10.3217/978-3-99161-014-4-062

ANALYSIS OF THE EEG RESTING-STATE SIGNALS FOR BCI.

Enrico Mattei[2]† and Daniele Lozzi[1,2]†, Alessandro Di Matteo[1,2], Costanzo Manes[2], Filippo Mignosi[2], Matteo Polsinelli[4] and Giuseppe Placidi[1,3].

[1]A2VI-Lab, Univ. L'Aquila, L'Aquila, Italy
[2]Dept. of DISIM, Univ. L'Aquila, L'Aquila, Italy
[3]Dept. of MESVA, Univ. L'Aquila, L'Aquila, Italy
[4]Dept. of DISA-MIS, Univ. Salerno, Fisciano, Italy

E-mail: enrico.mattei@graduate.univaq.it
† The first two authors contributed mainly as primary co-authors.

ABSTRACT: In the Brain-computer interface (BCI), the recognition of movements is useful for controlling external devices, such as robotic arms, helping people with disabilities or performing remote operations in unsafe places. In this work, we present a new method to build an online BCI for motor execution classification that takes into account not only the movements but also the resting period beging essential to recognize when an individual is not engaged in any activity. An artificial intelligence model, EEGnet, was first trained on three classes of left- and right-hand movements, and resting with 0.43 of accuracy. The same type of network was trained on two classes by combining the three classes above, thus having left-right, rest-left, and rest-right, with 0.73, 0.67, 0.63 of accuracy, respectively. Therefore, the 2-classes EEGnet were combined in a network tree that is able to correctly classify not only left- and right-hand movements but also resting signals to improve the accuracy to 0.55 of these three classes.

INTRODUCTION

The study of brain-computer interface (BCI) focuses also on recognizing movements of the hand, upper limb, wrist, and fingers from human neurophysiological signals to control external devices such as robotic arms. Brain signals are obtained through acquisition procedures that can be characterized as surgical, invasive, or noninvasive [1]. The noninvasive class includes electroencephalography (EEG), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), and near-infrared spectroscopy (NIRS). Among these, EEG strikes a good compromise between sensitivity, spatial-temporal resolution, and costs. In the literature, EEG-based BCI is used to decode a user's movement intention known as motor imagery (MI), and as well as to decode real human movements, motor execution (ME), using Artificial Intelligence (AI)[2]. The ME deep learning (DL) algorithms must be trained using EEG datasets. The ME datasets, available in the literature, collect many types of movements, ranging from the most complex to the most intuitive, and DL techniques are applied to classify these data. The EEG Motor Movement/Imagery Dataset [3] was developed by obtaining signals from the BCI2000 64-channel system by choosing 109 volunteer individuals who imagined opening and closing left or right hand, opening and closing both hands or both feet according to video stimuli, and then they are replicated with the real movement of the subjects. Another dataset is EEG Data for Voluntary Finger Tapping Movement which is a collection of EEG data acquired during voluntary asynchronous index finger tapping by 14 healthy adults. EEG was recorded using a TruScan Deymed amplifier with 19 channels for three conditions: tap of the right finger, tap of the left finger, and resting state, with a sampling rate of 1024 Hz. Each participant performed 120 tests, 40 for each of the three conditions [4]. In the case of online BCI, besides classifying movement, it must also be identified the no motion phase, also called resting state. Some work has been published that refers to classifying rest for MI. In [5] a hybrid model that combines convolutional neural network (CNN) and transformer architectures, ConTraNet, was implemented using their strengths to improve classification performance in various EEG applications, including categorization of rest. In [6] the VS-LSTM model was introduced to classify limb MI using EEG signals, with a particular focus on distinguishing between motor and resting states. In the study by [7], novel approaches for ME/MI classifications were introduced, achieving a high level of accuracy. However, the authors did not take into account the rest period for classification. In [8], the authors performed the classification on MI signals, open and close eyes, using Linear Discriminant analysis (LD), Naive Bayes (NB), and Support Vector Machine (SVM) classification algorithms achieving an accuracy of 91.18%, 95.41%, and 99.51% respectively. Moreover, in [9] the authors classified 2, 3 and 4-classes using EEGnet on MI and rest task, reaching and overall accuracy of 82.43%, 75.07%, and 65.07% respectively. Also in [10], the authors classified the MI signals and Rest, reaching an accuracy of 70.64% on 5 classes. This work shows that most of the studies conducted on resting state are carried out for MI, leaving out

Published by
Verlag der Technischen Universität Graz

10.3217/978-3-99161-014-4-062

ME. In [11], it can be observed that the two cognitive processes MI and ME are different. For this reason,the present work describes the activity of the first stage that focuses on analyzing the response of the rest signal to the real movement of the hand (left and right) for the robotic control arm in rehabilitation [12]. The objective of this research is to determine the optimal method for distinguishing EEG data of REST phases from EEG data of ME by employing a deep learning architecture, EEGnet[13]. This involves decomposing the three-class problem (REST, LEFT, RIGHT) into several binary classifications (REST vs LEFT, REST vs RIGHT, LEFT vs RIGHT), and addressing this through the construction of a *Network Tree* that integrates several EGGnet trained for identify the REST and the two movement-related classes, for enhancing classification performance compared to the EEGnet trained on three classes that shown low accuracy during our previous analysis.

MATERIALS AND METHODS

Data from 105 people from the Physionet Dataset [3] were used. The original data set consisted of 109 persons, but four subjects were excluded because they performed different numbers of trials with a different sampling rate. Each subject was recorded while performing an execution or the imaginated execution of opening and closing the right or left hand for 4 seconds. Before each exercise performed or imagined, there was a 4 seconds of rest. Each person was recorded three times and each recording contained approximately seven movements in each category, plus one rest period for each movement. Of 64 electrodes, we used only the following 15: Fp1, Fp2, F7, F8, Fz, P3, Pz, P4, O1, O2, F3, F4, C3, C4, Cz. This was done to reduce the number of channels and make the system lighter and more portable, given the possibility of using a cheaper EEG device (such as Enobio 20[1] or other light mobile EEG device). After exclusion, the epochs were extracted using one second of signal, starting from the marker, without any baseline reduction. Signals were downsampled the data from 160 to 80 Hz and a high-pass filter to 1 Hz was used.

In Fig 1, the pipeline for preprocessing applied to the dataset and the classification stage are shown.

Our work aims to create a deep learning model capable of recognizing the movement execution of the right hand, the left hand, and the rest period. For this reason, only the EEG data acquired during ME conditions were used. Finally, our dataset was composed of 4725 signals under “ME rest condition”, 2369 signals under “ME left-hand movement” and 2356 signals under “ME right-hand movement”. In each class, the corresponding trials of all selected subjects are grouped. In Fig. 2 the train-validation-test sets splitting is shown. The movement decoding process was carried out using the DL architecture EEGnetV4, from now on EEGnet [13], trained on the EEG signal from the EEG motor movement/image dataset [3]. Preprocessing and deep learning models were performed using Python with MNE library [14] for EEG data analysis, PyTorch [15] for the deep learning and [16] for the EEGnet architecture. Before training, starting from the original data, we performed the trasformation using Common Spatial Pattern (CSP) [17, 18] and used the transformed signal as the input for the network. This operation reduced the number of channels from 15 to 2, maximizing the distinguishability between classes. This process was repeated for all EEGnet used. All networks were trained using a balanced training set, so all classes had the same number of samples in both for training and for test. The training hyperparameters, displayed in the Tab. 1, were selected following sever al experimental trials. We noticed that signal downsampling did not affect performance, so we downsampled the signal to improve training speed. We used the Stochastic Gradient Descending (SGD) to improve the convergence of the training, applying also a dynamic Learning Rate, starting from a value of 0.004, that reduced its value automatically when, after 25 epochs of inactivity, it did not improve. The factor of reduction of Learning Rate was set at 0.2. Moreover, we used a double batch size [19] that changes when there was no more improvement of the network also after reducing the Learning Rate. Finally, we used a decay rate of 0.001 to improve the learning rate of the network. The signals of REST, execution of open close right-hand (RIGHT) and execution of open and close left-hand (LEFT) were considered. As a first step, the EEGnet network was trained on the three classes REST (0), LEFT (L), and RIGHT (R), called 0LR, with unsatisfactory results, as shown in Tab. 2 in the last row. Therefore, comparisons were made between the same EEGnet trained on two classes left-right, rest-left and rest-right classes defined as LR, 0L, and 0R, respectively. After this analysis, we observed that the 0LR network did not correctly distinguish the three classes to the LR, 0L, and 0R networks.For this reason, a *Network Tree* based on previously tested EEGnets was created to improve the classification accuracy and analyze the REST signal. Our “*Network Tree*”, was composed of three different EEGnetV4 [13] individually trained on different subsets of our dataset, to classify different types of signal:

- $EEGnet_{LR}$: the network was able to classify correctly the signals labeled as Left or Right;
- $EEGnet_{0L}$: the network was able to classify correctly the signals labeled as Rest or Left;
- $EEGnet_{0R}$: the network was able to classify correctly the signals labeled as Rest or Right.

To build the *Network Tree*, the classification of the class unknown to each network was tested with the following results:

- a Rest epoch, if given as an input to $EEGnet_{LR}$, was classified as Right;

[1] https://www.neuroelectrics.com/solutions/enobio/20

Published by
Verlag der Technischen Universität Graz

10.3217/978-3-99161-014-4-062

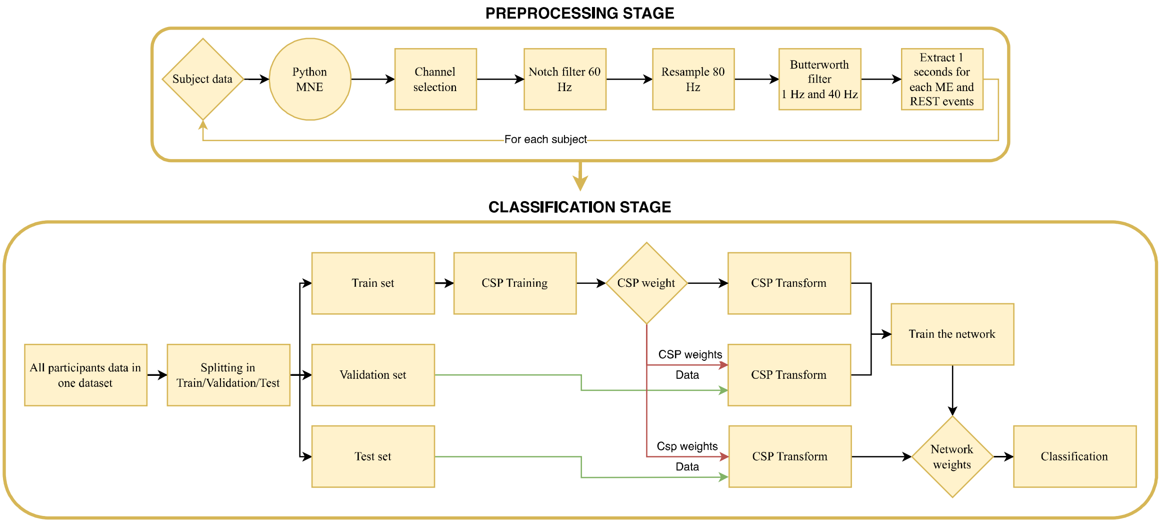

Figure 1: The pipeline used for data preparation and classification stages.

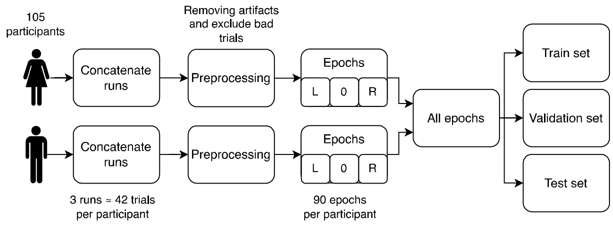

Figure 2: The split of the original set in train, validation and test set after preprocessing and epochs extraction.

Hyperparameter	**Value**
Sample shape	1, 15, 79
Sampling rate	80 Hz
N. channels	2
N. epochs	2000
Optimizer	Stochastic Gradient Descending (SGD)
Scheduler type	Reduce learning rate when a metric has stopped improving
Learning rate	0.004
Patience	25 epochs
Factor scale	0.2
Batch size	16, 32
Decay	0.001

Table 1: The hyperparameters used to train all EEGnet

- a Right epoch, if given as an input to $EEGnet_{0L}$, was classified as Rest;
- a Left epoch, if given as an input to $EEGnet_{0R}$, was classified as Right.

Each network started with a CSP transformation, and each CSP transformation was different for each network. Based on the results shown in the Tab. 2, our system was behaves as follows: a sample was given as input in $EEGnet_{LR}$: if it waas classified as Left, the original epoch was given to $EEGnet_{0L}$ for final classification in Rest or Left movement; If it was classified as Right, then the origianl epoch was given as input in parallel to two networks: $EEGnet_{0L}$ and $EEGnet_{0R}$. Based on the results, the truth table in Fig. 3 was applied to classify the epoch.

The network tree architecture is shown in Fig. 3. Tab. 3 shownthe results of the classification using the *Network Tree*.

RESULTS

For evaluating the model, Accuracy, Precision, Recall, and F1 metrics were used. In Tab. 2 the results are shown for all networks trained individually. In the last three rows of Tab. 2, the results for all the 2-class networks shown that the binary classification was more accurate related to the 3-class network (last row). The $EEGnet_{RL}$, shown a good discriminability power between Left and Right movements, while when a Rest signal was given as an input to this net, it created a light unbalancing classification result towards the Right class. It was interesting to note that a Right sample was classified as Rest if was given as input to $EEGnet_{0L}$, while a Left sample was classified as Right if was given as input to $EEGnet_{0R}$. Starting from these results, we built the *Network Tree* combining all 2-classes network in a classification cascade. The proposed network achieved an overall accuracy of 0.55, greater than the chance [20] and improving the performance respect to $EEGnet_{0LR}$. Moreover, in the $EEGnet_{0LR}$ the single classes were misclassified frequently, expecially Rest and Right, and it was shown looking the Recall metric. It must be emphasised that in the training of $EEGnet_{0LR}$, three classes were extracted with the CSP instead of two, so the resulting multivariate signal was composed by 3 channels. For comparison the results for the *Network Tree* are reported, in Tab. 3, showing a more stable behavior of the network in terms of classification. This aspect is well represented by the F1 score, which takes into account both precision and recall.

Published by
Verlag der Technischen Universität Graz

 10.3217/978-3-99161-014-4-062

Network	Class	Support	Precision	Recall	F1	Accuracy	Unknown Class	Prediction
	Rest	574	0.62	0.15	0.24		-	-
$EEGnet_{0LR}$	Left	594	0.39	0.96	0.55	0.43	-	-
	Right	606	0.72	0.18	0.29		-	-
$EEGnet_{LR}$	Left	600	0.74	0.73	0.74	0.73	Rest	0.46
	Right	582	0.73	0.73	0.73			0.54
$EEGnet_{0L}$	Rest	576	0.66	0.64	0.65	0.67	Right	0.73
	Left	609	0.67	0.69	0.68			0.27
$EEGnet_{0R}$	Rest	568	0.67	0.46	0.55	0.63	Left	0.42
	Right	614	0.61	0.79	0.69			0.58

Table 2: Prediction metrics table for all networks used in *Network Tree*

Network	Class	Support	Precision	Recall	F1	Accuracy
	Rest	591	0.48	0.45	0.46	
Network Tree	Left	586	0.57	0.61	0.59	0.55
	Right	596	0.58	0.59	0.58	

Table 3: Results of *Network Tree*

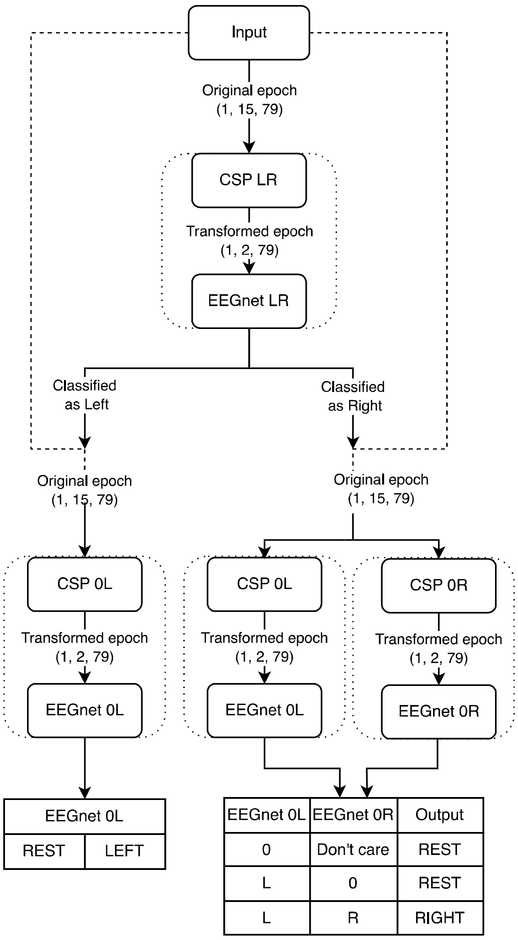

Figure 3: *Network Tree* - the first classification of the signal is performed by the $EEGnet_{LR}$ and then a classification check is carried out. If L is identified, the input signal is sent to the $EEGnet_{0L}$ for final classification between 0 or L. In case R is classified, the input signal is sent both to the $EEGnet_{0L}$ and $EEGnet_{0R}$. The result of their combined classification returns the result of the final classification between 0 or R. The input undergoes, before being sent to a network, a transformation by the associated CSP.

CONCLUSION

This work aimed to present a new method for a motor-based BCI. In an online classification, the EEG signal is recorded while performing L o R hand movement or while having a rest. In this field, there is a literature gap on the non-movement classification, also known as Rest, but this is fundamental in online application since there are many non-movement periods while using a BCI [21]. The novelty lies in the concatenation of a network tree of able of correctly classifying not only left and right hand movements, but also the rest signals. Future work should test the system in real-time by including a pre-processing pipeline capable of quickly cleaning the signals [22, 23]. Furthermore, other tasks, such as motor imagery on emotions [24], needs to be tested, and using different types of features extracted by the EEG data such as connectivity [25], independent components [26], or other features [27]. Moreover, future improvement of the *Network Tree* will include both subject-dependent and subject-independent cross-validation analysis, splitting the subjects into training and test groups before the training.

REFERENCES

[1] Saibene A, Caglioni M, Corchs S, Gasparini F. Eeg-based bcis on motor imagery paradigm using wearable technologies: A systematic review. Sensors. 2023;23(2798).

[2] Gwon D, Won K, Song M, Nam CS, Jun SC, Ahn M. Review of public motor imagery and execution datasets in brain-computer interfaces. Frontiers in Human Neuroscience. 2023;17:1134869.

[3] Schalk Gerwin McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. Bci2000: A general-purpose brain-computer interface (bci) system. IEEE Transactions on biomedical engineering. 2004;51(51).

Published by
Verlag der Technischen Universität Graz

10.3217/978-3-99161-014-4-062

[4] Wairagkar M. Eeg data for voluntary finger tapping movement. University of Reading. 2017.
[5] Ali O, Rehman M Saif-ur, Glasmachers T, Iossifidis I, Klaes C. Contranet: A hybrid network for improving the classification of eeg and emg signals with limited training data. Computers in Biology and Medicine. 2024;168:107649.
[6] Wang P, Wang M, Zhou Y, Xu Z, Zhang D. Multiband decomposition and spectral discriminative analysis for motor imagery bci via deep neural network. Frontiers of Computer Science. 2022;16:1–13.
[7] Fan C, Yang B, Li X, Zan P. Temporal-frequency-phase feature classification using 3d-convolutional neural networks for motor imagery and movement. Frontiers in Neuroscience. 2023;17:1250991.
[8] Taşar B, Yaman O. Eeg signals based motor imagery and movement classification for bci applications. In: 2022 International Conference on Decision Aid Sciences and Applications (DASA). 2022, 1425–1429.
[9] Wang X, Hersche M, Tömekce B, Kaya B, Magno M, Benini L. An accurate eegnet-based motor-imagery brain–computer interface for low-power edge computing. In: 2020 IEEE international symposium on medical measurements and applications (MeMeA). 2020, 1–6.
[10] Fadel W, Kollod C, Wahdow M, Ibrahim Y, Ulbert I. Multi-class classification of motor imagery eeg signals using image-based deep recurrent convolutional neural network. In: 2020 8th International Winter Conference on Brain-Computer Interface (BCI). 2020, 1–4.
[11] Bencivenga F, Sulpizio V, Tullo MG, Galati G. Assessing the effective connectivity of premotor areas during real vs imagined grasping: A dcm-peb approach. Neuroimage. 2021;230:117806.
[12] Placidi G, De Gasperis G, Mignosi F, Polsinelli M, Spezialetti M. Integration of a bci with a hand tracking system and a motorized robotic arm to improve decoding of brain signals related to hand and finger movements. In: International Symposium on Visual Computing. 2021, 305–315.
[13] Lawhern VJ, Solon AJ, Waytowich NR, Gordon SM, Hung CP, Lance BJ. Eegnet: A compact convolutional neural network for eeg-based brain–computer interfaces. Journal of Neural Engineering. 2018;15.
[14] Gramfort A *et al.* MEG and EEG data analysis with MNE-Python. Frontiers in Neuroscience. 2013;7(267):1–13.
[15] Paszke A *et al.* Automatic differentiation in pytorch. 2017.
[16] Schirrmeister RT *et al.* Deep learning with convolutional neural networks for eeg decoding and visualization. Human Brain Mapping. 2017.
[17] Koles ZJ, Lazar MS, Zhou SZ. Spatial patterns underlying population differences in the background eeg. Brain topography. 1990;2:275–284.
[18] Blankertz B, Tomioka R, Lemm S, Kawanabe M, Muller Kr. Optimizing spatial filters for robust eeg single-trial analysis. IEEE Signal Processing Magazine. 2008;25(1):41–56.
[19] Smith SL, Kindermans PJ, Ying C, Le QV. Don't decay the learning rate, increase the batch size. arXiv preprint arXiv:1711.00489. 2017.
[20] Müller-Putz G, Scherer R, Brunner C, Leeb R, Pfurtscheller G. Better than random: A closer look on bci results. International journal of bioelectromagnetism. 2008;10(1):52–55.
[21] Di Giamberardino P, Iacoviello D, Placidi G, Polsinelli M, Spezialetti M. A brain computer interface by eeg signals from self-induced emotions. In: VipIMAGE 2017: Proceedings of the VI ECCOMAS Thematic Conference on Computational Vision and Medical Image Processing Porto, Portugal, October 18-20, 2017. 2018, 713–721.
[22] Placidi G, Cinque L, Polsinelli M. A fast and scalable framework for automated artifact recognition from eeg signals represented in scalp topographies of independent components. Computers in Biology and Medicine. 2021;132:104347.
[23] Pion-Tonachini L, Kreutz-Delgado K, Makeig S. Iclabel: An automated electroencephalographic independent component classifier, dataset, and website. NeuroImage. 2019;198:181–197.
[24] Lozzi D, Mignosi F, Spezialetti M, Placidi G, Polsinelli M. A 4d lstm network for emotion recognition from the cross-correlation of the power spectral density of eeg signals. In: 2022 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT). 2022, 652–657.
[25] Lozzi D, Mignosi F, Placidi G, Polsinelli M. Graph model of phase lag index for connectivity analysis in eeg of emotions. In: 2023 IEEE 36th International Symposium on Computer-Based Medical Systems (CBMS). 2023, 348–353.
[26] Erfanian A, Erfani A. Ica-based classification scheme for eeg-based brain-computer interface: The role of mental practice and concentration skills. In: The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2004, 235–238.
[27] Jaipriya D, Sriharipriya K. Brain computer interface-based signal processing techniques for feature extraction and classification of motor imagery using eeg: A literature review. Biomedical Materials & Devices. 2023:1–13.

Published by
Verlag der Technischen Universität Graz