CLASSIFYING EEG SIGNAL SEGMENTS USING MACHINE LEARNING

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In this paper we approach the classification of electroencephalogram (EEG) signals segments with the purpose of predicting movement. Labeling these segments is of utmost importance for patients that have motor functions impairments that affect their lifestyle. We aim to create the artificial intelligence (AI) base for an application that could help patients move a cursor on screen using their brain activity captured by a series on electrodes placed on the surface of their scalp. Machine learning (ML), even though largely considered a simple way to solve such problems, proved to be largely accurate. The main idea of the present work is using the electric potential difference between the brain's hemispheres, as both global maxima and P300 features extracted from C3 and C4 channels, fed to a Random Forest Classifier, as a way to predict movement intentions.

Keywords: electroencephalogram, motor and speech impairment, machine learning, classification, assistive interaction

1. Introduction

Disabled people have always been a top priority for the progress of medical techniques. Along with the technological progress and implementation of computers in the patient's medical circuit, they have also opened the door to technologies that could make living easier, or, in the best-case-scenarion, reintegrate them in the day-to-day life without being affected by the lack of certain abilities. The same could also be applied to the elderly.

To achieve a greater degree of mobility or integration into society, the multi-disciplanary field of brain-computer interfaces (BCI) was created with the purpose of leveraging the advancement of technology.

In this paper [1], Yike et al., mention that more than 85% of present technologies used for this specific task are non-invasive which shows the interest of the research community to provide the most comfortable experience for the patients in need.

The main methodology this paper approaches is based on event-related desynchronization (ERD) [2] between the C3 and C4 signals extracted from the electrodes with the same indicator that are placed using the 10-20 system. ERD is represented by the fact that motor imagery creates an imbalance between the left

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and right hemispheres of the brain, thus making possible to observe the intention of movement. For this purpose, the alpha wave (8-12 Hz) was extracted.

2. Related work

Detecting the intention of movement is essential to support a large number of IT-based neuromotor rehabilitation or assistive solution, created within the last decade, as illustrated by papers such as [3] [4] [5] [6] [7].

A variety of methods have been developed, ranging from basic signal processing to advanced machine learning solutions, as classified in [6]. Most of the latest approaches favor neural networks to label the signals. Out of all the available work, we decided to focus on two highly relevant approaches, from a use case description point of view.

Li et al. [2] decided to use a dataset containing electroencephalograms (EEGs) of patients who imagined the direction (left or right) they wanted to move an object. This dataset underwent filtering between 4-35Hz, followed by a Continuous Wavelet Transform (CWT). The resulting power intervals took the form of an image, so Li et al. decided to use CNNs to classify the EEG signals.

Kim et al. [8] use electromyogram (EMG) signals acquired from the stumps of patients who have suffered upper limb amputations. Kim et al. [8] decided to use CNNs to classify the movements that the patient wants to perform. CNNs are largely used for performing operations on images, but by using Principal Component Analysis (PCA) and transferring the information obtained into a matrix format so that the most important components are in the center of the matrix, classification can be accomplished.

The main limitation of both of the articles mentioned above is: both methods depend on transforming the signal either through the CWT or through PCA which inherently lose some aspects of the original signal thus limiting the generalizability and accuracy of the models.

3. Database description

Database contains subjects who performed various motor/imagery tasks while 64-channel EEGs were recorded using the BCI2000 system (http://www.bci2000.org) [9] [10]. Each subject performed the following experimental runs:

Task 1: A target appears either on the left or the right side of the screen. The subject opens and closes the corresponding fist until the target disappears.

Task 2: A target appears either on the left or the right side of the screen. The subject imagines opening and closing the corresponding fist until the target disappears.

Task 3: A target appears either at the top or the bottom of the screen. The subject opens and closes either both fists (if the target is above) or both legs (if the target is below) until the target disappears.

Task 4: A target appears either at the top or the bottom of the screen. The subject imagines opening and closing either both fists (if the target is above) or both legs (if the target is below) until the target disappears.

The experimental runs were:

1. Baseline, eyes open
2. Baseline, eyes closed
3. Task 1 (open and close left or right fist)
4. Task 2 (imagine opening and closing left or right fist)
5. Task 3 (open and close both fists or both legs)
6. Task 4 (imagine opening and closing both fists or both legs)
7. Task 1
8. Task 2
9. Task 3
10. Task 4
11. Task 1
12. Task 2
13. Task 3
14. Task 4

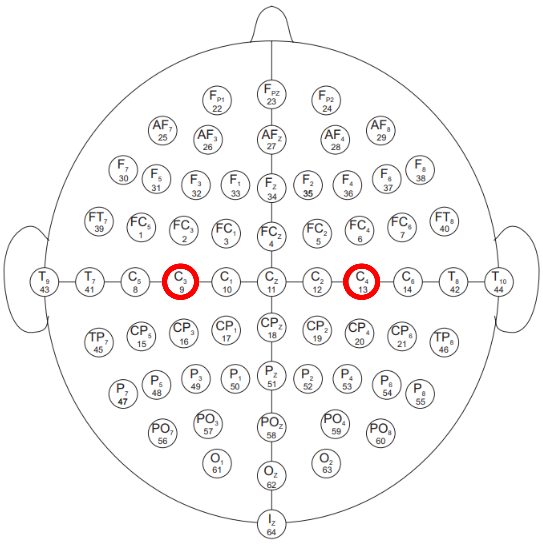

Fig. 3.1. Standard positioning of the EEG extraction electrodes with the electrodes of interest highlighted [9] [11]

Each annotation includes one of three codes (T0, T1, or T2):

- T0 corresponds to resting
- T1 corresponds to the onset of movement (real or imagined) of:
  - the left fist (in runs 3, 4, 7, 8, 11, and 12)
  - both fists (in runs 5, 6, 9, 10, 13, and 14)
- T2 corresponds to the onset of movement (real or imagined) of:
  - the right fist (in runs 3, 4, 7, 8, 11, and 12)
    both legs (in runs 5, 6, 9, 10, 13, and 14)

4. Implementation and results

In order to create the model, the following methodology was created:

1. Defining filtering functions: A band-pass Butterworth filter is used to isolate the signal between 8-12Hz frequencies (alpha wave) which contains most of the information related to the intention and execution of movement.
2. For each patient, associated files are opened. Each file represents a task performed by the subject. As specified in the database description, the average energy of task 1, which represents the subject's baseline brain activity when their eyes are open, is calculated. This task was chosen because the subject moves their limbs in response to a visual stimulus.
3. For each task, from the channels of interest (C3 and C4), lengths of segments called epochs are extracted, which have an annotation attributed at the end, representing the actual data for creating the confusion matrix at the end of prediction. Also, both signals of interest are filtered using the described Butterworth filter, a signal representing the energy for each sample is created, and the percentage difference from the average energy of the patient's baseline brain activity and the signal is calculated.
4. The maximum from the two signals is extracted and retained. The logic behind extracting the maximum is that: when a movement is made with the right hand, the left hemisphere of the brain will be activated which will result in a peak on the C3 signal, and likewise for the movement of the right hand.
5. The data is stored and the difference between the extracted maximums is calculated. Prediction of the annotation is made based on the difference by setting a threshold value which represents the maximum permissible difference between the two maximums for which a resting state can be predicted.
6. The prediction is computed using a Random Forest Classifier from the sklearn library that is an ensemble technique which creates multiple decision trees from which the vote of the majority is then outputted as the prediction, thus being a solid method for classifying. In this use case specifically, it was chosen as the

main method to be studied, because by averaging multiple decision trees, the Random Forest algorithm mitigates the risk of overfitting, which is a common issue and Random Forest handles data of this complexity well, often performing feature selection implicitly during the training process. A limitation of this model is training multiple decision trees can be computationally intensive and time-consuming, especially with large datasets.

Table 1

Confusion matrix resulted from the initial classification

	Predicted T0	Predicted T1	Predicted T2
True T0	11404	3672	4599
True T1	6027	1596	2233
True T2	5981	1826	2011

The results obtained are not satisfactory but can be improved by separately addressing the tasks for which T1 and T2 represent different movements. The first change made to the implementation was the re-annotation of the segments so that a label does not have two meanings. Thus, T1 in tasks 5, 6, 9, 10, 13, 14 becomes T3 and T2 becomes T4. Using the same implementation, the following results were obtained:

Table 2.

Confusion matrix resulted from classifying using features extracted from the global maxima of each channel's segments (C3 and C4)

	Predicted T0	Predicted T1	Predicted T2	Predicted T3	Predicted T4
True T0	18502	296	274	317	286
True T1	725	3992	58	90	86
True T2	732	85	3929	58	90
True T3	752	73	68	3955	57
True T4	650	65	67	90	4052

Table 3.

Per class and global results using global maxima

	T0	T1	T2	T3	T4	Global
Accuracy	94.03%	80.63%	80.28%	80.63%	82.29%	87.5%
F1 Score	90.17%	84.37%	84.58%	84.01%	85.35%	85.7%

A second change made to the implementation is the implementation of the P300 concept. P300 represents the first positive voltage wave (P) that appears approximately 300 ms after the patient is subjected to a stimulus (300) [12]. Using the same implementation, the following results were obtained:

Table 4.

Confusion matrix resulted from classifying using features extracted from the P300 of each channel's segments (C3 and C4)

	Predicted T0	Predicted T1	Predicted T2	Predicted T3	Predicted T4
True T0	17965	279	276	288	267
True T1	690	3902	68	65	76
True T2	712	63	3820	82	67
True T3	634	60	71	3905	81
True T4	681	68	64	83	3882

Table 5.

Per class and global results using P300 results

	T0	T1	T2	T3	T4	Global
Acccuracy	94.18%	81.27%	80.52%	82.19%	81.24%	87.74%
F1 Score	90.37%	85.07%	84.48%	85.13%	84.84%	85.98%

Table 6.

Confusion matrix resulted from classifying using features extracted both from the P300 and global maxima of each channel's segments (C3 and C4)

	Predicted T0	Predicted T1	Predicted T2	Predicted T3	Predicted T4
True T0	18738	77	67	107	86
True T1	865	3856	22	28	30
True T2	885	18	3790	23	28
True T3	811	28	30	3862	20
True T4	865	17	30	43	3823

Table 7.

Per class and global results using global maxima and P300 results

	T0	T1	T2	T3	T4	Global
Accuracy	98.23%	80.31%	79.89%	81.28%	80.01%	89.30%
F1 Score	90.87%	87.66%	87.29%	87.63%	87.23%	88.14%

5. Discussion

The results of this study show improved classification performance for EEG signal segments compared to other methodologies discussed. While Li et al. [2] used CNNs to classify motor imagery EEG signals based on continuous wavelet transformation, their classification accuracy was limited by the dataset and architecture choices. Kim et al. [8] also employed CNNs, relying on principal component analysis (PCA) to classify electromyogram signals in matrix form. Their network structure, however, was tailored to a specific dataset, and their accuracies were constrained by the variability of the signals collected from different participants.

Table 8

Comparison between the proposed methodology and the results obtained by the articles presented in the Related Work section

Method	CWT-SCNN [2]	PCA-CNN [8]	Max RFC	P300 RFC	**Max + P300 RFC**
Global Accuracy	83.2%	61.4%	87.5%	87.74%	**89.3%**

As presented in Table 8, our methodology, which involves utilizing both global maxima and P300 features extracted from C3 and C4 channels, surpasses the performance of both Li et al. [2] and Kim et al. [8] The confusion matrices generated show significant improvements in classifying signals from different motor tasks. The combined feature set effectively captures variations in motor imagery signals, allowing for more accurate predictions of movement intentions.

6. Conclusion

The ML-based classification model proposed here offers a more accurate means of analyzing EEG signals to predict movement. Despite being relatively simple in design compared to those in the related work, our approach produced better results due to its tailored feature extraction process, which includes combining global maxima and P300 features. However, the data's inherent imbalance remains a challenge, as evidenced by the confusion matrix, where the T0 class (rest state) dominates. Future improvements could involve refining the dataset to minimize this imbalance and enhance the model's robustness. Ultimately, this model holds potential as the basis for an assistive application that helps patients control computer cursors using their brain signals.

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