they considered normal signals is created. All these windows are of the same size. Then, a window, also of the same size, is extracted from the measured signal and is used to calculate the distances between it and every normal signal. The similarity measure between the signal window and the normal template is the lowest one, which is the higher distance obtained. If this similarity value is higher than the threshold, the signal window is classified as normal. Otherwise is an anomaly.

However, the aim of that study is to compare different distance metrics and calculate the optimal threshold for each one of them and their data. The method proposed in this paper only uses the Bhattacharyya distance (the one that obtained the best results in their study) as the similarity metric, the normal template is composed of windows without artifacts, the windows with the craniofacial myogenic artifacts are labeled as "abnormal" and, as the classification rule, an automatic threshold computed from the normal template is proposed.

In addition to the anomaly detection method, Machine Learning algorithms are also used for this purpose. The Supervised Machine Learning algorithms has the goal of learning and distinguish data patterns associated with a particular class. Then, when they receive a new input from an unknown class, the learner makes a prediction and classifies it into one of the target classes. The most commonly used learning algorithm for artifact detection is the Support Vector Machine (SVM) [3], [5], [9].

III. Automatic extraction of craniofacial myogenic artefacts

The structure of the automated removal of the craniofacial myogenic artifacts method proposed in this paper is as follows, as shown in Fig. 1. The method requires a set of templates representing windows that include normal or abnormal behaviour; in this study, we have use windows with 1 second length. This templates are pre-processed as explained later in this section.The raw EEG signal is windowed pre-processed and the features are extracted. Two more stages follow: i) the craniofacial myogenic artifacts detection and ii) their removal and reconstruction of cleaning EEG signal.

In the pre-processing stage, an EEG signal window is normalized and Notch and Butterworth filters are applied to remove undesired frequency components. Finally, the Power Spectrum Density (PSD) is computed, extracting the features that represent the current EEG window.

In order to develop an automated artifact detection and removal application, this paper proposes two different approaches for the AD stage: a dynamic threshold, based on [17], and a Multilayer Perceptron Neural Network (MLP). These techniques analyze the PSD of the windows of the EEG signal to be studied in order to classify them as normal or artifact windows. Both of them will be explained below.

Once a detection method classifies a window as abnormal, it means it detected a craniofacial artifact and the removal technique is applied to clean the current window. For the removal stage, the mixed method proposed by [10], a combination of CCA and EEMD algorithms is employed.

A. Automatic threshold for AD

The method proposed in this section is based on the thresholding detection method proposed in [17]. The idea is to compare an EEG window to each of teh normal templates in a dictionary; when the distance is higher than a given threshold, the EEG window is labelled as abnormal -that is, includes an artifact-. The distances are not calculated between two EEG raw windows; instead, the PSD is calculated and used for the distance measurement calculation by means of the Bhattacharyya Distance.

Given an EEG window (X_i), its 0-50 Hz PSD (p) is computed. Then it is compared using the Bhattacharyya Distance with the PSD (q) from each of the available templates. The distance is computed using Eq. 1 and 2, where $p(k)$ and $q(k)$ are the kth sample of the p and q window of K size and s^{BD} is the similarity value, which inverse d_{BD} is the distance value. Therefore, we compare the current EEG window to each of those included in the template set.

$$s^{BD} = -ln(\sum_{k=1}^{K}(\sqrt{p(k) * q(k)})) \tag{1}$$

$$d_{BD} = \frac{1}{s^{BD}} \tag{2}$$

Once the threshold values are obtained, the current EEG window is compared with each of the normal windows of the template computing the distance between them. The highest distance is extracted: this value represents the lowest similarity between the EEG window and the signals considered normal.

However, determining thresholds represents a challenge itself as they suffer variability from one participant to other and also the amount of signal might vary for the same participant along the test. To minimize these drawbacks, this paper proposes to use the Empirical Rule -a.k.a. 68–95–99.7 rule- to determine whether a point represents an outlier.

Let μ and σ be the mean and the standard derivation of the distances between all the normal template signals. These values are calculated once at the beginning and are constant throughout the process.

In this study, whenever the maximum distance among the current EEG window and a normal template holds the condition in Eq. 3, the window is labelled as abnormal -including an artifact-. In Eq. 3, μ and σ are the mean and the standard derivation of the distances between normal templates, respectively, while $d_{max}(X_i)$ is the highest distance between the current EEG window X_i and a normal template.

$$d_{max}(X_i) - \mu > 3 * \sigma \tag{3}$$

B. AD by means of MLP

As opposed to the previous method, MultiLayer Perceptron (MLP) neural network classifiers are also used to detect if an input window from the EEG signal has an artifact and compare the detection performance results. This network receives the PSD of the EEG windows as the input pattern and make a binary classification: the outputs are 0 for the normal windows or 1 for the abnormal windows with the craniofacial myogenic artifacts.

The MLP is trained with the PSD of the windows from both normal and abnormal templates and the windows extracted from a continuous EEG segment. All the training data are manually labeled as normal or artifact windows.

Different parameters, functions and number of neurons in the hidden layer need to be tested.

C. Removal of Artefacts from EEG channels

If the current window is labeled as anomaly, it means that it includes an artifact and the removal technique presented in [10] is applied to this window. CCA is applied to separate the uncorrelated source signals and ordered according to their kurtosis value. The artifact component is identified as the source with the highest kurtosis. Then, EEMD is applied only to that component to compute its IMFs and the artifact components are identified again by the same method: IMFs are sorted by kurtosis value. The higher ones corresponded to artifacts components. These artifact signals are removed and the rest of the IMFs are preserved to rebuild the CCA component and then all the sources are combined again to reconstruct the EEG signal, now clean and free of artifacts. The algorithm is outlined as follows:

1) if the current window is labelled as artifact
    a) CCA algorithm is applied to the current window, extracting the uncorrelated sources and sorting them by their kurtosis value. The highest kurtosis corresponds to the artifact component.
    b) EEMD algorithm is applied to that component, computing the IMFs and sorting them using the kurtosis value. The artifact data contamination corresponds to components with high kurtosis.
    c) Dismiss the IMFs from the artifact -i.e., the two IMFs with the highest kurtosis- and reconstruct the component using the remaining IMFS.
    d) Reconstruct the free-from-artifact EEG window from the components.

IV. Experiments and Results

This section introduces the data set used and the experiments implemented with their results. All the experiments were implemented in Python.

A. Materials

The data used in the experiments are from the public BCI Competition IV dataset. This data set is a compilation of various data sets about motor imagery and muscular movements. Thus, the data set used in this work is DataSet 1.

This data set was provided by [18] in the "BCI Competition IV" event. The data was obtained from 7 healthy subjects in two sessions: calibration and evaluation. In the latter session, the two more informative classes were selected from the three performed motor imagery tasks (right hand, left hand and one foot movements). The calibration data is the data used in this study: it is a continuous EEG signal composed of 100 trials of each selected class. In each trial, a visual cue was displayed for 4 seconds during which the subject had to perform the corresponding motor imagery task separated by 2 seconds breaks. The EEG was recorded from 59 electrodes, digitized at a sampling rate of 1000Hz and band-pass filtered between 0.5Hz and 200Hz.

The EEG signals were normalized and then filered using a Notch and a fifth-order Butterworth filters. The Notch filter acts as a band-stop filter with a 50Hz null frequency to reject the power supply components (quality factor $Q = 30.0$). The Butterworth filter acts as a band-pass filter with 0.5Hz to 50Hz cut-off frequencies used to eliminate high-frequency noise and extract the frequency bands of brain activity. After that, the PSD was calculated between 0Hz and 50Hz frequencies, resulting in 50 values per window, and has been used as window features.

The detection stage is performed in a single channel: F3 is the nearest electrode to the eye in this data set, so it's the electrode where the craniofacial myogenic artifacts can be detected easier. Otherwise, the removal stage is performed in 15 selected channels to reduce the amount of data.

Several sets of templates were manually created from the data set described in IV-A. Firstly, the training-testing subset, including 30 normal windows and 30 artifact windows (labelled as abnormal), was extracted from the F3 EEG channel of the first subject; all windows are of 1 second long. A second set of templates, called 150-WIN, is a continuous EEG fragment of 150 seconds extracted from the same EEG and split into 150 windows that have been manually labeled as abnormal or normal according to whether the window includes an artifact or not. Finally, a third set of templates (100-SEC) includes an EEG fragment of 100 seconds extracted but neither divided not labeled.

B. Experimental set up

The experimentation is split in two stages: the former compares the two techniques for artifact detection (experiment IV-B1), while the latter focuses on the performance of the complete proposal for artifact detection and removal (experiments IV-B2 and IV-B3).

1) Experiment IV-B1 - Comparison of the Detection Techniques: The aim of this experiment is to compare the two AD techniques (using a dynamic threshold and using a MLP) in terms of detection performance, so we can select the most promising one for the next experiments. The detection methods are applied in a single EEG channel: F3, the channel from the data set that is closest to an eye, so the craniofacial myogenic artifacts are more visible.

The training-testing subset together with the 150-WIN templates are used in a 10-fold cross-validation training and testing of the models, allowing us to compare their performances. Results from the evaluation using the testing part will be used for comparison purposes.

When tuning the automatic threshold method -that is, setting the threshold- only the normal windows are employed. For each window the PSD is computed. Afterwards, the Bhattacharyya Distance is calculated for each pair of PSDs. Finally, the mean and standard deviation are computed and the threshold is determined using Eq. 3.

On the other hand, two different neural network libraries for Python were used to create a MultiLayer Perceptron: Neurolab and Sklearn. Both of them have the same configuration: input layer with 50 neurons, output layer with a single neuron for binary classification, hidden layer with 20 neurons was tested and logistic Sigmoid function as the activation function of all neurons. These neural networks receive the PSD of a certain window as an input and generate a binary output to classify it: 0 corresponds to "normal" and 1 corresponds to "abnormal", i.e., a clean window or one contaminated with an craniofacial myogenic artifact.

2) Experiment IV-B2 - Craniofacial Myogenic Artifacts Removal in EEG activity fragment: The aim of this experiment is to evaluate the performance of the method on the 100-SEC data. The idea is to compare how the combination of methods work for each of the AD techniques with unseen EEG data.

This experiment, thus, considers only the 100-SEC data; a sliding window without overlap is applied all over the stream. Whenever a window is labelled as abnormal using the corresponding AD technique, the removal part of the method is applied to get the artifact filtered.

3) Experiment IV-B3 - Craniofacial Myogenic Artifacts Removal in a complete Motor Imagery signal: This experiment evaluates the complete proposal on the EEG signal from the first subject, which was the one for which the training of the models was performed. The complete EEG signal last for 32 minutes. The aim of this study is to analyze the robustness of the method for data from the same subject.

C. Results and discussion

In the following, the results of all the experiments are provided.

1) Experiment I Results - Comparison of the Detection Techniques: As mentioned in section IV-B1, two different neural network libraries for Python were used: NeuroLab and Sklearn. Both neural networks were tested but only the results of the Sklearn's MLP are provided. This is because the training of the Neurolab's network takes much longer than the Sklearn's one so it is discarded.

The performance of the two detection methods is depicted in Table I. Variations on the figures was a consequence of the relatively reduced size of testing data set as long as for one fold only two AD were included.

	Dynamic Threshold			Sklearn's MLP		
Fold	Acc	Sens	Spec	Acc	Sens	Spec
1	1.0000	1.0000	1.0000	0.9524	0.8571	1.0000
2	0.9474	1.0000	0.9375	0.9524	0.8750	1.0000
3	0.9474	1.0000	0.9375	1.0000	1.0000	1.0000
4	0.9474	1.0000	0.9412	1.0000	1.0000	1.0000
5	0.8947	1.0000	0.8750	1.0000	1.0000	1.0000
6	0.8947	0.5000	0.9412	0.9524	1.0000	0.9286
7	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
8	0.8421	1.0000	0.8125	0.9524	1.0000	0.9375
9	0.7368	1.0000	0.7059	0.7143	0.5000	0.8000
10	0.8421	1.0000	0.8000	0.8571	0.8571	0.8571
Mn	0.9053	0.9500	0.8951	0.9381	0.9089	0.9523
Mdn	0.9211	1.0000	0.9375	0.9524	1.0000	1.0000
StD	0.0774	0.1581	0.0905	0.0853	0.1576	0.0683

TABLE I: Results of Cross-Validation using Sklearn library (left) and Dynamic Thresholding (right). Mn = Mean. Mdn = Median. StD = Standard Deviation.

Welch's t-test was used to test whether the two distributions of values (one from the threshold method and the other from the MLP) were comparable. We performed the test for the three statistics and found that the two methods were comparable. As long as the artifacts that were proposed in this research are mainly peak type, it would be difficult for the threshold method to continue performing well with more complex artifacts: in this case, perhaps Hidden Markov Models for each type of artifact could become an alternative. On the other hand, the MLP also suffered for some of the folds, which suggest that more elaborated Neural Network models would be required to tackle more complex artifacts such as ocular artifacts.

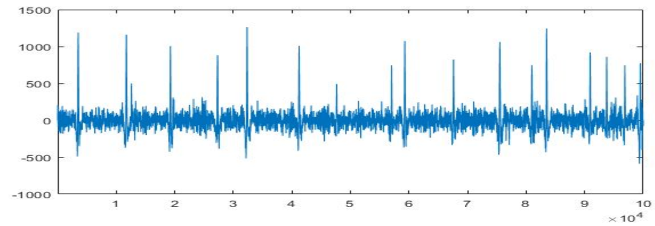
2) Experiment II Results - Craniofacial Myogenic Artifacts Removal in EEG activity fragment: From the results of the previous experiment, both detection methods (the dynamic thresholding and the MLP) are used for the detection stage. The combined removal method is applied only in the windows previously marked as an anomaly.

After applying the AD thresholding method to the EEG fragment of 100 seconds in channel F3, all the windows labelled as 1 are considered artifacts and the removal process is applied to each window separately to all 15 channels.

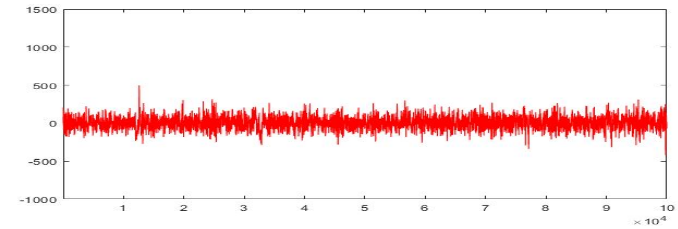
After apply CCA, the source with the highest kurtosis value corresponds to the craniofacial myogenic artifact.

After apply EEMD, the IMFs with higher kurtosis values correspond to the artifact data. The two highest IMFs are the ones eliminated.

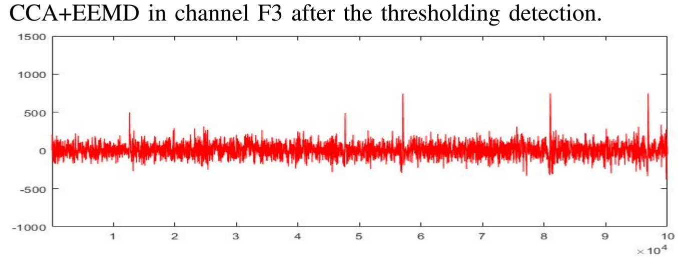
The results of the artifact elimination are shown in Fig. 2: the upper part depicts the F3 channel's EEG signal, while the reconstructed signal after the threshold-based artifact removal



(a) Original EEG channel F3 before AD and removal.



(b) Reconstructed signal applying the combined technique CCA+EEMD in channel F3 after the thresholding detection.



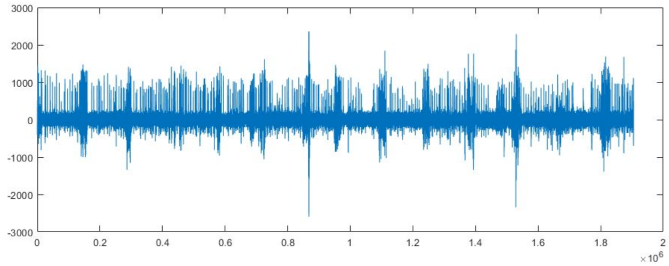
(c) Reconstructed signal applying the combined technique CCA+EEMD in channel F3 after the MLP detection.

Fig. 2: Results of the combined removal method.

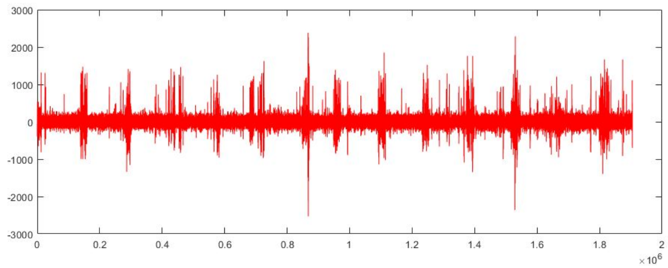
is included in the middle part; the reconstructed signal for the MLP-based removal is shown in the bottom part. As can be seen in 2b, all the craniofacial myogenic artifacts existing in have been successfully removed but preserving as much brain activity as possible despite one particular anomaly between seconds 1 and 2. This anomaly was not removed because it wasn't dispersed across all channels as all other artifacts and the CCA algorithm could not compute the artifact source. However, as can be seen in 2c, the results observed are worse: the MLP cannot detect the smallest artifacts.

3) Experiment III Results - Craniofacial Myogenic Artifacts Removal in a complete Motor Imagery signal: From the results of the previous experiment, the artifact removal process applied in the complete EEG signal of 32 minutes of duration uses the dynamic thresholding detection method.

As shown in Fig. 3, almost all craniofacial artifacts are eliminated preserving the dense motor imagery activity for the same reason as found above. Concerning the computational complexity, the AD phase represents a light algorithm in both cases, which is not the same for the artifact removal step -for 32 minutes it took nearly 3 hours to complete in a core i3 with 16 GB RAM-. While it is useful in off-line studies, for those cases requiring on-line analysis AD can assist in marking those time windows where there exists an artifact.



(a) Original 32-minutes EEG channel F3.



(b) Reconstructed 32-minutes signal in channel F3 after the thresholding detection.

Fig. 3: Results of the combined removal method.

V. Conclusions and Future Work

This paper has proposed a two-stage automatic artifact detection and removal procedure: in the first one, the detection stage, a dynamic thresholding method and a MLP neural network were proposed to detect the EEG windows contaminated with artifacts; in the second one, the removal stage, a combined technique formed by CCA and EEMD algorithms is applied to remove only the artifact data and preserve as much brain information as possible. This study also proposed a method based on the Empirical Rule to automatically determine the thresholds.

Normal and artifact windows of 1 second are extracted from the EEG to create a normal and an abnormal templates respectively. Also, a 150-seconds EEG segment is extracted and divided in windows of 1 second. All the windows are manually labelled as normal or artifact. The PSD of the EEG windows is calcuted as the feature to be analysed in the detection stage.

On the one hand, the results of the detection experiment shows that both detection techniques perform well for this type of simple artifact, being both comparable. Nevertheless, the performance with more complex artifacts might be in compromise and Hidden Markov Models or more complex Neural Networks structures should me required for these cases.

On the other hand, the results of the removal experiment corroborate that the combined CCA+EEMD applied can remove the artifacts correctly detected preserving brain information if they are well dispersed throughout the channels. However, this technique depends on the detection performance. Thus, the artifact removal have better results if it's applied with the thresholding method.

Future work includes the design of methods to tackle ocular artifacts, which are needed for the analysis of some epilepsy EEG analysis and biomarker development.

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