BCI 200 EEG SIGNAL ANALYSIS FOR MOVEMENT INTENT CLASSIFICATION: a practical approach.

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Abstract: Brain Computer Interfaces (BCI) has become a vital field of biomedical engineering and computation, which uses electrical signals obtained from electroencephalogram exams (EEG) to provide assistive technologies (AT) for humans. This article presents the results of analyzing specific movement intent of EEG signals to extract the appropriate features using statistical classification techniques and algorithms. The EEG characteristics in terms of power spectral density (PSD), spectral centroids, standard deviation and entropy techniques were selected and investigated from two different mental exercises; The selected signals are classified using Linear Discriminant Analysis (LDA), Common Spatial Patterns (CSP). The best accuracy was achieved by the power spectral density. The accuracies of this feature are 75% to 99%, depending on the quantity and quality of the data samples collected. Finally, the translation algorithm will be built using selected and classified EEG resources to control the ICM devices.

Keywords: Brain Computer Interface; Neural networks; Electroencephalogram Signs; Machine Learning.

ANÁLISE DE SINAIS EEG BCI 200 PARA CLASSIFICAÇÃO DE INTENÇÃO DE MOVIMENTOS: UMA ABORDAGEM PRÁTICA.

Resumo: A Interfaces Cérebro Computador (ICC) tornou-se um campo vital da engenharia biomédica e da computação, que usa sinais elétricos obtidos de exames de eletroencefalograma (EEG) para fornecer tecnologias assistivas (TA) para humanos. Este artigo apresenta os resultados da análise de intenção de movimento específica de sinais de EEG para extrair as características apropriadas usando técnicas e algoritmos de classificação estatística. As características do EEG em termos de densidade espectral de potência (PSD), centroides espectrais, desvio padrão e técnicas de entropia foram selecionadas e investigadas a partir de dois exercícios mentais diferentes; Os sinais selecionados são classificados usando Análise Discriminante Linear (LDA), Padrões Espaciais Comuns (CSP). A melhor precisão foi alcançada pela densidade espectral de potência. As acurácias desse recurso são de 75% a 99%, dependendo da quantidade e qualidade das amostras de dados coletadas. Por fim, o algoritmo de tradução será construído utilizando recursos de EEG selecionados e classificados para controlar os dispositivos ICM.

Palavras-chave: Interface Cérebro Computador; Redes Neurais; Sinais Eletroencefalograma; Aprendizado de Máquina.

1. INTRODUCTION

In this article, a study of datasets of EEG signals acquired from electroencephalogram exams and applied to neural networks for machine learning and creation of a computational decision model was carried out, to control electromechanical devices, such as: a wheelchair. In particular, data sets corresponding to experiments of imagination, or intention, of left and right wrist movement were analyzed. Brain activity was recorded in the prefrontal cortex, a region of the cerebral cortex responsible for imagining, or planning, the motor signals of the human organism, where there are oscillations, increasing and decreasing, of electrical activity, between 8 Hz and 12 Hz, which can be observed through the electrical signals obtained by electroencephalogram exams [1].

Specifically when a movement is performed, it is possible to identify a reduction in electrical activity, or a decrease in the “mu” band, in specific regions of the brain that deal with the part of the human body that is being moved at that exact moment, as well as, in an interval time before the move. The reduction of the “mu” band of the EEG signal is called event-related-desynchronization (ERD). By measuring the activity in different locations of the cerebral motor cortex, it is possible to determine which limb of the body the individual is moving, precisely by decreasing the frequency of the “mu” band of the EEG signal, in a certain region of the cortex. Through the concepts of neural network and mirror neurons, this effect also occurs when the individual imagines the movement, without yet performing it. This is a very important finding for application to ICM devices. Therefore, whenever a movement is imagined, it is possible to observe a decrease in the “mu” band activity in the EEG signals, around 8 Hz to 12 Hz, including Alpha and Beta frequencies, from 8 Hz to 30 Hz, transform it in data to identify a movement intent and apply it in the control of ICM devices through the acquisition, pre-processing, feature extraction and signal classification steps.

This article presents the results of analyzing specific movement intent EEG signals to extract the proper EEG signals, using statistical classification techniques and algorithms that can be employed to control ICM devices that can be used by disabled or paralyzed people.

2. METHODOLOGY

The Brain Machine Interface (ICM) suggests an innovative alternative of communication between humans and machines. It offers the individual a way to control electronic devices with thought, without involving any muscular movement. An ICM system can be divided into five steps: signal acquisition, pre-processing, feature extraction, classification, and device control.

2.1. Signal acquisition and experiment protocol

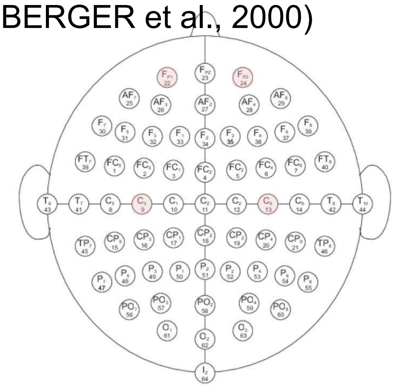
The signal acquisition step consists of obtaining data through Electroencephalogram (EEG) exams, where the reading of electrical brain signals occurs by the sensors, located in predetermined regions of the brain, or scalp, when invasive or non-invasive respectively. The extracted electrical signals are digitized and recorded in data files. The data used in this article were acquired from previous research published by the institutes: (i) PhysioNet, the Research Resource Center for Complex Physiological Signals [2]; and, (ii) Berlin BCI Group: Berlin Institute of Technology [3]. The database consists of more than one thousand five hundred (1500) recordings of one (1) and two (2) minutes of EEG signals, obtained from one hundred and nine (109) volunteers, following an experiment protocol. Subjects performed motor and imagery activities while brain electrical signals were collected and recorded on sixty-four (64) EEG channels from different brain regions [4].

The experiments consist of the respective states (task execution): (i) eyes open and (ii) eyes closed, which define the standard signals for base configuration and definition of brain signal patterns for each individual; (iii) task 1, which defines the opening and closing movements of the left and right wrists; (iv) task 2, which defines the imagination of the opening and closing movements of the left and right wrists; (v) task 3, which defines the opening and closing movements of the wrists and feet, and; (vi) task 4, which defines the imagination of the opening and closing movements of the wrists and feet. In this work, the study of tasks 1 and 2 was carried out only, and in this way, it allowed a more detailed analysis of the mathematical methods of feature extraction and classification of EEG signals, which will be described throughout the text.

2.2. Signal pre-processing and filtering

The stages of pre-processing and filtering of the signals consist of the selection of the channels corresponding to the regions of the brain, areas where there is greater incidence and intensity of the signals that are of interest to this analysis. Particularly, the signals extracted from the Fp1 and Fp2 channels, corresponding to the imagination of left and right wrist movements; and channels C3 and C4, corresponding to the motor performance of the left and right wrist. As illustrated in Figure 3, where the four channels have been highlighted in pink.

Figure 1. Distribution of electrodes in predetermined brain regions [4]. Source: (PINHEIRO apud GOLDBERGER et al., 2000)



In addition to channel differentiation, between EEG signal capture areas, the frequencies of these same signals were also filtered.

Generally, there are five frequency bands for each EEG channel, which are: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (14–30 Hz), and range (30–30 Hz). 45Hz) [24]. In this research, EEG data were filtered only into alpha and beta bands.

2.3. Feature Extraction

Feature extraction is the process of obtaining numerical or nominal values of brain patterns used in communication with an ICM.

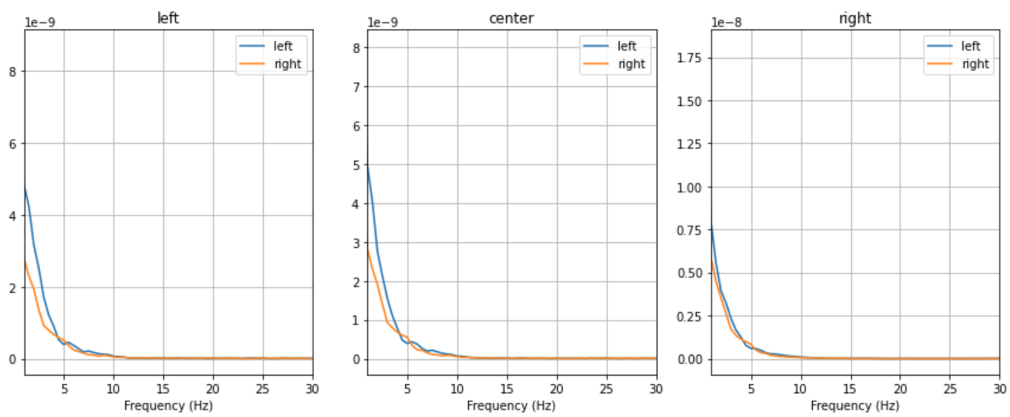
The reasons for doing that range from easier subsequent analysis to performance improvements in the next steps of data classification and model training. This occurs through a more stable representation or the removal of redundant or irrelevant information [5].

Some of the techniques used in feature extraction applied in this work were: average power spectral density (PSD); common spatial pattern (CSPs); linear discriminant analysis (LDA); spectral centroid; and, energy entropy of the alpha and beta bands. All of them were key pieces, very important to achieve better accuracy and training of the mathematical models created in this research. In addition to these, the methods of Fast Fourier Transform (FFT), power spectral density, applied to EEG data supported the results obtained.

To calculate the PSD, from each sample, the characteristic frequency of the signal was extracted in the Fp1 and Fp2 channels, prefrontal cortex, where a decrease in brain activity was successfully observed (), which means the existence of movement , and/or imagination thereof. Figure 4 graphically illustrates the PSD of the samples calculated in a similar way to the SSVEP data. In neuroscience, steady state visually evoked potentials (SSVEP) are signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz [6], the brain generates electrical activity at the same frequency (or multiples of) as the visual stimulus. The function [PSD] of the library [MLAB] written in Python was used in the calculation of the PSD, in the interval of [0.5-2.5s] of the tests, in two classes, left and right, made soon after the beginning of the suggestion imagination of the movement of the left and right wrists. Python: mlab.psd(trials[ch,:,trial], NFFT=int(nsamples), Fs=sample_rate).

Figure 2. Graphical representation of the calculated PSD data. Source:author

```
plot_psd(
    trials_PSD,
    freqs,
    [channel_names.index(ch) for ch in ['Fp1', 'Fpz', 'Fp2']],
    chan_lab=['left', 'center', 'right'],
)
```



This decrease is called Event Related Desync (ERD). By measuring the amount of “mu” activity at different locations in the prefrontal cortex, Fp1 and Fp2 channels, we can determine which limb the individual imagined. Through mirror neurons, this effect also occurs when the subject is actually moving his limbs. A peak of "mu" activity can be observed in each channel for both classes. In the right hemisphere, the "mu" activity for the left wrist movement is less than the right one due to ERD. On the left electrode, the "mu" for right hand movement is reduced and on the central electrode the "mu" activity is approximately equal for both classes. This is in line with the theory that the left fist is controlled by the right hemisphere and the right fist is controlled by the left hemisphere.

This article consists of the analysis of controlled movements in the prefrontal cortex, where there is an increase in “mu” activity (8-12 Hz) at the moment the movements were imagined. Accompanied by a reduction of this “mu” activity in specific regions that deal with the limb that is currently moving.

2.4. Data Classification and Training

In addition to the feature extraction step, signal classification and training of mathematical models play a key role in designing any ICM system because the proper selection of techniques and mathematical representations increases classifier accuracy and ICM device performance. The machine learning algorithm, described below, was created to build a model that classifies/distinguishes left and right wrist movements into two respective classes.

i.Find a way to quantify the "mu" activity present in a sample;

ii.Create a model that describes the expected values of the "mu" activity for each class;

iii.Test the model with new data to confirm the predictive ability of the algorithms to correctly determine the classes.

Following the classic design of an ICM, the logarithm of the variance of the signal in a given frequency band was used in all samples, as a characteristic for the classifier, to design a “bandpass” filter that uses the [scipy.signal.irrfilter] library, written in Python, to remove frequencies outside the [8 Hz, 15 Hz] window.

The [iirfilter()] function uses filter order: higher numbers mean a sharper frequency cutoff, and the resulting signal can be time shifted. Lower numbers mean a smoother frequency cutoff, and the resulting signal is less distorted in time. It also handles the lower and upper frequency limits, divided by the NYQUIST frequency, which is half the sample rate (i.e. “sample_rate” divided by 2).

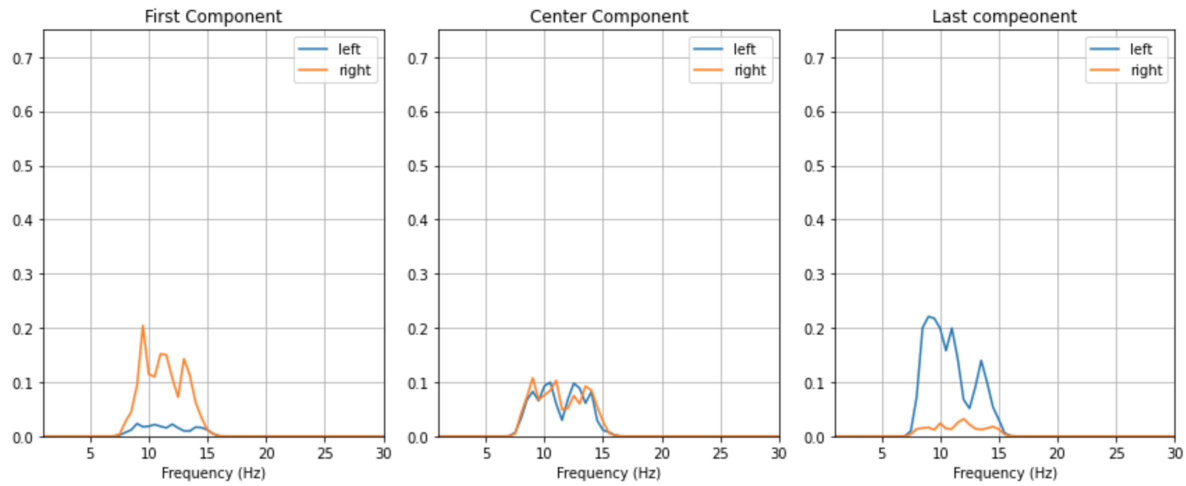
a, b = scipy.signal.iirfilter(6, [lo/(sample_rate/2.0), hi/(sample_rate/2.0)])

Most channels show a slight difference in the log-var of the signal between the two classes: left and right. The next step was to reduce from 118 channels to just a few channel combinations. The CSP algorithm calculates channel combinations (W), which are designed to maximize the variance difference between two classes. These combinations are called spatial filters, which also calculate the covariance for each sample and return the respective averages, by applying a combination matrix that basically multiplies the W (of each sample) with the matrix of EEG signals.

Instead of 118 channels, we now have 118 combinations of channels, called components, which are the result of 118 spatial filters applied to the data.

The first filters maximize the variance of the first class, while minimizing the variance of the second. The latter filters maximize the variance of the second class, while minimizing the variance of the first.

Figure 3. Combinations of channels, called components; Source: author.



From Figure 7, the following graphic shows the PSD result after the filter, applied to the three components. It is possible to differentiate well the two classes: left and right, in the scatter plot. It is a useful tool to visualize this difference. Both classes are shown in a two-dimensional plane: the x-axis is the first CSP component, the y-axis is the last. Then the linear classification algorithm was applied to draw a line on the above graph to separate the two classes. To determine the class of the new sample, check which side of the line it is presented on. For information purposes, the scatter plot was recreated and the decision threshold was superimposed as determined by the LDA classifier. The decision threshold is the line for which the classifier output is exactly zero (0).

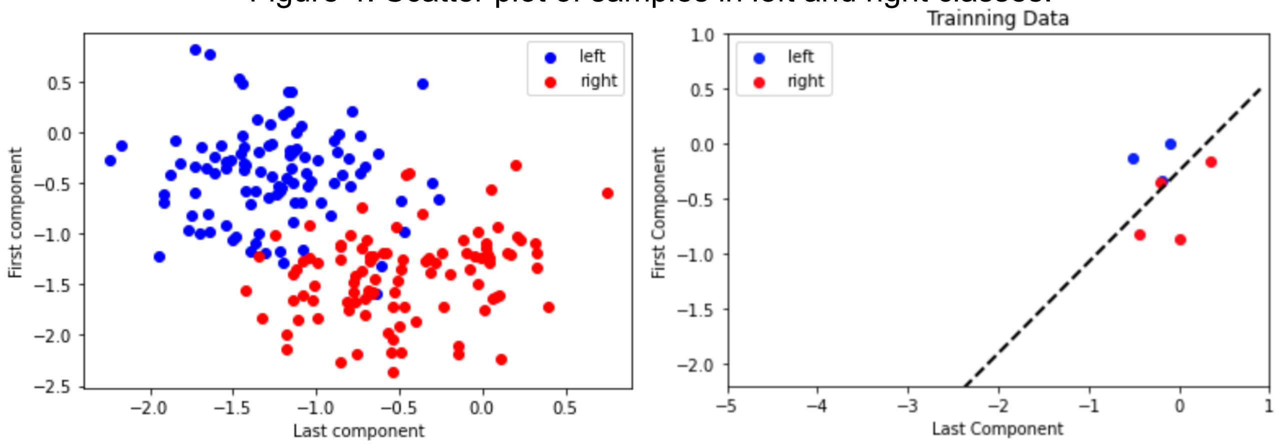
First, the decision limit is plotted with the training data used to calculate it. The following graph shows the limit of the test sample data, on which the classifier is applied. In it, it is evident that the classifier makes some errors.

As shown in Figure 8 below, the limit of the test data when applying the classifier, containing overlapping data, very close to the limit (dashed line). In addition to the division of classes, as mentioned before, the data is divided into training samples and a test set, whose percentage of samples to use in training follows the 50-50 division. The classifier fits a model (in this case, a straight line) on the training set and uses this model to make predictions about the test set, that is, it defines on which side of the line each sample of the test set appears. The CSP algorithm is part of the model, therefore, it must be calculated using only the training data.

For the classifier, the Linear Discriminant Analysis (LDA) algorithm was also used, which adjusts a Gaussian distribution for each class, characterized by mean and covariance. It determines an optimal separation plan to divide the two classes. With this, it is possible to calculate the result, positive or negative, to correctly classify the data, that is, to determine the class of a new sample. This plan is defined as:

$r = W_0 * X_0 + W_1 * X_1 + ... + W_n * X_n - b$, where: r is the output of the classifier; Wn are the characteristic weights; Xn are the characteristics of the samples; n is the dimension of the data, and; b is the offset, or standard deviation.

Figure 4. Scatter plot of samples in left and right classes.



In this case, with two-dimensional data, the separation plane was then defined as the straight line: $r = W_0 * X_0 + W_1 * X_1 - b$. The scatter plot seen in Figure 8. used X0 as the x-axis and X1 as the y-axis. To find the function $y = f(x)$ that describes the decision limit, we set r to 0 and solve for y in the separation plane equation.

3. RESULTS AND DISCUSSION

When training the LDA using the training data, the algorithm returns W: [24.0296518, -28.98866899] and b: 7.121690208432298. The LDA algorithm was built and fitted to the training data to be applied to the test data, whose results were represented in a confusion matrix, where the number on the diagonal represents the samples that were classified correctly, and any samples that were classified incorrectly, such as : a false positive or false negative; were represented in the corners. The precision was 0.857.

Confusion Matrix: `[[3 1] [0 3]]`

The confusion matrix shows that one (1) of the three (3) samples resulting from left wrist movement imagination were incorrectly classified as right wrist movement imagination, and there were no errors in classifying the wrist movement imagination samples. right, zero (0) of the three (3) resulting samples. In total, 85.7% of the samples were correctly classified.

4. CONCLUSION

In this research, two classes of mental exercise were classified with the four methods of classification and training of ANNs: Spectral Power Density, Spectral Centroid, Standard Deviation and Energy Entropy. The results obtained from the Physionet and BCI V databases reached the expected success rates, reaching up to 91% accuracy, depending on the quantity and quality of the samples tested. To classify the signals, platforms in the software platforms were used: Google Colab and Weka; and the algorithms: PSD, LDA, Random Forest, Dl4jMlpClassifier, SVM and K-NN, cross validation, multilayer perceptron, among others. All with the objective of achieving better performance and accuracy in the results. The best classification accuracy was obtained by combining the PSD, CSP and LDA algorithms, with 91%, and therefore applying the model and its methods to the translation algorithm to perform the ICM to control the electromechanical device, wheelchair.

The next steps consist of deepening this research, and exploring new methods. Not only in the application of ICM in electromechanical devices, but also in aiding medicine and diagnostic treatment, in the various variations of assistive technologies, and control and monitoring devices, applied in the health area.

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