RECOGNITION OF THE UPPER LIMB'S MOTION INTENTION USING ELECTROENCEPHALOGRAM AND MACHINE LEARNING TECHNIQUES

An Undergraduate Research Scholars Thesis

by

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Submitted to the Undergraduate Research Scholars program at
Texas A&M University
in partial fulfillment of the requirements for the designation as an

UNDERGRADUATE RESEARCH SCHOLAR

Approved by Research Advisors: Dr. Reza Tafreshi
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May 2020

Majors: Mechanical Engineering
Electrical Engineering

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ABSTRACT

Recognition of the Upper Limb's Motion Intention Using Electroencephalogram and Machine Learning Techniques

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The electroencephalogram (EEG) signals are a measurable brain electrical activity. EEG signals can be used to detect and classify motion intention of any voluntary action. Successful detection of EEG signals and classification of motion intention is crucial in Brain-Computer Interface (BCI) applications. BCI can be used for upper limb rehabilitation through the use of prosthetics or exoskeletons. In this project, a method is proposed to distinguish three motions, including moving an arm forward, grabbing an object, and moving an arm upwards as well as the rest position, a total of 4 different tasks. The data is collected using ENOBIO 8 system with seven electrodes. Four time-domain features extracted from the data include the mean absolute value, zero crossing, waveform length, and slope sign change. The k-Nearest Neighbor (k-NN) algorithm is used to classify the four classes. This study investigates various window sizes and different numbers of neighbors to achieve a higher classification accuracy. Using a grid search approach, it was determined that a window size of 1500 ms and a number of neighbors of 5

produced the highest classification accuracy. The classification accuracy was 85.6 ±2.38%, while previous studies were only able to achieve classification accuracies between 60% and 78%. This result proves that varying the window size and the number of neighbors profoundly influence classification accuracy of motion intention; therefore, improving rehabilitation techniques for people with minimal arm movement and muscular dystrophy. The classified signals can be used for further biomedical research and be utilized to expand the growing biomedical research field in Qatar that relates to Brain-Computer Interface (BCI) technology.

CHAPTER I

INTRODUCTION

An electroencephalogram (EEG) measures brain electrical activity. The analysis of EEG signals has great potential in the biomedical field as the brain controls the human body. Recognizing motion intention is vital for limb rehabilitation and the improvement of prosthetic and exoskeleton devices' performance. EEG provides an enormous advantage in diagnosing medical conditions, such as epilepsy (or any seizure disorders), brain tumors, sleep disorders, and dementia. Another application is the rehabilitation of patients suffering from limited to no movements due to paralysis, amputations, and any genetic disorders. Brain-Machine Interface (BMI) technology has been used for the detection and processing of brain signals to control an external device such as an exoskeleton or a robotic wheelchair [1].

However, analyzing EEG signals is usually challenging, as signals are noisy and are highly influenced by both anatomical and physiological properties. Moreover, EEG depends on the electrode placement and varies with the state of skin where electrodes are attached [2, 3]. In addition, information extracted from the signals may substantially vary between different subjects. Nonetheless, analyzing EEG signals can require significant pre- and post-processing as they are highly sensitive to motion.

Brain signals collected through EEG may be measured through non-invasive wet or dry electrodes with amplification as the signals typically have very low amplitudes. According to previous studies [4] and [5], dry electrodes can measure the EEG signals similar to the wet electrodes. Dry electrodes are also easier, faster to set up, and require no cleaning compared to wet electrodes.

Various studies with different machine learning algorithms have been investigated previously to predict the subject's motion intention. For example, Bandara et al. [6] classified different states of arm movement, including rest position and grabbing a cup of water using both artificial neural network (ANN) and support vector machine (SVM) algorithms. The authors [6] reported an overall accuracy of 71.3-72.6% and 81.9-82.1% for the ANN and SVM algorithms, respectively. Other studies have used the Linear Discriminant Analysis (LDA) to detect motion intention of different hand and arm movements [1, 7]. In [7], two healthy subjects and three-stroke patients were recruited to perform center-out upper limb reaching task. The obtained overall accuracies for the healthy and stroke subjects were 76% and 47%, respectively [7]. Another study found an accuracy of 83% using 12 subjects [1]. Different types of activity recognition have also been investigated such as reaching movements of either the left or right arm [1], cursor movement [8], different reach-and-grasp movements [9], individual finger movements [10], mouse movements using a visual stimulus [11], reach-and-touch tasks [12], and free arm reaching movements [13].

Studies on the motor imagery [14-18] have proven that the actual limb movement provided similar classification accuracies [19]. Furthermore, motor signals obtained from EEG contain valuable information such as movement intention before the motion is executed, which can further advance Brain-Computer Interface (BCI) devices' executions [19].

The limitation of the previous studies was not observing the effect of different window sizes on the classification accuracy of the machine learning algorithm. Different studies used different window sizes that ranged from 500-2000 milliseconds [1, 8, 9, 11, 20, 21], without identifying a widely accepted window size that would give the best accuracy. Various studies have also chosen a window size of 1 second without experimenting different window sizes;

therefore, classification accuracies were not high. For example, one study obtained a classification accuracy of 72% [11], a second obtained an accuracy of 80% [20], and a third one obtained accuracies between 76% and 79% [21].

This project utilized a subject-specific strategy to train the machine learning algorithm (k-NN). It aims to experiment and find the best window size and number of neighbors to help develop the algorithm, thus producing the highest percentage of classification accuracy for upper limb movement. The results of the developed algorithm will be beneficial for the rehabilitation of patients with upper-limb impairment in performing the activities of daily living, such as drinking water from a bottle. Moreover, it will help expand a growing field in biomedical research that relates to Brain-Computer Interface (BCI) technology, and improved prosthetics to help people with minimal arm movement, muscular dystrophy in a less invasive method.

CHAPTER II

METHODOLOGY

The experimental protocol and methods used in this study are described in the following subsections.

Experimental Protocol

A twenty-year-old healthy subject without any history of the upper-limb disorder and cognitive impairment was recruited for this research work. The study was approved by the Institutional Review Board (IRB) from both Texas A&M University, College Station, USA (IRB2019-1254DQ) and Qatar University (IRB 1222-EA/20). The participant signed a consent form in accordance with the protocols. The subject was asked to perform a total of four tasks (see Figure 1), including 1) rest, 2) moving the right arm forward, 3) grabbing an object, and 4) moving the right arm upward ten times each for twenty seconds. The subject was asked to follow the instructions given verbally by the instructors and trained to do the task several times prior to the actual data collection to ensure better execution and detection of motion. During the experiment, the subject was asked to perform ten trials for each task and then rest for 10 - 15 minutes.

Figure 1. Four Classes: (1) Rest; (2) Moving Arm Forward; (3) Grabbing Object; (4) Moving Arm Upward

Figure 2 shows the experimental protocol for task-4 (moving an arm upward) as an example. A break was also provided whenever the subject felt the need to rest to prevent arm fatigue. The tasks executed were self-paced. The subject was told to minimize eye blinking and head movement to reduce artifacts in the data.

Data Acquisition

The EEG signals were acquired using the Neuroelectrics' EEG module called ENOBIO 8 and the Neuroelectrics® Instrument Controller (NIC) software. The module includes a cap with 10-20 international positions for electrodes placement, and a control box for noise measurement less than 1 uV RMS with a bandwidth of 0-125 Hz. The sampling rate of the acquired data was 500 Hz. While wearing the headset and before placing the electrodes, a diluted glycerin solution was placed on the subject's scalp to reduce skin impedance and to increase the signal conductivity. Once the electrodes were placed, data were collected. The EEG data were acquired from 7 electrodes (Channel 1 - C3, Channel 2 - C1, Channel 3 - FC1, Channel 4 - Cz, Channel 6 - C2, Channel 7 - FC2, and Channel 8 - C4). The EEG module, dry electrodes, and the electrode placements on the scalp are shown in Figure 3.

Figure 2. Protocol for Task 4

(a) (b) (c)

Figure 3. Illustrations of EEG module (a) ENOBIO 8, (b) dry electrodes, and (c) electrode placements

Data Preprocessing

The signals were processed using MATLAB. A band-pass filter of 2-40Hz was applied to the data, which removed the 50 Hz line noise. The data was amplified from nanovolts to microvolts. The first two seconds of data were removed due to high noise. After mean referencing the EEG signals, the Fast Fourier Transform (FFT) of the data was used for each channel to observe the effect of the filters on the data and to ensure only noisy signals were filtered.

Feature Extraction

The filtered and mean referenced EEG signals were then segmented using the sliding window and overlapping strategy. The window size was varied from 500-2000 ms to observe the effect of different window sizes on the classification accuracy. In this study, 85% window overlapping was used to increase the number of observations. Window overlapping occurs when each window interval overlaps with the previous window, shown in Figure 4. Four time-domain features were extracted from each of the windows:

- Mean Absolute Value (MAV)

$$\text{MAV}=\frac{1}{N}\sum_{n=1}^{N}|x_n| \tag{1}$$

- Zero-Crossing (ZC)

$$ZC = \sum_{n=1}^{N-1}[sign(x_{n+1}x_n) \cap |x_{n+1} - x_n| \geq 0] \qquad (2a)$$

$$sign(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \qquad (2b)$$

- Waveform Length (WL)

$$WL = \sum_{n=1}^{N-1}|x_{n+1} - x_n| \qquad (3)$$

- Slope Sign Change (SSC)

$$SSC = \sum_{n=2}^{N-1} sign[(x_n - x_{n-1}) \times (x_n - x_{n+1})] \qquad (4)$$

where x_n is the EEG amplitude at the n-th data point and N is the length of the sliding window.

Classification

The k nearest neighbor (k-NN) algorithm was used to classify the four tasks specified in the experimental protocol subsection. The number of nearest neighbors was varied from 1 to 13 neighbors in order to evaluate its effect on the classification accuracy.

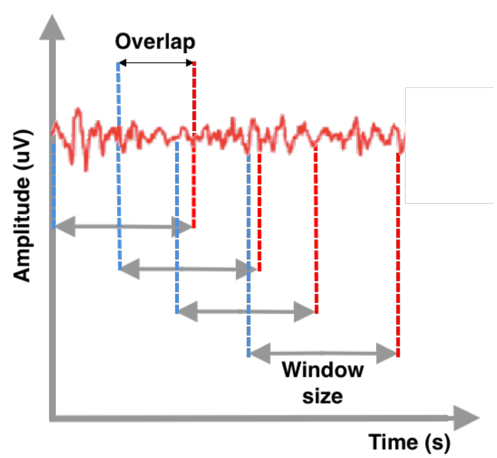


Figure 4. Illustration of sliding windows and overlapping windows in the time domain

To prevent bias in the algorithm, a holdout approach was used to evaluate the k-NN algorithm, where 70% of the data was chosen to be used in the training phase while the rest of the 30% was used in the testing phase. The data used in the training phase of the classifiers were chosen using a random permutation. The methodology outline used in the study is shown in Figure 5. A schematic of the holdout method is shown in Figure 6. The procedure was repeated 50 times to estimate the overall mean accuracy. The *K-fold* cross-validation was not used as some of the trials had corrupted data that was removed from the set, and so the four classes did not have equal numbers of trials.

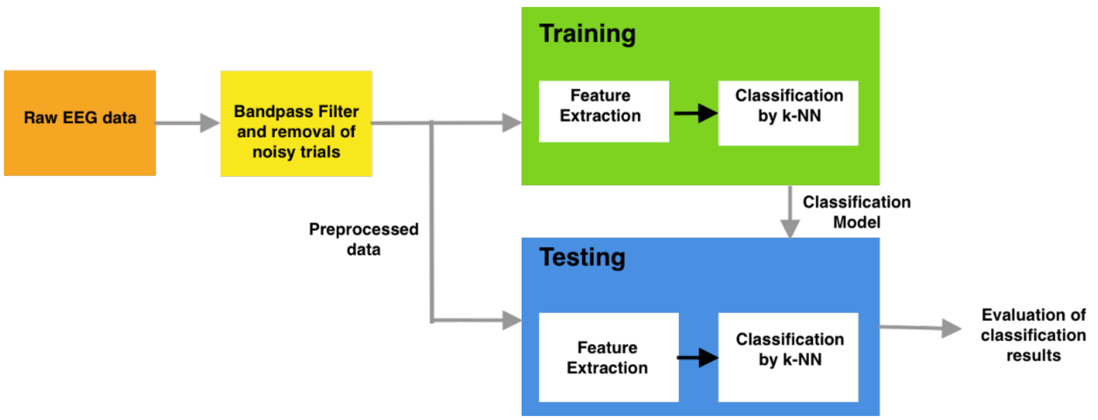


Figure 5. Methodology outline used in the study

Figure 6. Holdout method in choosing testing and training trials

Finally, the performance of the algorithm in classifying the motions was evaluated by the overall mean accuracy:

$$accuracy = \frac{1}{n}\sum_{i=1}^{n} I(\hat{y}_i = y_i) \tag{5}$$

where, n refers to the number of samples, I is the indicator function, $\hat{y}_i$ and y_i are the i^{th} predicted class and original class, respectively.

Data Analysis

A paired t-test was used to compare the classification accuracies between two classes. The level of significance was set at $p<0.05$. It should be noted that the holdout validation strategy was repeated for six additional times. As this study only includes one human subject due to unforeseen COVID-19 pandemic incident and the EEG signals are highly variable even within a subject in a different trial, each of the iterations was considered data from different human subjects.

CHAPTER III

RESULTS

The initial raw data of task-1 (rest) for all the channels is plotted in Figure 7. There is evident noise throughout the data. Figure 8A shows a sample Fast Fourier Transform (FFT) of EEG data for channel 1, task-1, where the evident peak at 50 Hz is due to the powerline noise. Figure 8B shows the FFT of bandpass-filtered data in which the powerline noise, as well as the low-frequency artifacts, were removed.

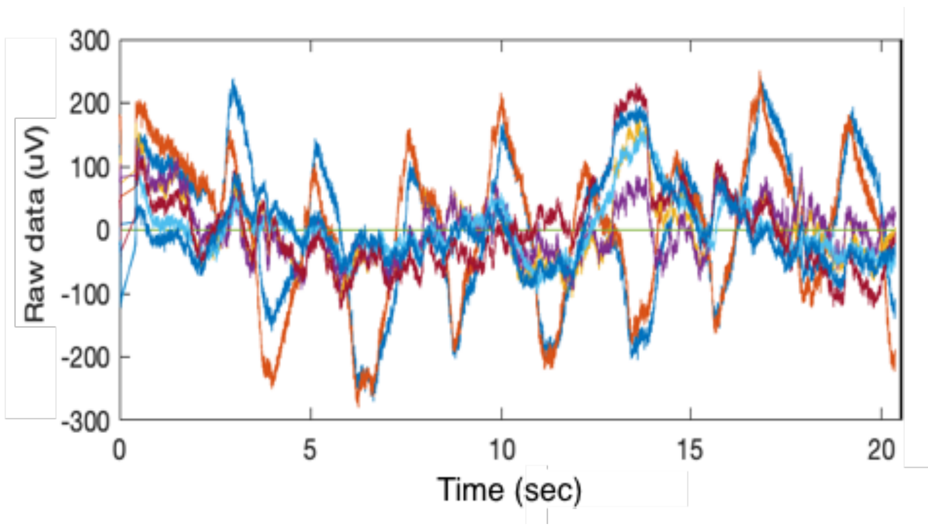
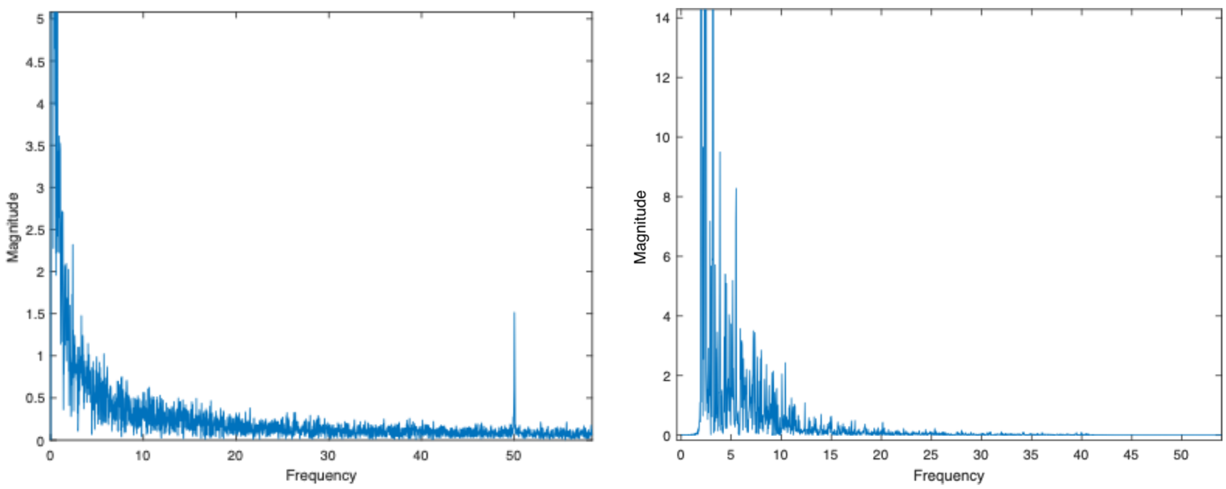
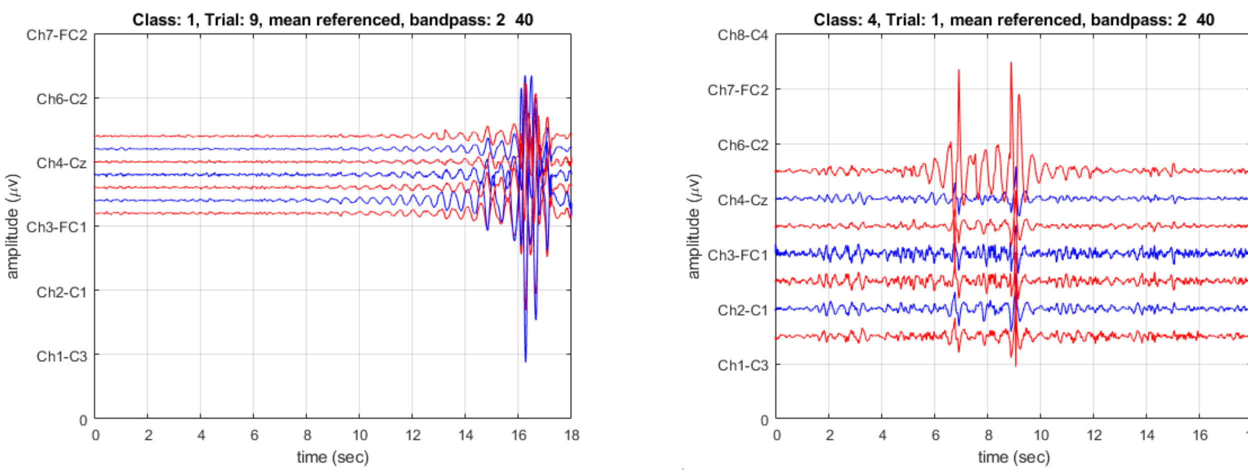


Figure 7. Raw EEG signals from seven channels for task-1 (rest)



(A) (B)

Figure 8. FFTs for task-1, channel-1 (A) before filtering, (B) after filtering



(A) (B)

Figure 9. Corrupted EEG signals from different trials due to head movement and eye-blinking

Besides filtering, the EEG signals from all trials were visually inspected for artifacts related to head motion and eye-blinking. Figure 9 shows examples of corrupted EEG signals, whereas Figure 10 shows clean EEG signals from each of the classes. The corrupted trials were discarded from the analysis.

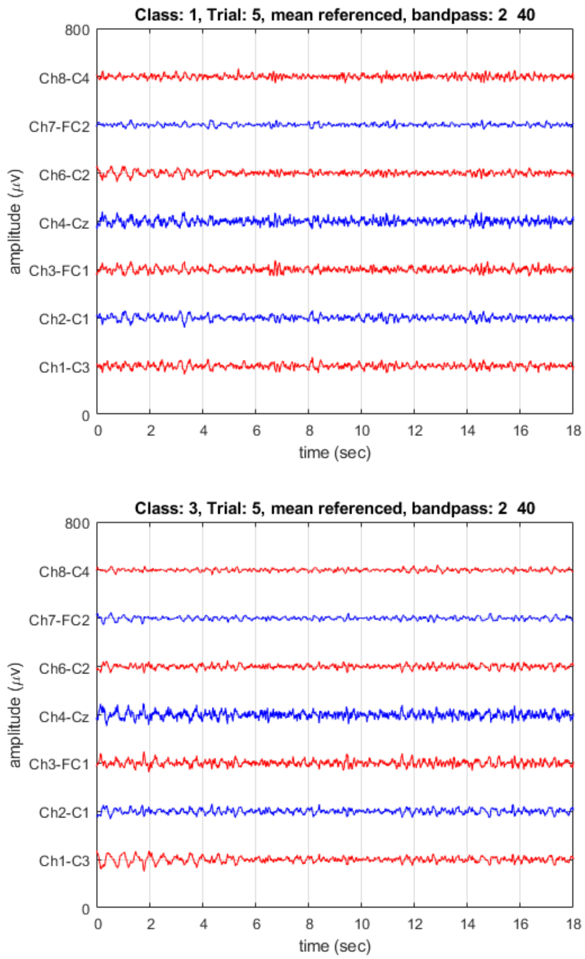


Figure 10. Filtered EEG signals without head movement and eye-blinking artifacts for each of the four classes

To determine the best window size and the number of neighbors for the k-NN algorithm, the accuracies for each window size and neighbors were computed and plotted in Figure 11. This analysis was conducted for all six iterations. For all the neighbors, the accuracy generally increases by increasing the window size. The number of neighbors in the range of 5 to 9 was found to produce better classification accuracies.

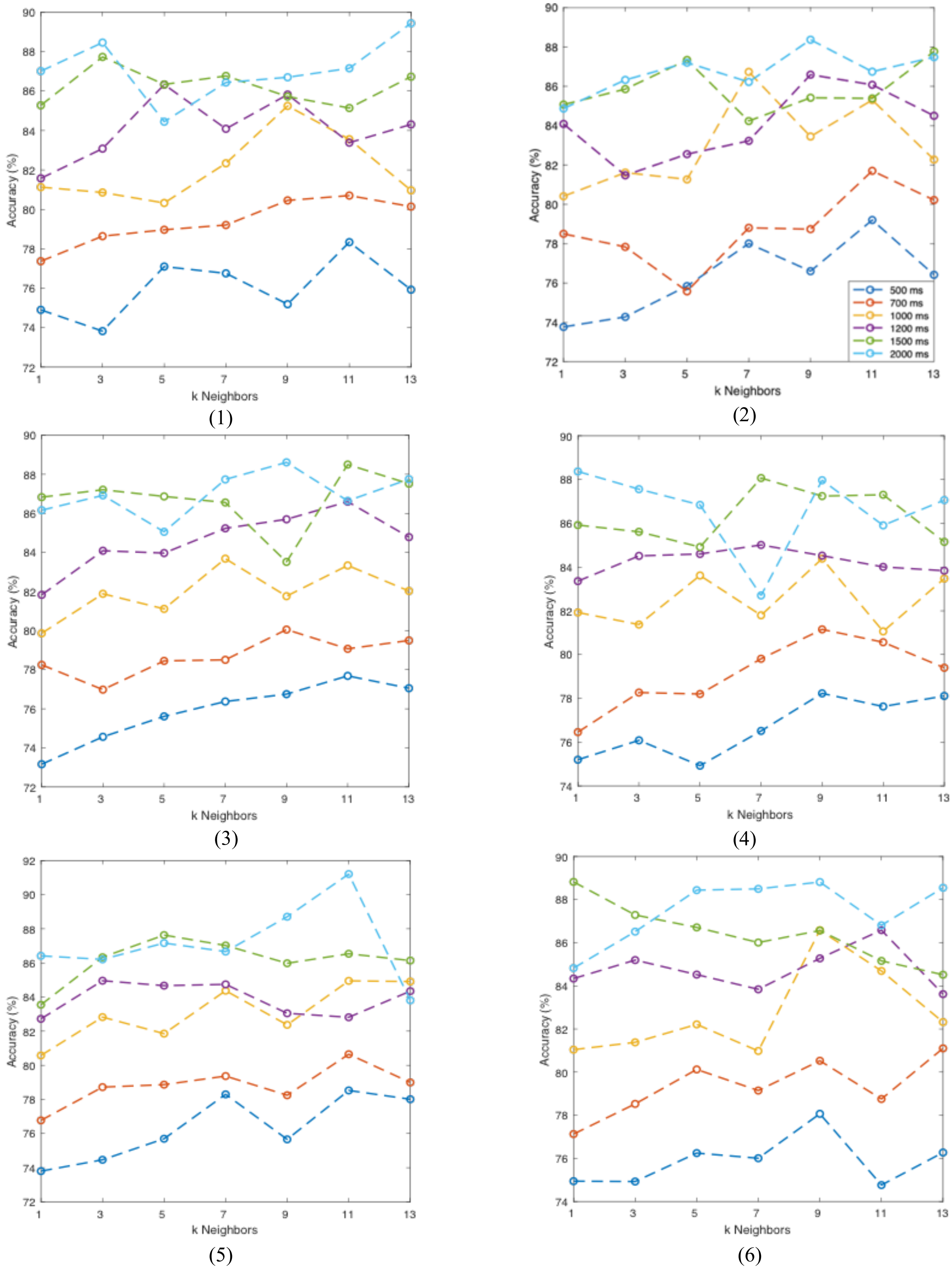


Figure 11. Accuracy versus nearest neighbor number for six iterations

The confusion matrix was computed using the window size of 1500 ms and 7 neighbors as they showed to produce better classification accuracies. The confusion matrices for all six iterations are shown in Figure 12. In the confusion matrix, the diagonal values represent the accurate classification, while the off-diagonal values indicate the miss-classification rate. The columns showed the predicted classes, whereas the rows showed the actual classes. For example, in Figure 12(1), 2444 instances were accurately classified by the k-NN algorithm as task-3 (grabbing an object, GR). However, the algorithm was falsely classified task-1, task-2, and task-4 as a task-3 for 136, 396, and 108 instances, respectively. Overall, the prediction accuracy for task-3 was 79.2%. The highest prediction accuracy was observed for the rest class (97.3%), closely followed by the moving upward task (95.2%). The class with the least accurate classification was the grasp class, which had an accuracy of around 73.8% in the sixth run. Approximately, the total number of observations per class was 50 times as the process was repeated 50 times for each of the confusion matrices. The model most accurately predicted the rest class, followed by move-upward class with a lower prediction accuracy in some of the runs.

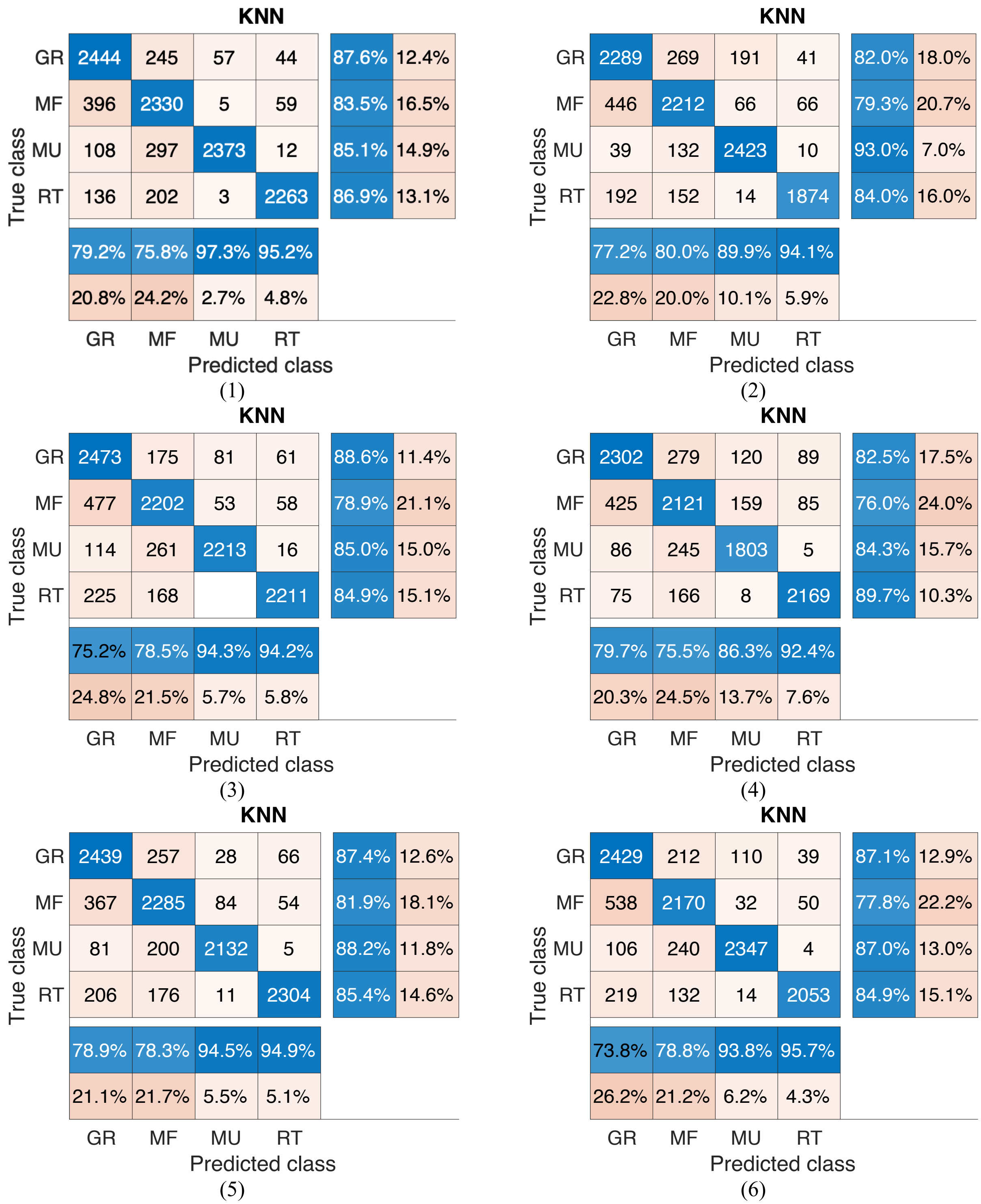


Figure 12. Confusion matrices for six runs that include the prediction accuracy for the four classes: GR, grasp; MF, moving forward; MU, moving upward; and RT, rest

Table 1 shows the mean and standard deviation for all of the matrices. The average classification accuracy was 85.6%, with the overall standard deviation of 2.38. Due to an inadequate number of subjects, the results from each iteration were considered as results from different subjects. A paired t-test was conducted to compare the prediction accuracies between task-1 (rest) and task-4 (moving up) as they produced the maximum values. Although the prediction accuracy was higher for task-1 (94.58%) compared to task-2 (92.68%), the difference was not statistically significant (p=0.18). This finding indicates that moving up produces more discriminative patterns in the EEG signals compared to other movement tasks and can be predicted with similar high accuracy of rest class. The results of the t-test are shown in Table 2.

Table 1. Prediction accuracy for the four classes within six iterations

	Prediction Accuracy (%)							
Iteration Number	**1**	**2**	**3**	**4**	**5**	**6**	**Mean**	**Std**
Grasp	79.2	77.2	75.2	79.7	78.9	73.8	77.33	2.39
Moving Forward	75.8	80.0	78.5	75.5	78.3	78.8	77.82	1.78
Moving Upward	97.3	89.9	94.3	86.3	94.5	93.8	92.68	3.92
Rest	95.2	94.1	94.2	92.4	94.9	96.7	94.58	1.42
Overall							85.60	2.38

Table 2. T-test results for two classes

t-Test: Paired Two Samples for Means

	Moving Upward	Rest
Mean	92.68	94.58
Variance	15.39	2.022
Degree of Freedom	5	5
P(T<=t) one-tail	0.0931	0.0931

CHAPTER IV

DISCUSSIONS

This research aimed to investigate the prediction accuracy of rest (task-1) and different hand movements, including moving the arm forward (task-2), grabbing an object (task-3), and moving arm upward (task-4). The EEG signals and the k-NN algorithm were used to predict these tasks. Furthermore, the best window size and neighbor numbers for the algorithm were determined. In most cases, it was found that the classification accuracy increased with larger window sizes for all the neighbor numbers. However, window size of 1500ms produces similar accuracy values compared to window size of 2000ms (Figure 11). The best window size was found to be 1500 ms with a nearest neighbor number of 7, as it showed the highest overall classification accuracy (over 70% for all tasks). The overall classification accuracy was found to be 85.6 ±2.38%. This accuracy was higher than that obtained in and most other studies reported in the introduction section (maximum 83% [1]).

The confusion matrices indicate a high accuracy value in predicting the four classes. The accuracy is consistent with every iteration of the algorithm, which indicates that it is reliable as each class's prediction accuracy does not vary drastically in the six iterations. Moreover, the classification of the moving upward and rest classes showed high prediction accuracies of 92.68% and 94.58 %, respectively. The classes with the least accuracies were grasp, followed by the moving forward motion. The higher prediction accuracy for moving upward compared to all other motions indicate that the EEG signals were more discriminative for the former task as it required a greater deal of musculoskeletal activities compared to other tasks. Another possible reason behind the lower prediction accuracy could be due to the data acquisition of their trials where a delay between the tasks and the commands occur.

The k-NN algorithm performed comparatively better when the window size and neighbor numbers were 1500 ms and 7, respectively. In Figure 11, the best accuracy was produced using window sizes 1500 and 2000 ms, while the lowest accuracies were for the lower window sizes. This is expected since lower window size usually unable to capture the discriminative features for tasks that may require less musculoskeletal activity such as grab an object or move forward.

This study has some limitations as only one subject was used, and a small number of motions were classified. A large number of trials were collected for the subject to increase the size of the data used in machine learning and reduce the impact of these limitations. A holdout method was used to reduce the effect of overfitting in machine learning where the model learns the details of the training data. Possible sources of error are inconsistency in the subject's task executions, as well as the delay time due to human reaction time. The lack of proper detection of artifacts can may increase error in the detection of tasks. Motion and eye blinking artifacts were removed manually through visual inspection by discarding trials with significant noise.

Although the results indicate good prediction accuracy, only one subject was used in the data acquisition. With a higher number of subjects as well as trials, the algorithm is expected to be more reliable and accurate at classifying the various tasks. The aim was to collect data from a total of 10 subjects but due to the unforeseen events surrounding the COVID-19 virus in spring 2020, complete data was unavailable at the time of publication.

CHAPTER V

CONCLUSIONS

Recognizing motion intention is very vital in a variety of areas, including limb rehabilitation, and improving the performance of prosthetic and exoskeleton devices. In this research, a k-NN machine learning algorithm was employed for accurate detection of arm motion by finding an acceptable window size for the data processing. The various window sizes investigated ranged from 500 ms to 2000 ms. The various neighbor numbers considered ranged from 1 to 13. The best window size was found to be 1500 ms with a nearest neighbor number of 5. The overall average accuracy of the classification was 85.6 ±2.38% for a total of six iterations. The employed technique was superior to previous research that showed accuracies ranging between 60% and 78% [22-24].

Future work includes testing different machine learning algorithms and extracting different features to identify the most accurate method. This will help improve BCI devices significantly, such as improving the functionality smoothness of exoskeleton and prosthetic devices through the recognition of the motion intention.

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