



Article

Enhancing cortical rhythms through robotic glove-assisted motor imagery training

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Abstract: Improving Motor Imagery (MI) results in amplified event-related Desynchronization/Synchronization (ERD/ERS), which is crucial for MI-based Brain-Computer Interface (BCIs) and neuromotor rehabilitation. Several attempts to enhance MI by providing visual guidance have been reported, however, this can be improved by using robotic systems for Kinesthetic MI (KMI), such as robotic gloves for hand movements. In this study, a novel protocol based on KMI tasks is proposed to analyze cortical rhythms against a standard MI protocol based on static Action Observation (AO). The results allow concluding that the use of the robotic gloves increases the ERDs by 3% during MI tasks, where neuromodulations were found to be more focused on the C₃ and C₄ electrodes during right- and left-hand closing MI, respectively, compared to opening. In conclusion, the proposed strategy based on passive movement is feasible and can enhance MI, which can be used for designing most robust BCIs.

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1. Introduction

Brain Computer Interfaces have gained importance in rehabilitation interventions in recent years as they allow the interaction of robotic devices and humans using brain information, usually through electroencephalography (EEG) [1–3]. For instance, the use of exoskeleton-based BCIs [4, 5] or Electrostimulators [6] have been reported for the rehabilitation of post-stroke individuals.

In this context, robotic gloves for rehabilitation have been of interest in combination with BCIs because it is possible to perform control actions with brain signals in lightweight devices (soft-robotics) and wearable for the subject, which allows greater comfort during task assistance [7, 8]. However, it is challenging to interpret subject intentions through EEG because these signals have a low Signal-to-Noise Ratio (SNR), are not stationary, and may often be in the presence of physiological or non-physiological artifacts [9, 10].

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Mental training tasks using Motor Imagery (MI) have been used to detect individual intentions in BCIs [11]. MI is a specific brain activity technique that occurs when a subject imagines movements or actions without performing them physically [12, 13]. Previous studies have reported that during MI tasks a decrease in power is observed with respect to the rest phase on Mu (μ) band (termed Event-Related Desynchronization-ERD) or an increase in power in the Beta (β) band (termed Event Related Synchronization-ERS) [11, 14]. In this context, the literature has focused on the MI recognition of hand movements, such as opening and closing. However, considering that this mental task is focused on the same limb, task recognition becomes more challenging, considering that cortical rhythms are similar [15, 16].

Several authors have attempted to address this issue using visual and sensorial stimulation, which are known as Visual Motor Imagery (VMI) and Kinesthetic Motor Imagery (KMI), respectively, [17]. Furthermore, complex computational techniques, such as Machine Learning or Deep Learning, have been used for detection [18, 19]. For instance, Alazrai *et al.* used neural networks to identify cortical rhythms of hand MI based on opening, closing, and resting [18], whereas Takalovan *et al.* implemented a protocol for identifying resting, grasping, and elbow movement MI tasks [19]. Despite significant advances in MI of the same limb, it should be noted that during the scanning of cortical rhythms, some electrodes may not demonstrate power differences, making task identification difficult. In this context, a hypothesis arises as to whether it is possible to discriminate brain rhythms during MI tasks of the same limb using other types of stimulation, such as passive motion with KMI, which is little known in the literature.

This study proposes a novel protocol to analyze the cortical rhythms of hand opening and closing MI tasks under two conditions: the first corresponds to visual cues based on Action Observation (AO) for VMI [20, 21], and the second corresponds to AO cues together with passive movement generated by a robotic glove (KMI), both right and left hand. Subsequently, changes in power with respect to the resting phase were found and compared, especially in the parieto-central brain cortex, where the hand motor function is more measurable [14].

This paper is divided into four sections. Section 1 provides a brief introduction to the context of this study. Section 2 describes the experimental design and methods used to calculate ERD/ERS. Section 3 presents the results and discusses the phenomena related to the cortical rhythms obtained in this study by comparison with the literature. Finally, Section 4 presents the conclusions and future work.

2. Methods and Materials

2.1. EEG acquisition

EEG signals were acquired using an OpenBCI board with 16 channels located on the brain cortex region by using the 10-20 international system for electrode positioning, considering the region where upper-limb MI is more discriminant: *FP1*, *FP2*, *F3*, *F4*, *FC4*, *FC3*, *FCz*, *CP3*, *CP4*, *C1*, *C2*, *C3*, *C4*, *C5*, *C6*, and *CPz* (see Figure 1) [15]. *A₁* and *A₂* are used as reference electrodes and are located on the earlobes. The EEG was acquired at a sampling frequency of 125 Hz. A GUI was developed in OpenViBE software (Inria, FR), which is compatible with Python and displays the visual stimulus indicating the MI task. This platform was synchronized with the robotic glove to generate the protocol sequences. The stimuli are displayed on a 15.6-inch computer screen, 60 cm away from the participants. More information about this scheme is available in [9].

2.2. Experimental setup

Two experimental designs were validated by focusing on the same limb MI tasks performed with and without the passive assistance produced by a glove. The assistive glove used here is a pneumatic robotic

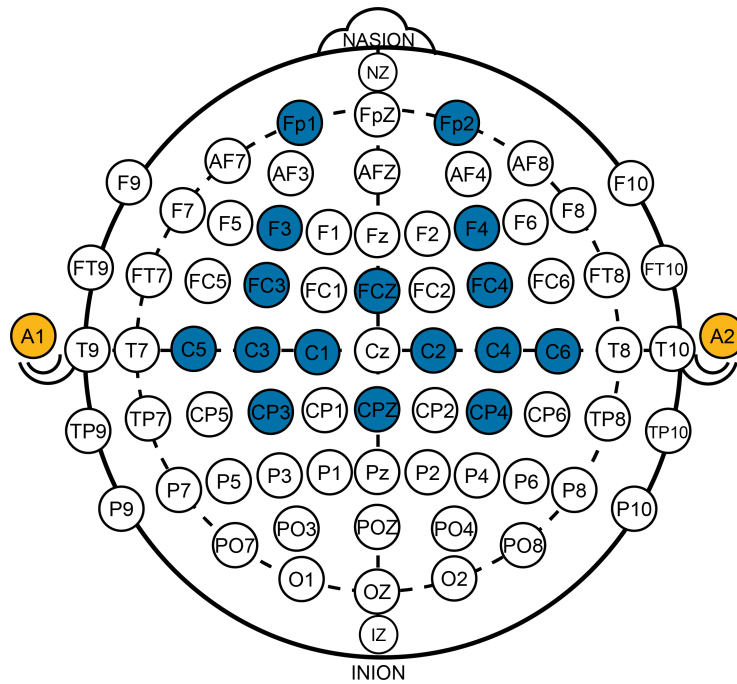


Figure 1. Location of the 16 electrodes following the 10-20 international system.

glove (Model ML-115A from Gendoing, CN), powered by 5 V/2 A, with a pressure range from -58 kPa to 120 kPa . An electronic circuit was built, which was based on a generic 6V solenoid valve, a voltage source, and a microcontroller board Arduino Mega 2560 (Arduino, IT). This circuit is in charge of inflating the glove pneumatic bags, and opening the glove, according to the protocol. In addition, each of the protocols was validated using two conditions for the respective MI task: right and left robotic gloves. The experimental protocol consisted of the following steps (see Figure 2):

1. A black screen was presented where the subject did not perform MI tasks (baseline), but executed passive movements.
2. An image with an open hand is displayed on the screen where the subject is instructed to imagine the same movement.
3. An image with a close hand is displayed on the screen where the subject is instructed to imagine the same movement.
4. Repeat 8 times the steps 2-3.



Figure 2. Visual stimuli presented in the experimental protocols for hand MI.

The experiment was repeated once more to obtain information from two sessions. Subsequently, considering the experimental setup presented in Figure 2, a protocol was executed considering passive assistance by the robotic glove. It is worth mentioning that passive assistance is synchronized with image presentation with the objective of inducing KMI and VMI. The glove involved in inducing the passive movement is shown in Figure 3.

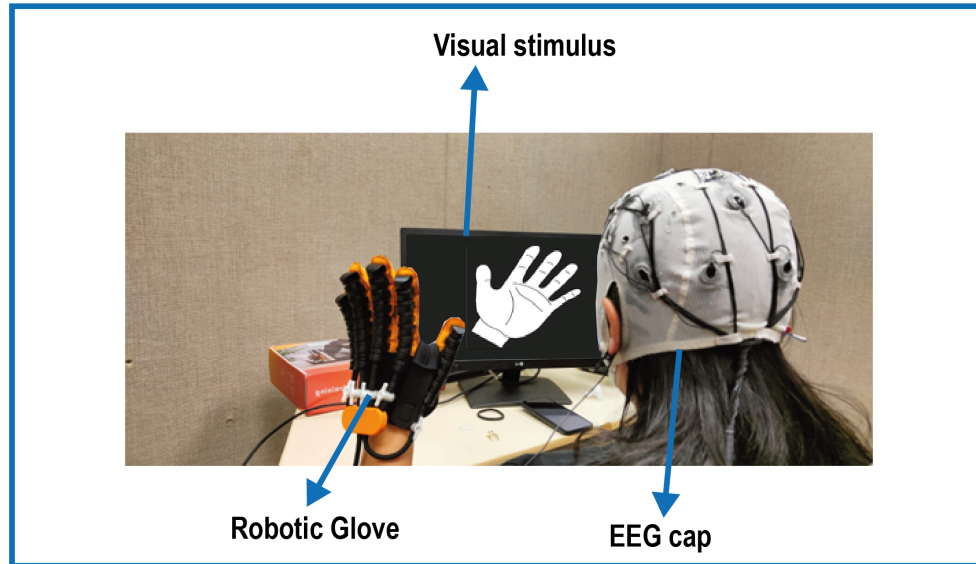


Figure 3. Experimental setup for EEG-based MI collection with the left robotic glove for passive movement.

2.2.1. Participants

The tests were conducted in a controlled environment to minimize noise and external interference. The protocols were executed by two female subjects (age between 25-40 YO), where a right handed subject used the right glove, and another left handed individual executed the protocol by using a left glove. Additionally, these subjects had similar physical characteristics, with no neurological characteristics, for comparison of the results. The protocols were executed according to the ethical requirements approved by the Ethics Committee of the Federal University of Espírito Santo (UFES) in Brazil (number CAAE:39410614.6.0000.5060).

2.3. Signal pre-processing

The dataset was segmented by considering the time windows related to the duration of each task (baseline, closed-hand MI, and open-hand MI). Subsequently, to reduce the common noise, a Common Average Reference (CAR) filter was applied to all electrodes. Following, considering the frequency bands where the MI are more discriminated, the signals were filtered with a 4-order zero-phase band pass filter between 8 and 30 Hz (μ - μ and Beta- β bands) to perform the data analysis.

2.4. Features based on Power Spectral Density

To identify the differences between the cortical rhythms produced by the glove implementation for passive movement, the frequency-domain information of the EEG signal was calculated. The Power Spectral Density (PSD) was computed specifically in the (μ) and (β) frequency bands for each state: baseline, closed-hand MI, and open-hand MI, using Equation 1.

$$PSD = \sum_{n=1}^N (P(X[n]))^2, \quad (1)$$

where PSD corresponds to the signal PSD, and $P(X[n])$ is the spectral information of the signal between the bands of interest. Subsequently, Equation 2 is used to calculate the ERD/ERS percentage.

$$ERD/ERS = \frac{(P_{MI} - P_B)}{P_B}, \quad (2)$$

where P_{MI} is the signal power calculated during MI tasks (hand opening or closing), and P_B is the signal power at the baseline. It is important to note that ERD or ERS depends on the value obtained from Equation 2 of the MI power with respect to that of the baseline. Thus, if the value decreases, it would correspond to ERD, whereas ERS would be reported if the value increases.

3. Results and Discussion

Initially, two MI task protocols, with and without the use of a glove, either left or right, were proposed. Figure 4 shows the spatial distribution of ERD/ERS averaged for all trials in different situations in the frequency bands of interest. In Figure 4a, it is possible to observe the presence of ERD at electrode C_3 during left-hand MI performance (ipsilateral section). Although the literature reports that the most influential channel during left-handed MI is the C_4 channel, this phenomenon may be associated with the lack of concentration of the subject and difficulty of task execution with the same limbs. However, Figure 4b shows an ERD in all frequency bands over the C_4 channel, which is in agreement with the results of previous studies [11, 15]. Subsequently, the difference in the influence of the glove during left-handed MI is presented in Figure 4c, where it can be observed that the channels that report the greatest power changes are associated with the right brain region, for both hand closure and opening.

Regarding the MI tasks associated with the right hand, Figure 4d shows the spatial distribution of power for the protocol without using the glove, which does not represent ERD with any specific pattern. In contrast, in Figure 4e, it is possible to observe the presence of an ERD over electrode C_3 in the μ band during the closing and opening tasks. This difference in electrode C_3 is more evident in Figure 4f for all the frequency bands. This result is in agreement with previous studies because the left region presents power changes in tasks performed with the right hand (contralateral section) [11]. It is worth noting that the baseline implemented passive movement, but without mental tasks.

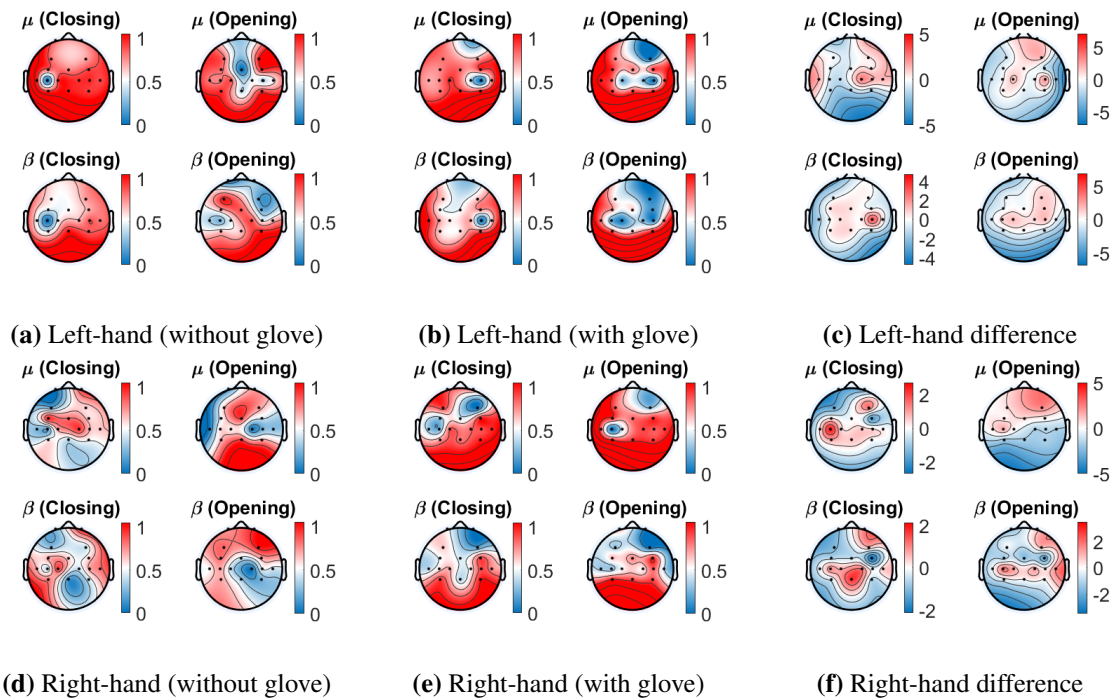


Figure 4. Grand averaged ERD/ERS for each MI task on interest frequency bands. (a) Comparison of ERD/ERS during left-hand MI tasks in the protocol without passive assistance. (b) Comparison of ERD/ERS during left-hand MI tasks in the protocol using the robotic glove for passive assistance. (c) Difference between ERD/ERS of the experimental design for left-hand with and without passive assistance. (d) Comparison of ERD/ERS during right-hand MI tasks in the protocol without passive assistance. (e) Comparison of ERD/ERS during right-hand MI tasks in the protocol using the robotic glove for passive assistance. (f) Difference between ERD/ERS of the experimental design for right-hand with and without passive assistance.

Subsequently, considering the above results and the importance of the C_3 and C_4 electrodes during the performance of the right and left upper limb MI tasks, the average ERD/ERS was compared in a more specific manner, as shown in Figure 5. In this Figure, it can be seen that there is an average difference of approximately 2% and 3% in the μ band between the left and right gloves. These findings are in accordance with the spatial power distributions indicated in Figure 4c and 4f, where it is possible to see that the ERD is more evident for hand closing tasks than for opening. This may be due to the fact that the anatomical position of the hand during opening tasks is related to resting tasks, while closing may be more pronounced by the robotic glove actuators [22].

Based on these results, it was possible to detect a higher ERD during the execution of MI tasks using robotic glove assistance for both the left- and right-hand movements. The implementation of robotic devices during passive movement may improve the cortical rhythms behavior, which is in accordance with previous studies presented in the literature, where Delisle-Rodriguez *et al.* demonstrated that these type of movements activated by BCIs during MI tasks [23], could improve the identification of mental tasks. On the other hand, Cheng *et al.* reported that the use of a robotic glove with virtual reality and visual feedback could have a positive impact for the rehabilitation of people with stroke [7]. The aforementioned studies reported that the assisting limb movements assisted involved in the MI tasks can increase sensory stimulation in the cerebral cortex, where cortical rhythms are produced owing to the presentation of KMI.

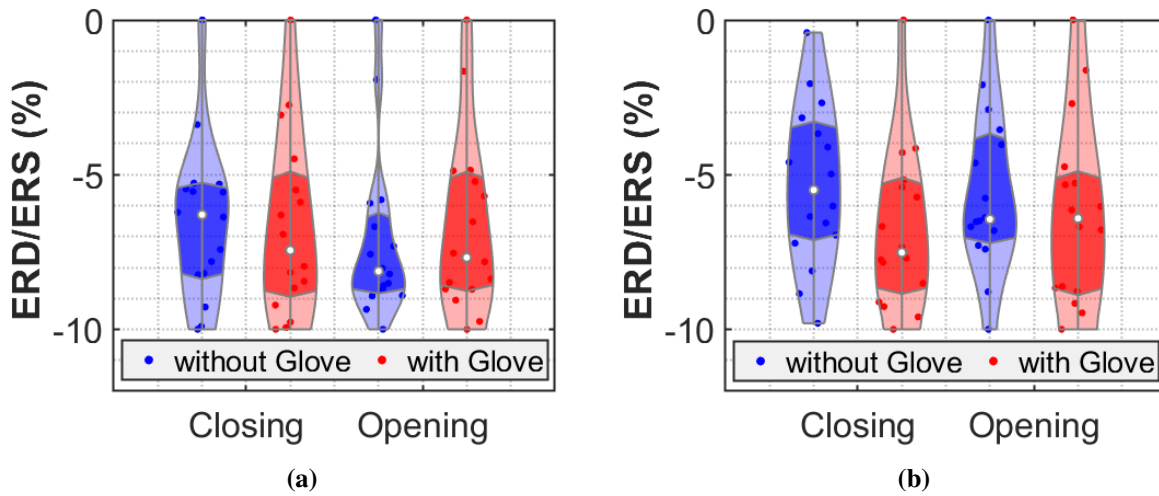


Figure 5. Comparison of ERD/ERS on C₃ and C₄ electrodes in Mu band for both protocols during hand MI of (a) Left hand; (b) Right hand.

Nevertheless, these studies did not report the differences or advantages of using robotic assisted movement over standard paradigms.

In this context, the use of robotic devices to assist movements may make it easier for subjects to imagine movements [7, 24], which is in accordance with the deeper ERD found in this study during the execution of the protocol using the robotic glove. In addition, this type of experimental design can help differentiate between MI tasks performed with the same limb, such as complex hand movements [25]. The difficulty in discriminating hand complex tasks, such as closing and opening, corresponds to the power changes in EEG rhythms that are presented on the same contralateral side of the brain. Additionally, other studies reported that the execution of multiple tasks performed on the same limb can provoke deeper ERDs [16]. For example, Guerrero-Mendez *et al.* implemented a study on grasping VMI with AO, where it was possible to find significant ERD/ERS in the parieto-central cortex, which allowed concluding promising approaches for visual stimulation during MI tasks [20]. However, that study did not combine VMI with KMI, which could limit the evocation of cortical rhythms. In this context, a study performed by Song *et al.* showed that the use of visuo-tactile stimulation can improve ERDs to a percentage level that is very close to those of real movements [26]. Nevertheless, the aforementioned study did not implement KMI with a robotic glove.

Assisted movement could help in the generation of KMI because the subject is able to perceive sensorial feedback during the development of hand MI tasks, which may induce more profound ERD/ERS when using this type of device [16]. The results of this study are in line with the literature, where it was possible to evidence ERD/ERS related to KMI tasks. Studies in the literature have gathered efforts to increase the magnitude of these metrics using different strategies such as haptic or visual feedback, obtaining ERD/ERS changes with mean absolute values between 10% and 50% [5, 27]. In this context, our preliminary analyses may be limited by the use of only two healthy participants, where further evidence with a larger sample is required to obtain more generalized conclusions. Finally, the use of these strategies based on the execution of protocols using assistive devices can potentially be applied to study the EEG rhythms of more complex mental tasks, which would be interesting for the scientific community because it would be possible to develop more controllable, usable, and effective rehabilitation devices for the intervention of people with disabilities during the execution of activities of daily living [16].

However, the literature reports that there are still limitations in BCI-controlled robotic devices for generating interaction in an accurate manner using MI [28]. In addition, several patients experienced

discomfort during the use of massive robotic setups to perform therapeutic exercises [29], which decreased motivation and affected movement recovery performance. Therefore, the implementation of the robotic glove in this study plays an important role, where it is worth noting that the weight of the actuators is negligible, offering better comfort and wearability to the patient.

On the other hand, the study of EEG signals during MI tasks is still of difficulty, because such signals can be influenced by physiological and non-physiological factors, which can affect the performance of BCI systems [10]. Therefore, the study of EEG rhythms in complex MI tasks using device-assisted movements is a promising strategy to address the artifacts on BCIs, leaving the door open to the execution of new studies on cortical rhythm changes when performing MI tasks from the same limb [22].

One of the limitations of this study was the number of participants. Nevertheless, it is important to mention that the persons who implemented the protocol showed a cortical difference produced by the glove of approximately 3%, specifically in the μ band in both the right and left gloves, more evident during hand closing, which are promising results. Therefore, it is recommended to expand the study for a larger population sample.

4. Conclusions

The objective of this study was to analyze brain cortical rhythms during the execution of left- and right-hand opening and closing of MI tasks. The results of this study indicate that the ERD in μ band during the combination of AO and passive movements generated by a robotic glove is more profound than the execution of this type of task without sensory stimulation. This cortical response was mostly detected in electrodes C3 and C₄, which are related to the right- and left-hand movements, respectively. Considering this ERD comparison, it is possible to highlight the benefits of passive assistance during MI, generating more focused neuromodulations in the cortical cortex close to 3%. However, it was possible to find more evident power changes during MI tasks related to hand closure compared to the open hand, which may be influenced by the complexity of the task.

The findings of this study contribute to the field of BCIs due to the cortical effects of the use of robotic gloves during MI tasks, whose strategies can be used for the incorporation of more robust systems for therapeutic interventions for people with neuromotor impairments, such as post-stroke populations. Future studies should focus on the design and validation of an upper limb-based BCI using different feedback strategies to induce neuroplasticity based on previous analyses. Finally, the recruitment of a larger sample will be considered to better generalize our system.

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