A preliminary study of neural signals of Motor Imagery task of Arm movements through Electroencephalography data Classification with Machine Learning

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Abstract In this study, we aimed to observe whether the neural signal of Motor Imagery (MI) tasks of different major and subtle movements of an arm is possible to be distinguished through classification analysis of Electroencephalography (EEG) so that they can be used for controlling Robotic Arm or Exoskeletons in a humanoid arm way. We also aim to observe whether this distinguishing procedure can be done through live data using current technology, bypassing lengthy preprocessing and costly computation of traditional EEG data usage. We considered a total of 20 movements of one arm, including several subtle movements. We collected the EEG data while participants were performing the MI task of these chosen arm movements upon instructed by visual presentation. For this preliminary study, we performed analysis for only the dominant hand and used the non-invasive technique of EEG to collect neural signals from the cortex. We performed multi-class classification analysis on the EEG data to identify the movements using the Machine-Learning (ML) technique. We used seven widely used supervised classification algorithms of ML to check accuracy through 10-fold cross-validation and compare their efficacy for this model. We used K Nearest Neighbor (KNN), Random Forest (RF) classifier, Decision Tree (DT), Support Vector Machine (SVM), Logistic Regression (LR), Linear Discriminant Analysis (LDA), and Naïve Bayes (NB) algorithms to find out the most appropriate one and found that KNN and RF can provide the highest average accuracy up to 99 percent. We also compared the model overall (across all participants) as well as individual levels to compare which way we can achieve better accuracy.

Keywords Human-Robot Interaction, Brain-Computer Interface, Electroencephalography (EEG), Motor Imagery (MI), Machine Learning (ML)

I. Introduction

Humanoid Robots have become a topic of research interest recently with the advancement of Robot technology. As human and bio-inspired designs and models are providing more and more success for practical purposes, researchers are more penchant to designing robots and machines that are more similar to humans or human-friendly animals (e.g., dogs), which helps to build better teaming with the human partner. Intelligent robotic limbs can be considered as one kind of robot as they have their own intelligent system. When it comes to the use of an intelligent humanoid limb, such as automated robotic arms, intelligent prosthetics, exoskeleton augmentation, or rehabilitation devices, the (human)user-system interaction should be as smooth as possible. When we mention "smooth," we refer to ease of usage and avoiding heavy calculation, which can lead to time lag and reduced complexity of the process. Because, in most cases, these external robotic limbs are used by vulnerable users or are in a challenging situation. Intelligent machines are usually self-learning and thus can improve the performance of the model by continuously re-assessing and adding training data. This gives a huge opportunity for BrainComputer Interface (BCI) technology to be integrated with Human Robot (or Robotic limb) interaction. In the BCI area, neural signals or brain signals are used to control the external computerized systems by bypassing the use of external communication techniques or peripheral nerves, such as moving one's own limb, voice, or muscle movements. Therefore, BCI technology offers a huge opportunity in rehabilitation and distance operations. But to fully use the potential of live learning (of the system) with continuous input of data, the system needs to be fast and robust enough to cope with the speed and complexity of human brain functions because, in terms of neural signal, the brain generates huge amounts of data in each milli(/micro) seconds. In this paper, we are addressing the issue by investigating the less complex process that bypasses the common preprocessing steps of neural signals.

BCI (Brain Computer Interface) controlled health support systems (e.g., wheelchairs), robotic arms, and exoskeletons, which are more likely used by a single human for frequent and prompt use, require fine-tuning with their human counterpart. A number of ways are being delved into to improve the communication between humans and machines in these kinds of situations. Numerous techniques, including different

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physiological responses such as heart rate, muscle response, and eye gaze signals, are being used to invent and improve these human and humanoid machines. Using human brain signals to operate machines or devices is comparatively a new domain

where bypassing limbs of extremities and peripheral nerves is possible; therefore, it has the potential to offer many advantages in rehabilitation fields and as assistive tools for people who have a motor impairment. For BCI technology, one of the most preferred techniques is Motor Imagery (MI), which is, as its name indicates, an imagination task and thus does not need external limbs or nerves.

Motor Imagery is a technique where a human imagines moving limbs without actually moving them [1]. This has been used as a method to improve performance in athletics and rehabilitation by introducing neuroplasticity. One significant benefit of motor imagery is that its performance can be improved through training [2], [3]. The MI technique is considered to have so much potential in this field that numerous studies are addressing how the performance of MI can be improved by employing different methods of training as well as by different classification techniques. Also, it is found that the neural phenomenon associated with actual motor movement and imaginary movement is very similar, which makes it more useful for controlling the robotic limbs. Motor imagery is specifically associated with the imagination of motor functions (that is, moving limbs), while there are other kinds of "Mental Imagery" techniques where humans can imagine moving other objects (other than their own limbs). One such technique can be mentioned here, which is "Object Movement Imagery," which is another kind of mental imagery. In this technique, people imagine moving objects directly, such as imagining a box moving from left to right direction. This technique is also being investigated for controlling BCI devices.

To use Motor Imagery for controlling robots, we need to get information about the "imagination," which means we have to do "mind-reading" of the user. Though the term "mind-reading" sounds really charming and exciting, it is not so straightforward when it comes to using it in advanced technological situations, such as commanding a robot or moving a wheelchair. To make the "mind-reading" magic real, we have to go through quite a number of technical procedures, and the outcome is not so magical yet. Researchers are working to delve into the full potential of using human brain signals for commanding robots from every possible perspective, as it has so much usefulness in the practical world. In the following sections, we will discuss our approach to using brain signals to command humanoid robotic arms. Our approach targets moving a whole robotic arm using brain signals. We will use Motor Imagery for different arm movements and collect the corresponding brain signal as EEG data. Our goal is to develop a model suitable for practical purposes in the future; keeping that in mind, we are considering only brain signals, i.e., without the assistance of other neurophysiological signal collection methods, which will help to reduce complexity. We are also considering using this model in a live scenario, where the brain data will be collected and directly fed to the machine without further lengthy preprocessing.

This study is a preliminary step toward that goal. Here, we considered 20 major movements of one arm, including some finer movements. We considered the dominant arm of the participants here. We collected the motor imagery neural signal of those movements as EEG data and used the machine learning technique to observe whether these movements were identifiable by the classification analysis by machine learning algorithms and observed which algorithm provided better accuracy. We observed the efficacy of the model for seven popularly used algorithms for different instances, such as overall and individual scenarios. We achieved satisfactory accuracy and are considering this model for future study, as it has great potential to command a humanoid robotic arm with brain signals.

II. Literature Review and Background

Utilizing neural signals in brain-computer interface or human-machine interaction is no longer an avant-garde topic. Numerous studies are addressing this topic from different perspectives and finding new discoveries that are presenting new opportunities and, in turn, new challenges. There are different ways to collect and image brain signals, but among them, electroencephalography has become popular due to its low cost, better resolution, better usability in laboratory environments, and, of course, its non-invasive nature. In particular, the advancement and commercialization of EEG made it more possible to capture human brain signals with better readability and classifiability [4], [5],[6], which made it feasible to use it in HRI technology [7]. To achieve better performance, sometimes EEG is combined with other modes, such as Electromyography (EMG), for purposes like rehabilitation; one such study was conducted for hemiplegia patients with a fusion of EEG and EMG to control the Human-exoskeleton and found up to 88.44% accuracy with lower limbs [8]. Another study, including EEG and EOG (Electrooculography), used human vision and coordination along with motor-imagery evoked brain signals to manipulate wheelchairs [9]. EEG data-driven robotic arm movement is also under development, though in the preliminary stage [10]. Human brain signal is also used combined with a gaze-tracking system to control semiautonomous robotic arm [11]. The use of immersive virtual reality in neural applications provides a better scope to explore human brain performance and, thus, better interpretability to use the brain signal to connect with the machine [12].

As brain signals are being used to command robots and machines, Mental Imagery or Motor Imagery is considered to have a high potential as a technique to command humanoid robots or humanoid robotic limbs. Mental imagery can be described as a multimodal simulation process by which the human mind can experience perceptual information in the absence of real sensory input [13]. In this domain of mental imagery, Motor Imagery is another construct in which motor movement is imagined using working memory without actually executing a physical movement [14]. This process of Motor Imagery is well accepted as a technique to practice and thus enhance performance in athletics, clinical rehabilitation, and music [1]. It also introduces neural plasticity, which allows the human brain to reshape its structure in a better way as a result of repeated and systematic experience [15]. Neural studies through fMRI and TMS data found similarities in brain signals and activation in motor imagery and motor execution;

particularly, these studies found primary motor cortex activation during motor imagery [13]. A graph theory study found differences in ME and MI in terms of brain area activation, such as, for Motor
Execution, the supplementary motor area is the main key node, while for Motor Imagery, the right premotor area is the main key node [16].

Due to the popularity of the EEG method, commercial companies are coming forward to offer advanced and less complex options for EEG devices. These advantages of EEG have made it feasible to understand the brain even for novel and complex cognitive issues like trust or decision-making [17], [18]. Different studies are focusing on how EEG data classification performance can be improved by different preprocessing techniques; one such study developed a two-stage filtering method to improve MI-based EEG data by 3% [18].

Along with understanding the brain, EEG signals are also being used for more practical purposes, such as the identification of mental commands through the classification of neural signals collected by EEG. Researchers are working on how classification accuracy can be improved in EEG data [19]. Best channel selection for data optimization and discomfort (of the user) reduction is being considered for EEG data classification of MI data; different kinds of features such as band power, entropy, statistical features, and wavelet features are delved into to find out the maximum performance measure with reduced features and could reach up to 94.28% accuracy for left and right hand MI classification using statistical feature [20].

Motor-imagery-based EEG data has been considered for rehabilitation purposes for the last few years. A study considering features like band power and autoregressive parameters of EEG data has been able to achieve 100% accuracy for the classification of two functions- left and right- after a few days of training of a tetraplegic patient [3]. Another study conducted a comparison between neural signals of Motor Imagery and Object Movement Imagery and found that accuracy for two-class classification is higher with Object Movement Imagery [21]. This can be fuel for thought if we can properly classify motor imagery signals of movements of a whole limb and use them to command humanoid robotic limbs; maybe object movement imagery will provide better accuracy for that task.

However, in our study, based on the current literature findings, we are approaching the development of a system with motor imagery for an arm addressing major movements, including some finer movements. We observe the performance of some machine learning algorithms; we investigate the distinguishability of the movements; we also tap into whether we can reduce the number of electrodes without losing significant accuracy.

III. Methodology

A. Participants

The participants took part in the study in a voluntary manner. Informed consent was taken from them as per IRB approval, explaining the study. The participants had normal or corrected to normal vision, were free of current or past neurological and psychiatric disorders, and were in a stable mental state during the study. The 5 participants' age ranges are 19 years to 59 years. Among them, three are male, and two are female by their selfidentification. Two are South Asian, one is Asian, one is Caucasian, and one is African American. All of them acknowledged the right hand as their dominant hand. They were free to quit participation at any point in the study.

B. Tools and technique

In this study, we used the Emotiv EpocFlex device, which consists of a head cap that is to be fitted to the participant's head to collect the neural signal and EmotivPro Software to record the neural signal as Electroencephalography (EEG) data. We used 30 channels that follow 10-20 systems of electrode management, as shown in Fig 1(a), and used saline/gel solution to maintain conductivity between the scalp and the electrode. The data sampling rate was 128 Hz. The collected signal is recorded as voltage in a microvolt unit for each sampling point. The participants were seated on a chair in front of a computer monitor, where visual instruction was presented on the screen, as shown in Fig 1(b).

C. Procedure

The participants have clearly explained the procedure first. There was a training session prior to the recording session so that the participants could perform it properly during their Motor Imagery Task.

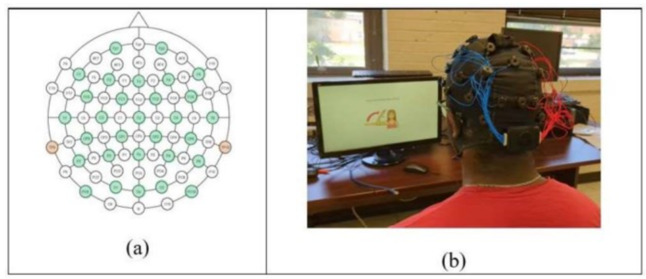

Fig. 1(a). Extended 10-20 electrodes system with highlighted electrodes that are used in this study, (b) A participant is performing Motor Imagery task according to instruction presented in front of him, wearing an EEG head cap.

There is a total of 20 movements of one hand, as described in Table I. The instructions for movements are presented on a computer monitor screen in front of the participant with images and text, examples shown in Fig 2. Each slide consists of instructions for one movement. Each slide appears for 5 seconds, and then immediately, another instruction slide appears.

TABLE I. Motor Imagery Task ID And Text Instruction

ID	Movement Instruction (text form)
M1	Please lift your right arm at the side (90 degrees with body) as shown in the picture, palm relaxed.
M2	please do grip (still arm extended)
M3	please release your grip (still arm extended and palm relaxed)
M4	please do arm flexion (palm relaxed)
M5	please do arm Extension (palm relaxed)
M6	please keep your wrist straight and palm facing upward (still arm extended)
M7	Please rotate your wrist so the palm goes downward, facing.
M8	Please rotate your palm so fingertips point upward, still palm facing downward.
M9	Please rotate your palm so fingertips point downward, still palm facing downward.
M10	please put your hand down straight at your side (palm relaxed)
M11	please put your right hand up position as in the below pictures, palm relaxed
M12	please put your right hand down, hanging straight at your side
M13	please put your right hand forward at 90-degree, palm relaxed
M14	please do grip (still arm forward)
M15	please bring the fist to your chest (like you are pulling or bringing something to you)
M16	please extend your gripped arm forward as you are giving sth away
M17	Please release your grip.
M18	Please extend your arm to the side.
M19	bring your arm forward
M20	please bring your hand beside you in a relaxed position

There is no blank screen or break between consecutive instruction slides. Participants are to remain in the same position (according to the movement) until the next instruction appears. Participants are asked about their dominant hand, and instructions are given for that specific hand. In this study, all the participants were right-handed. There are several training sessions that consist of real movements to make sure the participants understand the movement instructions properly and can perform properly with their actual motor movement.

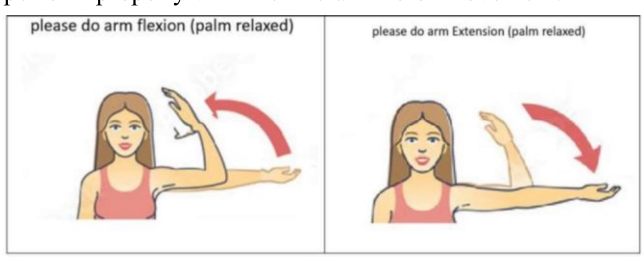

Fig 2. Instruction slides for S4 and S5 movements are shown as examples

Once the participants are able to do it properly in real movement in the training session, the recording session is conducted for the Motor Imagery tasks. In this recording session, the participants were seated in front of the computer monitor and asked to minimize their physical movement. Then, they were instructed to perform the same movements using their imagination without moving their physical arm in reality. For each participant, two runs were conducted at the recording session.

D. Data Analysis

After collecting the recording, we marked the signal data for each movement in the associated timeframe. Then, we used the data directly for classification analysis without any cleaning or artifact removal. The purpose of avoiding cleaning and preprocessing is to reduce computational cost and make the processing time efficient, as well as to mimic the practical world scenario, where a lengthy routine of preprocessing might not be feasible in all situations. We considered each movement as a class and all 30 channels as individual features. All the sampled data in the corresponding timeframe is considered as data points. Therefore, as we have 5 seconds of data for each movement, two runs for each participant (and all the movements), the sampling rate is 128 Hz (which means 128 data points for every second), we have 1280 data points for each movement of each individual and for total 20 movements, we have 25,600 data points for each participant and for all 4 participants we are to have 97,280 datapoints ideally. However, due to some connection error issues during the recording (which can happen in practical scenarios, too), we have a smaller number of data points than that.

We used these datasets for classification analysis using the Machine Learning technique. We have used six commonly used algorithms, which are also considered the best algorithms of ML, to compare their accuracy in our model; those six algorithms are Support Vector Machine (SVM), K Nearest Neighbor (KNN), Decision Tree (DT), Logistic Regression (LR), Linear Discriminant Analysis (LDA) and Naïve Bayes (NB) [22]. We used 80% of the data for training and 20% of the data for testing. 10-fold cross-validation is performed [23], to calculate the average accuracy over the training dataset.

- Logistics Regression is a widely used tool for binary classification scenarios. For multi-class problems, such as ours, it performs classification for each class as a binary problem, whether the outcome belongs to the class or not [22].

- Linear Discriminant Analysis uses the technique of feature selection and reduction before classification analysis and has the limitation of being better suitable for linearly solvable problems and normally distributed datasets [22].

- KNN is a non-parametric approach that works well with multi-class datasets and works well with noisy data. That is why we consider this algorithm highly suitable for our model, as our data is not preprocessed; it certainly consists of some noise [22].

- The Decision Tree classifier can use different feature subsets as well as decision rules for classification. It also works well with multi-class and non-linear problems, which makes it another potential good algorithm for our datasets [22].

- Gaussian Naïve Bayes algorithm assumes normal or Gaussian distribution for the dataset. Still, the nonexpensiveness nature encouraged us to explore this algorithm's performance [22]. Which sometimes also can be referred as Naïve Bayes.

- Support Vector Machine is another widely used algorithm for supervised Machine Learning problems and is suitable for multi-class problems. However, we had to select the parameters to get better performance carefully. As our focus of this study is not machine learning, we are not discussing this in more detail [22].

- Random Forest (RF) is another algorithm suitable for large datasets with noise, but it takes a longer time to train; therefore, it needs to assess the context of interest and whether it would fit the model [22].

We performed the analysis for all 5 participants individually as well as for the overall dataset. As per our findings, as we observed that the individualistic approach provides better results, we delved more into individuals' data. We identified the 15 best features (i.e., channels) for all the participants and compared the results to how much it affected the accuracy. To identify the best channels, we used a Univariate Statistical test.

IV. Result

The classification analysis results are shown in Table II.

TABLE II CLASSIFICATION RESULT AS AVERAGE ACCURACY (IN %) OF 10FOLD CROSS-VALIDATION OF THE SELECTED ALGORITHMS

Participant ID	**All partici pants**	**P1**	**P2**	**P3**	**P4**	**P5**
Gender(Age)		F(27)	M(19)	M(22)	F(59)	M(30)
KNN	90.8	99.3	95.2	99.8	68.5	96.6
RF	90.9	98.9	94.6	99.7	71.9	96.9
SVM	59.5	98.8	87.9	94.5	78.1	80.1
DT	67.4	83.6	69.9	92.9	37.8	78.3
LR	21.7	63.2	52.3	47.1	57.0	66.9
LDA	21.0	57.1	49.1	45.1	56.5	42.8
NB	15.8	39.3	44.9	36.0	18.3	84.7

We can find that the K-Nearest Neighbor algorithm provides the best accuracy in most cases, providing more than 90% accuracy except for one participant (P4). Random Forest classifier provides slightly better accuracy in the overall scenario and for one individual scenario. The Support Vector Machine algorithm provides good accuracy, too, in most cases, though it is not as good for the overall scenario as it is for individualistic scenarios. Another good algorithm is the Decision Tree algorithm.

Four of the best algorithms are shown in the graph in Fig 3.

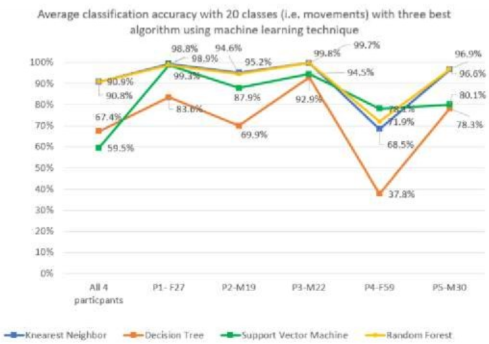

Fig. 3. Visualization of four best algorithms

We also identified the best features (i.e., channels) for every individual and performed classification analysis with the best four algorithms as identified and stated in the previous section with the best 15 channels the classification accuracy with the 15 best channels presented in Table III. The 15 best features of each individual participant are presented in Table IV.

TABLE III THE CLASSIFICATION ACCURACY WITH THE 15 BEST CHANNELS OF INDIVIDUAL SCENARIOS.

	P1	P2	P3	P4	P5
KNN	89.5%	85.2%	99.6%	38.8%	94.5%
RF	87.1%	84.2%	99.7%	49.3%	95.1%
DT	66.7%	61.0%	92.6%	26.7%	79.7%
SVM	80.0%	66.9%	82.1%	50.9%	67.2%

V. Discussion

From the result presented in the previous section, we can notice that our aim for the classification of neural signals elicited by Motor Imagery action corresponding to detailed arm movements is well achieved in this preliminary study. In most cases, we have been able to achieve more than 90% accuracy. If we consider the individualistic approach, we can observe that the classification accuracy can reach up to 99.8% or more than 95% in most cases. So we can state that as per this study, individualistic approach provided better result than the generalistic (using pooled data) approach. In one case, for P3, we received fewer data points than others; the reason was a connection interruption while recording the neural signal. As the data is collected 128 times in a second, disruption of connection for the split of a second can cause a loss of a number of data points, which makes this system very sensitive. But we can still achieve good accuracy with that dataset as presented. This proves that in real-life scenarios, this method will be able to handle minor connection issues.

TABLE IV SHOWS THE 15 BEST FEATURES OF INDIVIDUALS

P1	P2	P3	P4	P5
FC6	FC5	T8	P3	Fp1
O2	P3	C3	Fp2	Fp2
T7	T8	P7	T7	C3
Cz	O1	P3	PO10	T8
F3	Cz	FC1	C4	FC2
CP5	PO9	CP5	CP6	CP5
CP1	CP2	Cz	FC5	C4
P7	Pz	Pz	P8	CP6
FC1	Fz	T7	F3	Pz
C3	Oz	C4	O2	F8
P8	F7	FC6	FC1	T7
Fz	P8	F8	Pz	CP1
PO9	FC2	FC5	P4	O2
CP2	Fp1	P4	T8	CP2
FC5	C4	CP6	Fz	FC6

In another case, for P4, the accuracy is not as good (still, it is 78.1% with SVM) as others. It can be a subject of further study whether any specific factor (e.g., age) is affecting the MI performance of that individual. As previous studies found that training can improve MI performance, we can expect that this classification method will perform better once the MI performance is improved. For the overall approach, we have achieved 91% accuracy with KNN and RF, which can be accepted as well enough, but to confirm that this model is robust enough to provide this good accuracy for all cases, we will need more training data collected from a good number of participants. Also, to confirm that this model can provide nearly 100% accuracy for most individuals, we will need to test this model with more individuals.

As we worked on reducing the number of channels, we observed that the best channels are different across individuals. And if we reduce the number of channels, we also lose some accuracy. Yet, in some cases, we can achieve as good accuracy as all the channels. As an example, we can say that for P3, we barely lose any accuracy. However, what accuracy is reasonable and what number of channels can be employed would totally depend on the usage environment and scenario.

One strength of this approach is that it works for both individualistic and generalistic scenarios, as this preliminary study found. Therefore, we will be able to use this method where individual team-up with machines is needed and possible, such as exoskeleton and robotic arm, etc.; and we can also use it where individual adjustment and training is not possible by using previously trained model (with other people's data).

This study is limited to only right-handed people and also has only five participants, which is why we cannot draw any solid conclusion here. Also, this study conducts a procedure where people perform MI tasks followed by a training session where they perform real hand movements. Further investigation will be needed to ensure whether this training session is providing better accuracy of classification, and if so, what the alternate procedure for people who are unable to perform real movements will be. Will this method perform as well as this study for them? Further study is needed to confirm these factors.

The extension of this study will investigate more about this study with more participants; the future study will address the above-asked questions as well as other factors to increase the efficiency of the method, such as the possibility of further reducing the number of electrodes to lessen the discomfort. Also, it can be another topic of further study whether cleaning and preprocessing data can increase the accuracy; if so, whether it can be included in a live model.

VI. Conclusion

This preliminary study presents a strong potential to use human brain signals of Motor Imagery to use humanoid limbs, which can be beneficial for rehabilitation issues, medical purposes, remote operation, and so on. To make this approach more robust and usable for practical purposes, an extended study is planned, including the selection of the reduced number of electrodes without losing much accuracy, data presentation, or stimuli for Motor Imagery. With the current finding of this study and future plan, we hope to develop a system to use the humanoid robotic arm by brain signal.

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