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Decoding Lower Limb Movement Speed: Unraveling the Disparities Between Motor Imagery and Relaxation

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Abstract. This study investigates the feasibility and efficacy of decoding lower limb movement speed through the examination of differences between motor imagery and relaxation states. Electroencephalography (EEG) signals are utilized as the input data source, and commonly used machine learning approaches are employed for classifying imagined lower limb movement speed. Healthy individuals without lower limb motor impairments participate in the experiment, and their EEG signals are recorded using Emotive's 32-channel gel electrode EEG cap EPOC FLEX. Preprocessing and feature extraction techniques are applied to the collected EEG data to develop a specialized classification model. Results indicate significant differences in EEG signals between imagined lower limb movement speed and relaxation states. Ten-fold cross-validation confirms the reliability and accuracy of the classification model, achieving above-chance classification accuracies. The findings provide valuable insights for the development of brain-computer interface systems, rehabilitation therapies, and applications related to lower limb movement. This study establishes a foundation for further exploration in decoding lower limb movement speed.

Keywords. Decoding lower limb movement speed; machine learning; motor imagery; electroencephalography; brain-computer interface

1. Introduction

Brain-Computer Interface (BCI) is a cutting-edge field of research that aims to establish a direct communication pathway between the human brain and external devices or computer systems. By interpreting neural signals recorded from the brain, BCI technology enables individuals to control devices, communicate, or interact with their environment using only their thoughts[1].

BCI systems typically involve the acquisition and analysis of electroencephalography (EEG) signals, which capture the electrical activity of the brain. EEG is a non-invasive and cost-effective neuroimaging technique that offers high temporal resolution and multi-channel recording capabilities. These advantages make EEG a valuable tool for studying brain function and cognition. Its non-invasive nature ensures participant

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safety and facilitates research with diverse populations. The high temporal resolution of EEG allows for the precise measurement of rapid neural events, providing insights into the timing and dynamics of cognitive processes. Additionally, EEG's multi-channel recording capability enables the examination of neural activity across different brain regions, shedding light on functional connectivity and brain networks. Moreover, EEG's suitability for real-world settings allows for the study of brain responses in ecologically valid situations. Overall, EEG's unique advantages make it a widely used method for investigating brain activity and advancing our understanding of various neurological and psychiatric conditions[2]. EEG signals are processed using advanced signal processing techniques, such as feature extraction and classification algorithms, to decode the user's intentions or cognitive states[3–7].

Motor imagery, the mental simulation of movement without physical execution[8, 9], is a fundamental aspect of many brain-computer interface (BCI) systems. However, achieving accurate classification of lower limb motor imagery poses significant challenges[10]. One of the main difficulties in decoding lower limb motor imagery lies in the complex neural representations involved in the generation of imagined movements[11]. The neural patterns associated with lower limb motor imagery are relatively weaker and more distributed compared to those observed in upper limb motor imagery tasks. This makes the extraction of informative features from electroencephalography (EEG) signals more challenging.

Despite this challenge, advancements in signal processing techniques, machine learning algorithms, and feature extraction methods have shown promising results in decoding lower limb motor imagery[12–14]. Efforts are being made to develop more robust and accurate BCI systems for lower limb motor control and rehabilitation applications. In this study, we employed a commonly used machine learning approach for detecting lower limb movement speed imagery[15], utilizing a binary classification model. Our aim was to provide insights into the generation of imagined lower limb movement speeds. Through our analysis, we observed distinct differences in the EEG signals between the resting state and the imagined lower limb movement conditions.

2. Methods

2.1. Data collection

Two right-handed participants, aged 25, without any lower limb motor dysfunction, were recruited for this experiment. EEG data were recorded using Emotive's 32-channel gel electrode EEG cap EPOC FLEX, with an EEG sampling rate of 128 Hz. Based on the high incidence area of motor imagery, a specific set of 15 channels was selected for collecting the EEG data. These channels included FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, and CP4. In addition to these 15 channels, two reference electrodes were placed on the earlobes. The electrode placement is illustrated in Figure 1. This specific channel selection aimed to capture neural activity predominantly associated with lower limb motor imagery, allowing us to focus on the relevant brain regions involved in our investigation. By targeting these specific channels, we aimed to enhance the sensitivity and specificity of our EEG data analysis, enabling a more precise examination of the neural correlates related to lower limb motor imagery.

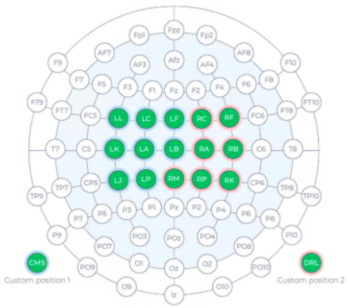


Figure 1. Location of electrodes according to the 10-20 system.

Figure 2. Participant in the experiment.

The use of the Emotive EEG cap and the selected channel configuration ensured optimal data acquisition, providing us with high-quality EEG signals for subsequent analysis. Figure 2 demonstrates a participant sitting with EEG caps on his head and following a video guide to imagine lower limb movements. After completing the experiment, for each participant, we collected a total of 120 trials, each lasting 2 seconds. These trials were labelled as relaxation or motor imagery.

2.2. *Signal preprocessing*

MNE is a comprehensive open-source package widely used for processing EEG signals within the Python environment. It offers a broad range of functions and tools for various aspects of EEG data analysis, including preprocessing, visualization, time-frequency analysis, source localization, and other processing and analysis techniques for EEG and MRI data. Consequently, in this study, we utilized the MNE package to analyze the acquired EEG data in a Python 3.9 environment.

One crucial component of EEG analysis is Independent Component Analysis (ICA), a statistical signal processing technique that aims to separate independent source signals from mixed observations. ICA assumes linearity and independence in the mixing process, and by applying linear transformations, it allows for the decomposition of signals into independent components.

In the context of EEG analysis, ICA plays a crucial role in removing artifacts such as eye blinks, muscle activity, and other unwanted sources, thereby revealing the underlying brain signals of interest. Hence, we employed the ICA function provided by MNE to perform decomposition of the EEG signals, effectively eliminating any non-EEG components that could potentially confound our analysis.

The use of MNE's ICA functionality in our study enabled us to enhance the quality and reliability of the EEG data, facilitating a more accurate investigation of the neural activity associated with our research objectives. By eliminating artifacts and isolating the relevant brain signals, we were able to gain valuable insights into the underlying cognitive processes and neural mechanisms that contribute to our research inquiry.

2.3. *Model decoding*

EEGNet is a deep learning-based neural network specifically designed for feature extraction from EEG signals. Figure 3 shows the overview structure of EEGNet. It takes multi-channel EEG signals as input, that each channel at each time point forms the input data dimension[16]. The first step of EEGNet is a one-dimensional convolutional layer. This layer performs a sliding window convolution operation on the input signal using a set of convolution kernels. It helps to extract local features and temporal patterns of the signal. And second step of EEGNet is a depth-separable convolutional layer. This layer applies depth convolution and point-by-point convolution operations on each channel separately to further capture correlation and timing features between channels.

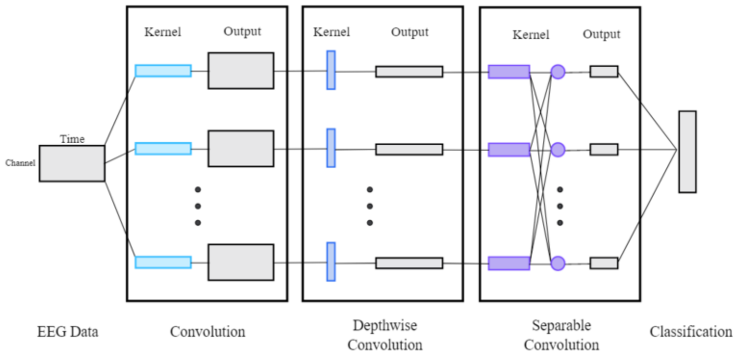


Figure 3. Overview of EEGNet.

After the convolutional layer, EEGNet uses mean pooling operations to reduce the dimensionality and extract higher-level features. Mean pooling reduces the dimensionality of each channel's time series data to a fixed-length vector. However, EEGNet utilizes a combination of multiple depth-separable convolutional layers and mean pooling. This layered structure enables the network to progressively extract increasingly abstract and high-level features from the input EEG signals. At the end of the network, EEGNet uses global mean pooling to aggregate the feature vectors of all channels into a fixed-length feature representation.

With such a layer structure and feature extraction process, EEGNet is able to extract features with higher levels of abstraction from raw EEG signals. Therefore, we used EEGNet for the binary classification tasks of relaxation and motor imagery. Ten-fold cross-validation with randomly divided training and test sets is used here, in order to ensure that the classification results of the models we use are plausible[17].

3. Result

The results obtained from our experiments provide valuable insights into the effectiveness and performance of our proposed approach. In this section, we present a comprehensive analysis and discussion of the key findings, comparing them to existing methods and addressing the research questions posed earlier.

After experiencing ICA, we removed all non-EEG components. As shown in Figure 4, it shows the brain components obtained from our post-ICA analysis, in which there is a significant power increase at the Cz electrode location.

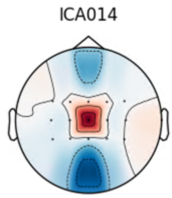
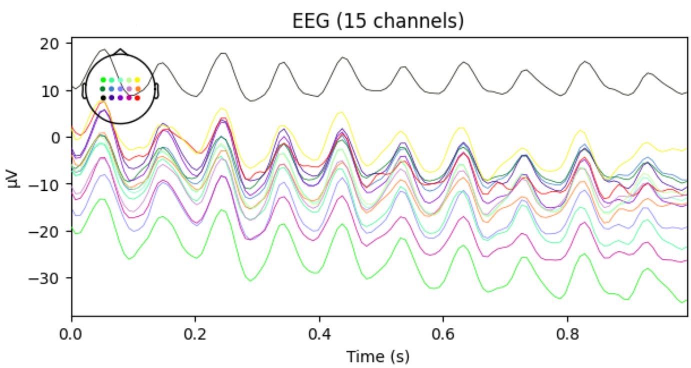
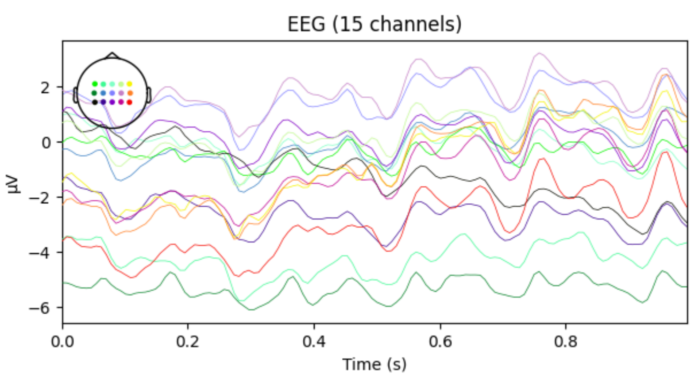


Figure 4. Brain component.

The increase in power indicates that stimulus events were generated in this corresponding brain region, i.e., the participant invoked the relevant region for the motor imagery task. The power increase in the Cz region is also consistent with the corresponding region in Hardwick's work[18] for the lower limb motor imagery, so the participant were actively involved in the imagery task and stimulation was well generated in the corresponding brain region when they performed the lower limb motor imagery task.



(a) Relaxation Signal



(b) MI Signal

Figure 5. A is Relaxation EEG signal on 15 channels, b is MI EEG signal on 15 channels. The top left corner shows the topology of each channel according to colour. In subfigures a,b are shown the average EEG time-power plots for relaxed and MI states.

For the clean data obtained, the EEG data of relaxation and MI were averaged separately. From the Figure 5, we can observe the signal waveforms in the last 1 s on different channels, and intuitively there is a difference between relaxation and lower limb movement MI.

There is a ten-fold cross-validation to ensure the reliability of the classification results of the model. After ten-fold cross-validation, we obtained ten validation results and the mean value of the validation results was 1.00, $p<0.05$, the result confusion matrix was shown in Figure 6. This result suggests that the classification results obtained by our model are reliable. Therefore, we verified that there is a difference between the lower limb movement motor imagery signals and relaxation signals. Furthermore, our model can accurately detect the generation of MI.

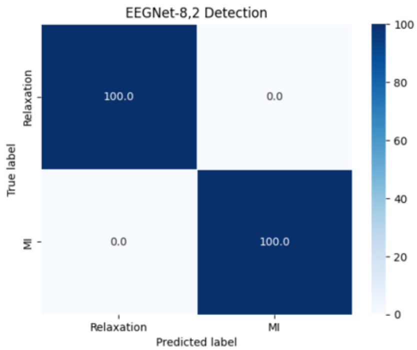


Figure 6. Confusion matrix for validation results.

In summary, we demonstrate that there is a difference between lower limb movement speed motor imagery and relaxation. This finding suggests that the brain can also generate unique signals for lower limb movement speed motor imagery control. This finding fills a gap in the lower limb motor imagery region and enriches the scope of lower limb functional design in the field of brain-computer interfaces.

4. Conclusion

The results of our study contribute to the growing body of knowledge regarding the neural correlates of lower limb motor imagery. By utilizing machine learning techniques, we were able to discern patterns in the EEG signals associated with the mental simulation of lower limb movement speeds. These findings highlight the potential for developing more accurate and reliable methods for decoding lower limb motor imagery in brain-computer interface (BCI) systems. Furthermore, the observed differences between the resting state and lower limb movement imagery provide valuable insights into the underlying neural mechanisms involved in motor imagery processes. These findings can inform the development of targeted interventions for motor rehabilitation, assistive devices, and neurofeedback training to improve motor function and control.

Overall, our study contributes to the understanding of lower limb motor imagery and its potential applications in BCI systems. Further research in this area can build upon these findings to advance the field and enhance the usability and efficacy of BCI technologies for lower limb motor control and rehabilitation.

Acknowledgment

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