Classification of fine hand movements of the same limb through EEG signals

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Abstract

Discriminating fine movements within the same limb using electroencephalography (EEG) signals is a current challenge to non-invasive BCIs systems due to the close spatial representations on the motor cortex area of the brain, the signal-to-noise ratio, and the stochastic nature of this kind of signals. This research presents the performance evaluation of different strategies of classification using Linear Discriminant Analysis (LDA) method and power spectral density (PSD) features for three tasks: make a fist, open the hand, and keep the anatomical position of the hand. For this, EEG signals were collected from 10 healthy subjects and evaluated with different cross-validation methods: Monte Carlo, to implement an Offline Analysis And Leave-one-out for a pseudo-online implementation. The results show that the average accuracy for classifying the start of each task is approximately 76% for offline and Pseudo-online Analysis, classifying just the start of movement is 54% and 62% respectively for same both methods and 45% for and 32% classifying between classes. Based on these results, it can be said that the implementation of a BCI based on PSD features and LDA method could work to detect the start of one of the proposed tasks, but to discriminate the movement it is necessary to implement a different strategy for increase accuracy in the classification problem.

1 Introduction

A brain-computer interface (BCI) is a technology that allows a human brain to communicate with the outside world through an artificial pathway Chaudhary et al. [2016]. It is a system that translates a mental task into commands that can operate a device Wolpaw [2007]. This translation can be done through the recording of brain activity by invasive and non-invasive techniques Lebedev and Nicolelis [2006] and the controlled devices can allow the user's spelling with a virtual keyboard Scherer et al. [2004], navigating the World Wide Web Birbaumer et al. [2004] or controlling exoskeletons and prostheses Al-Quraishi et al. [2018]. While these BCI examples achieve their goals with some degree of success, they are based on discrete task classification, and the need to classify tasks that involve continuous estimation of parameters such as the fine motion of a human hand remains a latent challenge for the successful operation of non-invasive BCI Hosseini and Shalchyan [2022].

One of the most used technologies to implement non-invasive BCIs is electroencephalography (EEG) due to its good temporal resolution, cost-effectiveness and portability Hooda et al. [2020], nevertheless, the use of these types of signals to discriminate the motor task of different movements within the same limb is an actual challenge due to the stochastic nature of these signals, the signal-to-noise ratio, and close spatial representations in the motor cortex area for these kinds of tasks Yong and Menon [2015], Shiman et al. [2017].

The protocol proposed in this research involves motor execution: the test subject executes and maintains by 5 seconds the movement that is requested through a visual stimulus. This type of

36th Conference on Neural Information Processing Systems (NeurIPS 2022).

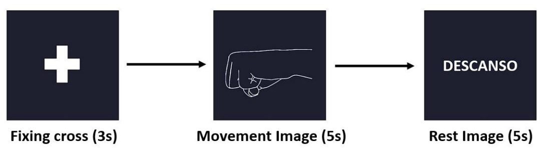
task induces changes in power values across the frequency bands that EEG signals are commonly analyzed, but it is expected that the relevant changes for this process will be in the power values of the sensorimotor band Graimann and Pfurtscheller [2006], Hooda et al. [2020]. The idea is that while the test subject performs these tasks, brain activity is recorded, and then power spectral density (PSD) features are extracted to be used as discriminant variables between these movements. It is because power spectral changes are observed during motor tasks such as movement execution, imagery, or attempt Hernández-Rojas et al. [2020].

2 Materials and Methods

The present research evaluates different classifiers based on power spectral density (PSD) features and linear discrimination analysis (LDA) to determine two things: first, if it is possible to determine the fine movement onset of the hand, and second if it is possible to discretize between the movements of the same hand. This analysis is done with electroencephalography signals acquired from 10 test subjects (4 females and 6 males with an average age of 23).

2.1 Experimental Protocol

To collect the raw signal, a experimental protocol was run that guided test subjects through visual stimuli by attention, execution, and rest sections. These images that were presented to the subjects, as well as the duration times of each image, are shown in figure 1. This protocol allowed measuring the electroencephalography signals during 90 trials in each session, which means that for each subject 30 trials per class were recorded.



(a) Images presented and their duration in a trial for the different sections of an experimental session.

(b) Images presented to test subjects to tell them what type of task to perform.

Figure 1: Visual stimuli by attention, execution, and rest sections

A trial is a time section of 11 seconds, as can be seen in figure 1, which consists of three sections: attention, execution, and rest. In the first stage of attention a fixation cross is placed on the screen indicating to the test subject that they should be aware of the type of movement that has to do after this cross. This visual stimulus is presented for 3 seconds and the subject is asked to try not to blink or make sudden movements while the screen presents this image.

After presenting the fixation cross, a visual stimulus is presented for 5 seconds that indicates the movement that must be executed. This image can instruct the test subject to make a fist, extend the hand, or simply do nothing. During this stage of motor execution, the subject is asked to execute the requested movement with the greatest possible force and to hold it until rest advice appears.

The final step in the recording process of a trial is the resting stage that cover lasts 5 seconds. An image is presented with the word "descanso" that indicates to the test subjects that they can blink, adjust their position to be more comfortable, and prepare for the next trial that will start with the next fixation cross.

This experiment aims to evaluate the difference in brain activity during the fixation cross attention task, which is the first stage of the instruction given to the test subject, and the different motor tasks (including holding anatomical position) and evaluate the differences between the performed tasks. Because the fact that the physiological responses are different for each subject in terms of the energy of the signals, these analyzes must be developed subject by subject to obtain optimized results for each one and although an LDA classifier can be evaluated after a normalization process of the features Cohen [2014], this research focus on individuals analysis to evaluate the eventual implementation of an online BCI.

2.2 Data Collection

To collect the data analyzed in this research, a high-performance neuroscience research system was used, the g.HIamp by g.Tec. With this device, 32 EEG channels were recorded simultaneously with a sampling frequency of 1200 Hz. The configuration of channels that was used in this investigation is shown in figure 2

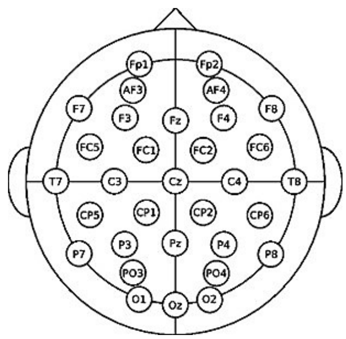


Figure 2: 32-channel configuration for recording EEG signals

2.3 Pre-processing

to pre-processing the signals, the first step is to resample the frequency to 256 Hz, then a band-pass Butterworth filter was applied from 2 to 30 Hz. This frequency range is sufficient for the feature extraction needs that are used to train and test the classifiers. In addition to this bandpass filter, a notch filter was applied to reject the noise that the electrical network could apply to the analyzed signal.

Once these filters were applied, the signals obtained were analyzed with the intention of eliminating noisy data from channels and entire trials that, due to artifacts, movements, or any other situation, generate noise and can generate bad classifications or a malfunction in the implemented classifiers.

2.4 Power Spectral Density (PSD)

The features used to classify the different tasks in this research is the power spectral density (PSD) of the EEG signals. It is a widely used feature in tasks such as motor execution, motor imagination, or movement intention because a change in spectral power can be observed in these types of tasks Hernández-Rojas et al. [2020]. This feature is a way to represent the distribution of the frequency components of the analyzed signal, that is, it can represent the proportion of the total power of the signal that is contributed by each frequency component Dempster [2001]. For each of the classification methodologies, the PSD was calculated in a range from 2 to 30 Hz with a resolution of 1 Hz in analysis windows of one second.

2.5 Feature selection

The features used correspond to Power Spectral Density and are calculated with a resolution of 1 Hz, this means that for each data 893 features were obtained, with 28 frequency-related values per each of the 32 electrodes. To adjust the number of features to 3 times the amount of data, Spearman's correlation coefficients were measured and the features that obtained the lowest values of correlation with the classified task were discarded.

2.6 Classification methodologies

Different linear discriminant analysis (LDA) classifiers were implemented in this research due to its low computational cost Ahmadizadeh et al. [2021]. The objective of this research is to evaluate the possibility of implementing a human-machine interface capable of classifying the start of a movement and discretize between different movements in the same hand, For this, two types of cross-validation were implemented: Monte Carlo to perform an offline analysis and leave-one-out to implement a pseudo-online analysis. With each of these validations, the performance of the implemented classifiers was analyzed to detect the start of each of the tasks described in section 2.1 and to discretize between them.

2.6.1 Offline Analysis

The Monte Carlo Cross-validation technique was implemented for the offline analysis, where the training set corresponds to 80% of the recorded trials and the remaining 20% to test it. This process was repeated 500 times and for each time the data sets were randomly defined. To obtain the features, two analysis windows were used as shown in Figure 3. The analysis window for the fixation cross was taken in the last second of that section and the analysis window for each tasks execution was taken from 3.2 seconds to 4.2 seconds, that is, 0.2 seconds after the image indicating the execution of the movement has been presented.

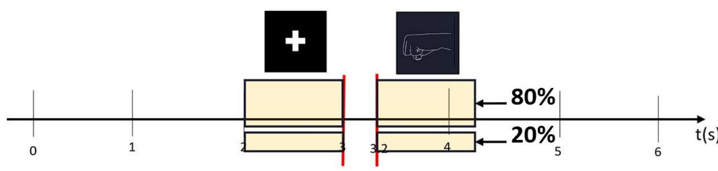


Figure 3: Monte Carlo cross Validation windows for offline Analysis

Classifying the start of the movement: To classify the task onset, the data corresponding to each one was isolated and the PSD features were obtained for the fixation cross and task execution analysis windows, then the Cross-validation technique was applied to the data. After eliminating the noise trials, an average of 28 trials for each of these tasks by subject, that is, to achieve this classification objective, there were by subject approximately 56 data per task; 44 for training and 12 for testing. After classifying each of these tasks, the second objective was to classify the start of a movement, this is, only the trials corresponding to making a fist and extending the hand were added to the data set.

Classifying between tasks To discretize between the three classes of making a fist, extending the hand, and maintaining the anatomical position, The features of PSD were acquired and the same technique of cross-validation was implemented. But to achieve this objective, the features corresponding to the fixation cross were avoided, a data set was created only with the information corresponding to the beginning of the movement, that is, from 3.2 seconds to 4.2 seconds.Figure 4 shows the position of the analysis windows for both training and testing data sets.

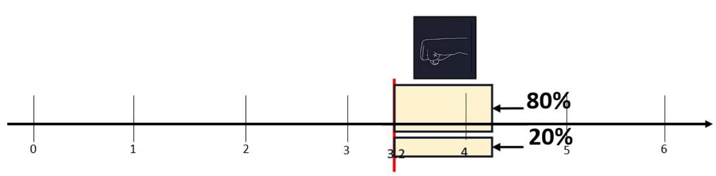


Figure 4: windowing strategy for classification between classes using Monte Carlo cross-validation

2.6.2 Pseudo-online Analysis

The implementation of the leave-one-out Cross-validation technique allows a pseudo-online analysis to be carried out with the same objectives as the analysis presented in section 2.6.1 for the offline analysis: evaluate the performance of a classifier to detect the movement onset and to discretize between the classes that are evaluated in this research. For this Analysis all the trials except one are used to train the LDA classifier and the rest is used for testing it. This is repeated until each of the trials is used as test data. Figure 5 shows the windows for the pseudo-online analysis. For the training data set, the PSD features for the fixation cross and tasks execution windows are obtained in the same way as they were taken for the offline analysis. Regarding the test data set, a mobile window was implemented with the same duration as the training windows. This mobile window gets the PSD features through time in trial test from its first position between 1 and 2 seconds to its last position between 7 and 8 seconds with an overlapping of 0.1 seconds.

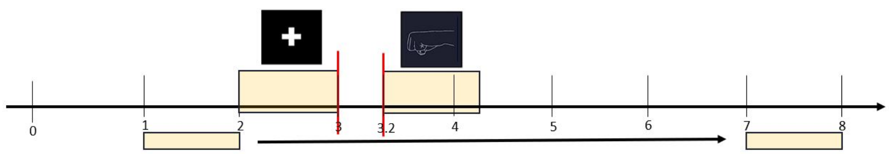


Figure 5: Leave-one-out cross validation windows for pseudo-Online analysis

Classifying the start of the movement In the same way that was done with the offline methodology, for this methodology the classification between the fixation cross and each tasks was carried out, followed by the classification of the start of the movement. For these two types of tests, the features with which the classifiers were trained were obtained from fixed windows that are shown in Figure 5: a window for the fixation cross from 2 to 3 seconds and another after 3.2 seconds for the execution of each task.

Classifying between tasks For the classification between tasks, PSD features of each one of the executions of the tasks were obtained, but also features of the fixation cross were used to train and test the classifier. this implies a bias problem in the implementation of the classifier because for each of the recorded trials there is a set of data for the fixation cross and another for the task, which means that when the features were obtained, there were 3 times more data for the fixation cross than for each one of the tasks. To solve this, the data from the fixation cross were randomly chosen and the size of the data was adjusted to the maximum size of the data of the remaining classes.

3 Results

The results of this performance evaluation of classification, show an average accuracy of approximately 76% for the detection of the start of each task and 78% for the detection of the start of a movement in the offline analysis. Regarding the online analysis, the results show approximately 76% on average for both: the start of each task and each movement. For the classification between the tasks, the results were much lower, having a result of approximately 45% for the offline analysis and 35% for the pseudo-online analysis. The results of the processes developed to evaluate the performance of the classifiers proposed here are shown below.

3.1 Trial Rejection

The elimination of trials and noisy channels is done to prevent classifications from being made on signals that are not related to mental tasks but that may be the result of muscle artifacts or poor electrode positions that can be generated by movements of the test subjects. Table 1 shows the results of the trials and the number of electrodes that remained at the end of this process. The electrodes that were eliminated for each of the subjects that were part of this investigation are also named.

3.2 Offline classification

The first objective of the offline methodology was to see the performance of classification for the detection of the start of the movement. Table 2 shows the average results after executing the methodology with the Monte Carlo Cross-validation technique 500 times. It can be seen that the one who had the best performance was subject 4 with an average classification of 91%, while subject two had the lowest classification rate with 59%. Regarding the classified tasks, it can be seen that they

Test Subject	# of trials	# of EEG Channels	Eliminated EEG Channels		
S1	83	32			
S2	87	29	C4	CP5	O2
S3	85	31	CP5		
S4	84	30	CP5	O2	
S5	90	30	C4	CZ	
S6	87	29	FZ	CP6	O2
S7	82	29	P8	OZ	O2
S8	89	30	T8	CP6	
S9	78	29	P3	T8	FZ
S10	87	32			

Table 1: Summary of the data after the elimination of trials and noisy channels

all had a similar classification average, with opening the hand being the lowest average with 73% followed by making a fist with 74%, and maintaining the anatomical position with 75%.

Task	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
Make a fist	0.66	0.60	0.74	0.92	0.68	0.82	0.84	0.59	0.80	0.71
Extend the hand	0.64	0.60	0.82	0.94	0.67	0.81	0.73	0.58	0.77	0.77
Do not move	0.87	0.56	0.71	0.87	0.63	0.79	0.81	0.68	0.79	0.81

Table 2: Average accuracy for the classification of each of the tasks

Table 3 shows the results average of movement initiation classification. It can be seen that subject 4 again has the best performance with 77% accuracy and subjects 2, 5, and 8 have the worst performance with 61 and 62%.

	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
Mean accuracy	0.77	0.61	0.79	0.93	0.62	0.83	0.84	0.61	0.82	0.82

Table 3: Average accuracy for classification of movement start for each of the subjects

Evaluating the classification between the proposed classes, table 4 presents the average values of precision and recall for each class by subject. It can be seen that subject 9 is the one with the best performance with an accuracy of 59% and that subject 8 is the one with the lowest performance with an accuracy of 33%. Likewise, it can be seen that the class with the best recall on average is the one related to not moving the hand with approximately 53%.

	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
Accuracy of classifier	0.44	0.38	0.48	0.43	0.39	0.53	0.49	0.33	0.59	0.43
Recall for make a fist	0.37	0.40	0.46	0.36	0.36	0.42	0.39	0.32	0.59	0.44
Recall for extend the hand	0.29	0.43	0.45	0.50	0.43	0.47	0.52	0.31	0.58	0.37
Recall for do not move	0.68	0.32	0.56	0.47	0.40	0.72	0.58	0.40	0.62	0.52

Table 4: Average accuracy for classification of movement start for each of the subjects

3.3 Pseudo-online classification

The objective of the implementation of a pseudo-online classifier is to evaluate the performance of an eventual brain-machine interface implementation. Initially, the behavior of the classifier was evaluated to detect the start of each task. For this, the classifier was evaluated using the test data shown in the section 2.6.2 and an array of performance values was obtained. Table 5 shows the max accuracy values for each of the evaluated tasks. It can be observed in this type of analysis that the best performance is again obtained by subject 4 with an average value of 89% in the detection of each of these tasks. Even so, the 3 classes presented have a similar performance in all subjects, where making a fist has 76%, extending the hand 78%, and not executing any movement 80%.

Task	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Make a fist	0.75	0.68	0.89	0.87	0.62	0.76	0.89	0.63	0.81	0.67
Extend the hand	0.74	0.66	0.88	0.95	0.63	0.79	0.85	0.73	0.70	0.82
do not move	0.86	0.69	0.76	0.85	0.65	0.83	0.86	0.71	0.91	0.89

Table 5: Average accuracy for classification of movement start for each subjects

Figure 6 shows the accuracy curve obtained for subject 4 and the task of reaching out. In this graph, each value of the x-axis represents the accuracy obtained by the classifier with the features of the last second, that is, for t=2 seconds the value in the graph (0.72) corresponds to the accuracy obtained when classifying the window that goes from 1 to 2 seconds. It is easy to notice that in the period between 3 and 4.2 seconds the classifier has more difficulty determining if the movement is finishing or paying attention. It should be remembered that after 3 seconds the test subject is presented with the image that indicates to execute of the movement and depending on the configuration that is being used in this pseudo-online analysis only up to 4 seconds, the obtained features have no data from the fixation cross period.

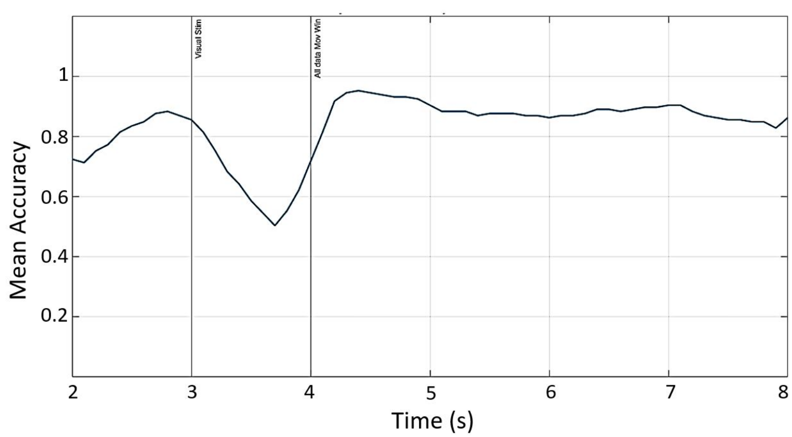


Figure 6: Accuracy curve for Leave-one-out cross-validation for subject 4 and "make a fist"

Table 6 presents the mean accuracy values obtained through the leave-one-out cross-validation methodology for detecting the start of a movement. It can be seen that subject 4 has the best performance with 80% and subject 8 has the lowest accuracy. the figure 7 shows the accuracy curve for subject 8, although it has a classification class rate of 0.53, the maximum classification value reaches 0.65 for time values of 2.7 and 4.5 seconds and, as in the previous case, the accuracy decreases when the analyzed data contains information of both classes: the fixation cross and the motor execution.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Mean Accuracy	0.59	0.54	0.54	0.80	0.49	0.63	0.75	0.53	0.58	0.55

Table 6: Mean accuracy for classification of movement onset for each subject

As expected from the results obtained in the offline strategy, the multiclass classification with the technique described in that section shows lower precision values with respect to the detection of movement initiation and the detection of initiation of each of the classes. Table 7 shows the average precision for each evaluated subjects, however these results can be confusing: according to these values, subject 4 has an average precision of 42%; however, in figure 8 it can be seen that the precision can become 77% before parsing the window in which there is task execution information and the fixation cross.

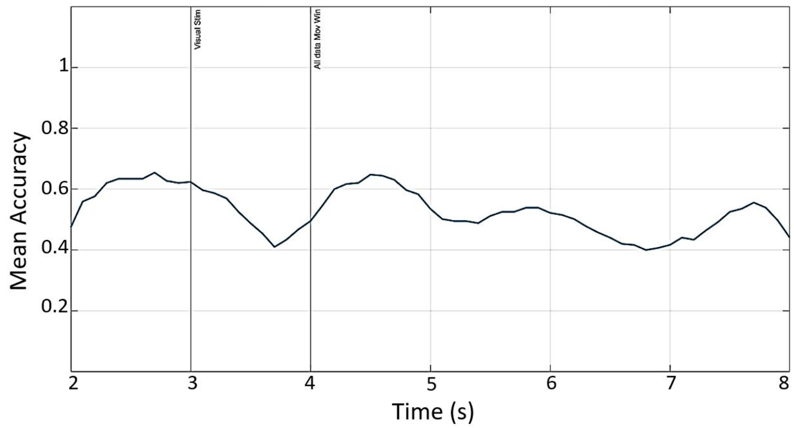


Figure 7: Accuracy curve for Leave-one-out cross-validation for movement onset for subject 8

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Mean Accuracy	0.34	0.25	0.31	0.42	0.25	0.33	0.39	0.25	0.33	0.33

Table 7: Mean accuracy for classification of each task for each subjects

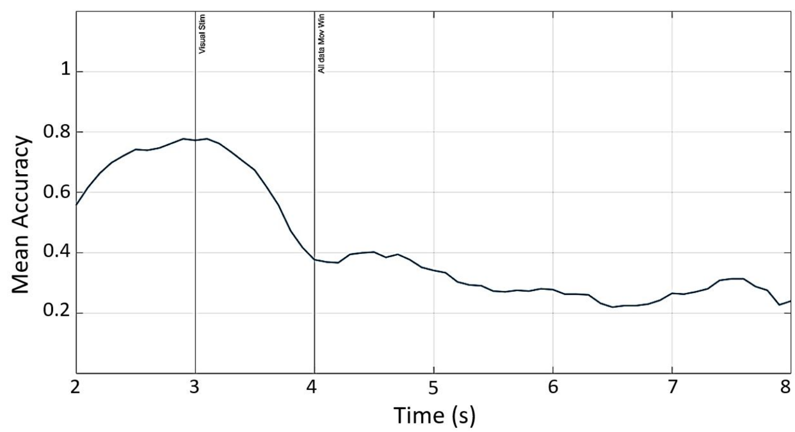


Figure 8: Accuracy curve for Leave-one-out cross-validation for classifying each task for subject 4

4 Discussion

The main concern in developing this work is whether it is possible to perform a BCI based on EEG to classify fine movements of the hand. It is a current challenge in the implementation of BCI technologies due to the stochastic nature of these signals, the signal-noise ratio, and close spatial representations in the motor cortex area for the evaluated tasks. The results of this research generate a discussion about the role of electroencephalographic signals when it comes to predicting the onset and type of fine movement of the hand that is executed: the start of movement has a good performance with LDA classifiers and PSD features. However, when determining what type of movement, the subject wants to make, it is necessary to add other types of technologies to implement a hybrid interface that improves system performance.

In the future, this type of BCI will be evaluated in patients diagnosed with neurodegenerative diseases to try to use this technology to improve their mobility. However, there is another discussion that needs to be resolved and it is referring to the kind of task that is classified in this research: the results raise doubts as to which is the participation of the motor task and which of the attention task when the intention of the movement is classified through the methodology proposed. In future works, it will be necessary to implement different protocols to verify how it affects the attention task to the results obtained.

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