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Article

Classification of opening/closing hand motor imagery induced by left and right robotic gloves through EEG signals

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Abstract: This study presents a novel strategy for classifying Motor Imagery (MI) related to hand opening/closing actions using electroencephalography signals. This approach combines the passive motion induced by a robotic glove and action observation. Two groups of subjects executed a protocol based on left and right hand movement MI to address this. Subsequently, spectral features were used on *mu* and *beta* bands, and machine-learning algorithms were used for classification. The results showed better performance for right-hand motion recognition using k-Nearest Neighbors (kNN), which achieved the highest performance metrics of 0.71, 0.76, and 0.28 for Accuracy (ACC), true positive rate, and false positive rate, respectively. These findings demonstrate the feasibility of the proposed methodology for improving the recognition of MI tasks of the same limb, which can contribute to the design of more robust brain-computer interfaces for the enhancement of rehabilitation therapy for post-stroke patients.

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1. Introduction

In recent years, Brain-Computer Interface (BCI) through Electroencephalography (EEG) signals applied to upper-limb have been implemented to enhance rehabilitation therapy and improve post-stroke patients' quality of life. For example, a review by Khan *et al.* [1] reported several approaches for BCI systems that combine electrical stimulation, assistive devices, and the use of noninvasive biosensors. On the one hand, this review suggests maximizing rehabilitation therapy outcomes by providing realistic, exciting, and motivating environments to increase patient interaction with the therapeutic intervention, where the outcomes of designed BCI systems have enhanced gross motor function and functional activities. The authors suggested that longer exposure to the BCI system facilitated the acquisition of motor patterns

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and better performance in the execution of the movement [2]. In this context, literature has demonstrated the feasibility of using Motor Imagery (MI)-based BCI to increase neuroplasticity during therapeutic interventions [1,2].

MI-based BCIs are normally based on data acquisition, pre-processing, feature extraction and selection, classification, and applications, which can be used in robotic devices to enhance movements. Several studies have presented the implementation of methodologies or complete systems for upper-limb rehabilitation BCIs. For instance, Gu *et al.* studied the correlation between MI and motor ability by analyzing Event-Related Desynchronization (ERD) and motor abilities through EEG acquisition. The results indicated that hand dexterity and fine motor coordination are significantly related to MI tasks and may play an important role in rehabilitation interventions with EEG [3]. In contrast, the literature presents several processing algorithms such as those based on ERD or Event-Related Synchronization (ERS) combined with a Filter Bank Common Spatial Pattern (FBCSP) and Fisher's linear discriminant classifier, as implemented by Cheng *et al.* [4]. That study implemented a strategy for the activation of a soft robotic glove-based BCI as a stroke rehabilitation proposal; however, the classification problem consisted of rest and MI, and opening and closing were overlooked. Other types of EEG devices have been used for glove control, such as Guo *et al.*, who implemented Steady-State Visually Evoked Potentials (SSVEP) for user intention detection and robotic soft robotic gloves for post-stroke rehabilitation. Nonetheless, visual fatigue is present in the system due to the use of SSVEP for a long time [5].

EEG-based BCIs may present disadvantages related to a low Signal-to-Noise Ratio (SNR), and the presence of physiological and non-physiological artifacts becomes challenging for the recognition of intentionality [6]. In this context, Foong *et al.* [7] highlighted the correlation between visual feedback and mental fatigue in BCI. This study considered the use of the F3, F4, C3, and C4 channels owing to the importance of this cortex during upper-limb tasks. On the other hand, Yamamoto and Hamaguchi used information from motor task-related channels, specifically C3 and C4, which are associated with upper-limb movement [8].

Moreover, the literature mentions classification using Machine Learning (ML) techniques with two classes (rest and MI) of right- or left-hand movement or three classes (right, left, and rest). For instance, Archila *et al.* used time- and frequency-domain features from EEG signals, such as relative power, mean, variance, skewness, kurtosis, and Hjorth parameters, for the classification of hand MI [9]. However, this type of MI classification is often implemented with visual instructions or Visual Motor Imagery (VMI).

In addition, the literature has reported Kinesthetic Motor Imagery (KMI) with robotic devices as sensorial feedback [4], however, the combination of passive motion in rehabilitation therapy and the study of MI tasks in the same hand has not been deeply explored. It is worth commenting that, the use of robotic gloves and the analysis of motion in the same hand is a challenge for the scientific community. This study aims to develop a strategy for binary classification using EEG signals during MI tasks of hand opening and closing through visual instructions (VMI) and movement assisted by a robotic glove. The main contribution of this study corresponds to the classification of MI tasks of the same hand opening and closing using ML of an EEG protocol that involves KMI and VMI simultaneously. For the best knowledge of the authors, this kind of research has not been reported before. Moreover, a comparison between right and left-hand performance was established using movement performed by a robotic glove in the entire protocol.

2. Methodology

The methodology is illustrated in Figure 1, which was used for the classification strategy for the opening and closing hand MI task discrimination.

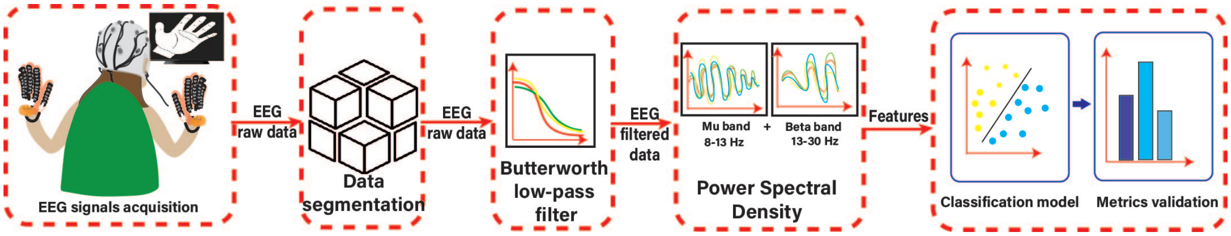


Figure 1. Methodology of the classification system for open and closed hands considering the stages of preprocessing, feature extraction, classification, and performance metrics.

2.1. Signals acquisition

An in-house database for hand MI tasks that encompassed passive motion and visual stimuli was registered using information from eight subjects (aged 32 ± 11 YO, all right-handed). Four out of these eight subjects executed right-hand MI tasks and the other four subjects executed left-hand MI tasks. All participants were right-handed, without physical or mental restrictions, considering their lack of experience in the use of BCI systems or robotic devices. EEG signals were acquired using an OpenBCI device with a sampling frequency of 125 Hz, where the acquired channels corresponded to $FP1$, $FP2$, $F3$, $F4$, $FC4$, $FC3$, FCz, $CP3$, $CP4$, $C1$, $C2$, $C3$, $C4$, $C5$, $C6$, and CPz, $A1$ and $A2$ were used as references placed in the earlobes of the subject as implemented in previous studies [7,8,10,11]. Figure 2 illustrates the positions of the electrodes employed in our MI classification system.

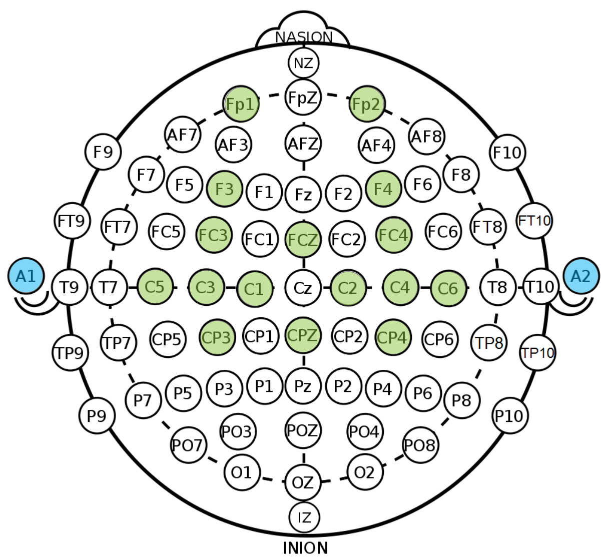


Figure 2. EEG electrode location using 10-20 international system for upper-limb recognition.

The established protocol is composed of 6 s of baseline, 7.3 s for the open hand, and 4 s for the closed hand, as shown in Figure 3. This configuration considered a higher time of hand opening execution because of the mechanical delay generated by the air pumps functioning in the robotic glove.

In the protocol experience, the user watches **(1)** a black screen in which the subject does not perform MI tasks, as previously mentioned, which is called baseline period. Then, **(2)** the user focuses on executing the opening-hand MI task followed by the **(3)** closed-hand MI task guided by a visual stimuli and receiving passive movement whit the robotic glove which is executing the same movement as shown on the screen. In the protocol, one session includes 8 trials and two sessions were conducted per subject. This strategy is

Figure 3. Protocol implemented in the system using a period of baseline, opening and closing hand with Action Observation (AO).

being implemented because the literature has mentioned the importance of performing kinesthetic motor imagery due to a feeling of movement is effectively experienced [12].

2.2. Data randomization and pre-processing stage

Considering the time per class established in the protocol, opening trials were balanced by excluding information from the beginning and end of the trial and establishing the same number of samples in both open and closed trials. The performance of the system is affected by whether the classes are unbalanced. Open and closed hands were tagged, such as the classes in the classification system.

Moreover, the data were segmented per trial and randomly chosen by k-fold cross-validation with $k = 5$. Moreover, the data were split into training and validation sets of the model. With separation per trial, it was possible to generate the labels of the system considering open and closed tasks. Subsequently, a Common Average Reference (CAR) filter was implemented to avoid common noise in all channels [13]. In addition, a zero-phase Butterworth pass-band filter between 8 and 30 Hz was considered to select the frequencies that are commonly evidenced by cortical activity, in that case, for upper-limb MI tasks [14].

2.3. Feature extraction

Spectral Power Density (PSD) was computed by considering the Fourier Transform in bands Mu (μ, 8-13 Hz) and beta (β, 13-30 Hz), specifically the low-beta (13-17 Hz) and high-beta (18-24 Hz) bands. In addition, the PSD obtained per trial was used, such as features considering the ease of implementation and effectiveness in the literature [15]. Subsequently, feature normalization using the z-score was performed prior to model training [16].

2.4. Classification models

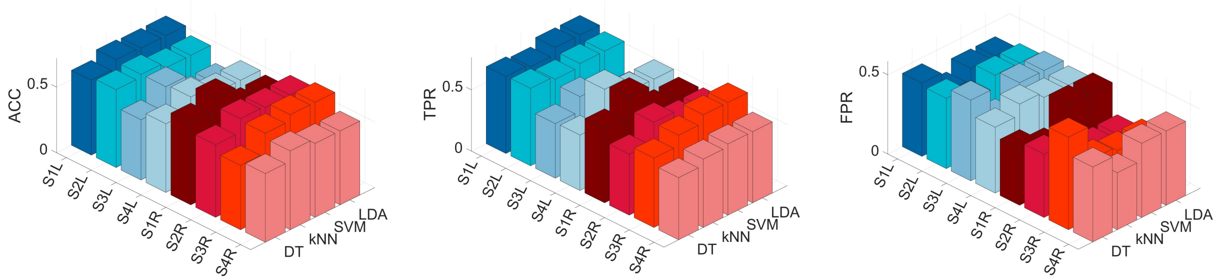
Four classifiers were considered: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Decision Tree (DT). The classifiers were considered because of their wide implementation in the literature for MI tasks [9, 17]. Deepening into the classifiers, LDA is a supervised classification technique that aims to find a linear combination of features that best separates different classes of data. LDA determines a projection of the feature space that maximizes the distance between the means of different classes while minimizing the variance within each class [18]. kNN can be applied to classify upper-limb movements based on the similarity of brain signals. It assigns a class label to a data point based on the majority class of its k-nearest neighbors, where $k = 1$ was used for the implementation of our system [19]. Moreover, an SVM can be used to classify upper-limb movements from brain signals by finding a hyperplane that maximizes the margin between different classes [18, 20]. In our study, SVM used a linear kernel with $C = 1$. In addition, DT is interpretable, making it easier to understand and visualize the decision-making process due to tree fundamentals [21].

2.5. Metrics evaluation

Criteria such as decoding Accuracy (ACC), True Positive Rate (TPR) or sensitivity, and False Positive Rate (FPR) were used to validate the performance of the classifiers, which were defined by considering the confusion matrix per classifier. ACC is the rate of correctly predicted MI trials relative to the total number of targeted MI trials; TPR is the percentage of positive MI trials predicted to be positive; and FPR is the percentage of false positives predicted as positive from negative MI classes [18].

3. Results and Discussion

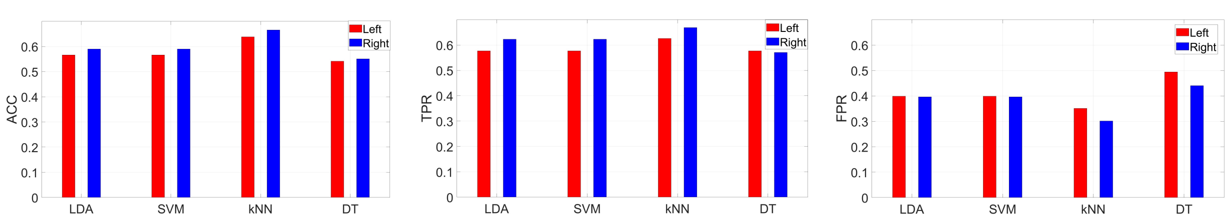
The hand MI task per subject was analyzed by considering all classifiers. Such as aforementioned, four right-handed subjects participated in the right-hand MI task and four right-handed subjects participated in the execution of the left-hand MI task. All the subjects performed movements with the respective robotic glove for the MI task. Figure 4 shows the ACC, TPR, and FPR performance for all subjects by considering the blue bars for the left hand and red bars for the right hand. Figure 4a illustrates ACC by considering a maximum accuracy of 0.63 for the left hand in subject 4 (S4L) by considering the kNN classifier, and 0.72 of the right hand MI in subject 1 (S1R) with kNN. Moreover, in terms of TPR, Figure 4b shows a maximum value of 0.72 for subject 4 and 0.76 for subject 1 by considering the kNN for both hands. Finally, Figure 4c represents the FPR with maximum values of 0.48 for the left hand and right hand. In general, it is possible to discriminate that S1 in the left hand obtained better performance metrics in comparison with other subjects, as well as S1, S2, and S3 for the right-hand MI task performance.



(a) ACC both hands **(b)** TPR both hands **(c)** FPR both hands

Figure 4. Performance metrics of all subjects per classifier (left hand: blue colors; right hand: red colors); a) ACC both hands, b) TPR both hands; c) FPR both hands.

Figure 5 shows the mean performance metrics by considering the left (red bar) and right (blue bar) hands to determine which classifier performed better. Figure 5a shows that kNN performed better classification tasks than the other classifiers, with a mean ACC higher than 0.64. Figure 5b shows the mean TPR per classifier, with a maximum mean TPR higher than 0.67. Finally, Figure 5c shows the FPR for the kNN with a value lower than 0.35 for both hands.



(a) ACC mean **(b)** TPR mean **(c)** FPR mean

Figure 5. Mean performance metrics of all subjects per classifier considering both hands; a) ACC mean, b) TPR mean; c) FPR mean.

Based on previous results, implementing kNN or LDA for binary classification by considering PSD features in the time domain can discriminate between opening and closing MI tasks with better performance results. It is worth commenting that features have been widely used for upper-limb MI recognition [9], as well as the use of the classifiers implemented in this approach [9, 17, 18, 20].

A novelty of this approach is the implementation of KMI in the execution of the protocol, which can improve the concentration of the subject or accelerate the rehabilitation process for stroke patients, as mentioned in the literature [18, 22]. It is worth noting that our protocol incorporated passive motion during baseline and MI in order to reduce the effects of physical motion on EEG signals that can generate additional noise and increase cortical behavior of hand MI, as has been done in previous studies [6, 23, 24]. Subsequently, our methodology focuses on the Mu and Beta frequency bands, implementing frequency filters related to the execution of the movement, such as the one present in the Theta band [25]. In our previous study, we have shown the discrimination of using the robotic glove by presenting a decreased ERD compared with the non-use of the robotic glove. It is worth highlighting the protocol performed was the same as shown here but it was an analysis of cortical changes based on the use of the robotic glove [26]. This study allow conclude the importance of using the robotic glove to indicate a better MI performance as has also been mentioned by the literature [12]. Moreover, the generalization of the system was achieved by considering a 5-fold cross-validation for a real implementation of the MI-based BCI system.

The literature reports a comparison of two imagery tasks, namely opening/closing and flexion/extension movements of the hands. Several authors implemented a Common Spatial Pattern (CSP) for feature extraction and classifiers such as LDA and SVM, obtaining an ACC between 60% and 95% for opening/closing hands of the same hand by utilizing data from 11 subjects [27]. Moreover, considering the higher ACC results of the authors, there is still a lack in terms of the use of passive motion using a robotic glove that could accelerate rehabilitation therapy and activate specific regions of the brain, even generating neuroplasticity.

Additionally, in the Cheng *et al.* [4] study, the ACC results were above 60% for controlling a robotic glove hand using MI; however, it is worth mentioning that this study excluded one subject who presented an ACC lower than 57%. This allows us to determine that the system is not generalized and the methodology selected the best ACC values, which is not feasible, considering that the system could not work for all types of subjects based on the inclusion and exclusion criteria, limiting usability. These results may be compared with our study, where the higher ACC result was 64%, and the generalization of the system by considering data randomization makes the system reliable and increases the target population.

In a review by Khan *et al.* [1], Frolov *et al.* reported the enhancement of motor function in patients with different durations, severities, and stroke locations [28]. The authors designed a BCI by considering three mental tasks: motor relaxation, imagery of left and right openings, and an exoskeleton. The authors also considered passive motion, achieving an ACC of between 36% and 65%. Nonetheless, patients reported fatigue after 20-30 min of training, and the MI tasks were based on the upper-limbs, which may be easier to implement than tasks related to the same limb [18]. In this context, an advantage of our system is the classification of both opening and closing tasks using both hands and gloves by implementing opening/closing movements, which could increase usability. Another use of robotic gloves and BCIs can be seen in a study by Guo *et al.*, who implemented SSVEPs for controller design [3]. However, these types of signals are evoked, which can be affected by non-physiological factors such as the amount of light, or physiological factors such as visual fatigue and concentration level, which can affect the performance of the BCI [29].

Some limitations of our study were the unbalanced classes due to the delay in the opening hand action of the robotic glove, which affects MI processing and classification. Therefore, for future implementation, we consider the robotic opening and closing times with synchronized time activity to generate better sorting strategies and avoid overfitting.

4. Conclusion

A strategy for open/closed hand MI classification from EEG signals was developed here using KMI through a robotic glove and AO. To address this, the protocol was executed for two groups: the first group performed left-hand-MI tasks, whereas the second group executed the protocol for the right hand. This study implemented a feature extraction stage based on PSD in mu and $beta$ bands with ML classifiers, where kNN achieved the best performance metrics with mean ACC of 0.64 and 0.67, highest TPR of 0.62 and 0.67, and lowest FPR of 0.35 and 0.30, for the left and right hands, respectively. Based on the results, the highest classification performance was reached using the right-hand side, where it is important to highlight the metrics obtained by S1, with an ACC of 0.71, TPR of 0.76, and FPR of 0.28. It is worth noting that our proposal uses data randomization and a class-balancing strategy, which decreases overfitting. The results allowed concluding the feasibility and precision of our strategy for opening/closing hand MI classification considering static AO and KMI using a robotic glove for left and/or right hand tasks. Future studies will focus on the implementation of this methodology for a robotic-glove-based BCI for rehabilitation purposes in post-stroke patients.

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Compliance with ethical requirements: The individuals willingly agreed and signed a document stating that they were informed about the study, according to the Declaration of Helsinki. The study protocol was approved by the Ethics Committee of Federal University of Espirito Santo (UFES) in Brazil with the number CAAE:39410614.6.0000.5060.

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