WRIST MOVEMENT CLASSIFICATION FROM EMG SIGNALS USING MACHINE LEARNING

submitted in partial fulfillment of the
requirements for the award of the degree of

BACHELOR OF TECHNOLOGY in
ELECTRICAL AND ELECTRONICS ENGINEERING

by

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DECLARATION

We hereby declare that the Thesis entitled **WRIST MOVEMENT CLASSIFICATION FROM EMG SIGNALS USING MACHINE LEARNING** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** for the award of the degree of **Bachelor of Technology** in **Electrical and Electronics Engineering**

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This is to *certify* that the Thesis entitled **WRIST MOVEMENT CLASSIFICATION FROM EMG SIGNALS USING MACHINE LEARNING** submitted by *Garvin Pokhra, Shrutha D, Ria Mishra* 191EE214, 191EE249, 191EE237as a record of the work carried out by them is *accepted as the U. G. Project Work Report submission* in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Electrical and Electronics Engineering** in the Department of **Electrical and Electronics Engineering**.

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ABSTRACT

Robotics and artificial intelligence can be used to improve the mobility of persons with impairments. This is achieved in part by enabling individuals to engage with robots to perform daily activities with greater freedom. Muscle activity offers an easy interface for executing hand motion analysis in the context of hand prosthesis control. Surface electromyography (sEMG), a non-invasive technique, is used to record this activity. Surface electromyography (sEMG) interpretation is an emerging research field that seeks to analyze the direction of muscle action.

The goal of electronic device control is to produce control instructions that are more convenient and simple to use. More functionality is added to devices and associated software applications, necessitating the use of more complicated systems to manage or utilize these functions. Currently, gadgets that are controlled by body motions are being developed, with some employing cameras and photos and others directly using EMG signals. These signals are utilized to measure strength and muscle activation variations induced by neuromuscular disorders, as well as to operate medical equipment.

Machine learning approaches may be used to create models that analyze complicated systems, such as the progression of hand movement data from forearm sEMG arrays, to identify gradual finger mobility responses based on input sequencing. Despite several studies on the processing of EMG data, there is no model in which the signal between movements is sufficiently differentiable to build a simple classification model that can be utilized in real-time processing. The goal of this project is to construct classification models utilizing commonly picked features to enhance measurement separation across classes. Such accomplishments have the potential to be applied in multifunctional prostheses, exoskeletons, rehabilitation treatments, and novel technologies such as hand gesture control.

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1 Introduction and Literature Survey

Electromyographic (EMG) signals convey data regarding muscle activation. These signals provide information on the natural control of muscle contraction, but they struggle to establish temporal pattern characteristics for various degrees of motion of voluntary hand movements. Each motion in hand movements includes the activation of different combinations of forearm muscles, which create diverse electrical patterns. Furthermore, detecting these motions is possible by examining muscle activation patterns reflected by EMG data. Because the complexity of these signals makes movement prediction challenging, feature extraction and selection techniques are a suitable choice for transforming time-domain data into a new space domain to improve recognition.

[1] investigates the combined effect of forearm orientation and muscle contraction levels on the generalizability of the EMG pattern recognition. They performed six classes of wrist and hand movements at three muscular contraction levels with three forearm orientations. A number of recent time and frequency-domain EMG features have been utilized to study EMG classification. [2] uses a power transformation approach to extract features from the time domain signal. [1] demonstrates a Fourier transform based features extractor and also use the Symmlet family of wavelets for a five-level signal decomposition in their techniques. [4] proposes a deconvolution-based preprocessing technique to enhance the signal for feature extraction to better characterize different upper limb motions. [6] proposed a novel technique for muscle onset detection using surface EMG signals without removal of ECG artifacts. They used a combination of time-frequency analysis and statistical methods to detect muscle onset, and found that their approach was able to accurately detect muscle activity while minimizing the effects of ECG artifacts.

The existing work in this field mainly uses multiple channels to classify the movement. Our projects aims to classify the EMG signals using machine learning into various wrist movements using single channel which reduces the cost of the final setup as well as reduces the complexity of the system. This paper has 4 chapters, which describe the data collecting, data processing, feature extraction and the ML model used to classify the EMG signal. This is followed by the results, conclusions and future scope of the project.

2 Data Collection

This section describes the data collection procedure which was used to collect the data required for the project. The data was collected with the help of 9 subjects 5 male and 4 female subjects. All the subjects aged between 20-25 and were normally limbed with no neurological or muscular disorder.

2.1 Hardware used for collecting the data

All the components used for collecting the data are mentioned below:

1. NI-DAQ System: This system is used to collect the sEMG signal from sEMG sensor to the processor, i.e. laptop in this setup.

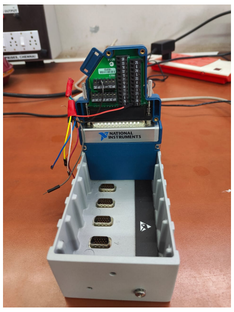

Fig. 2.1 NI-DAQ system

2. Sensor Isolator: This is used to isolate the power supply from the sEMG sensor. This is used to protect the subject in case of any electrical over-voltages.

Fig. 2.2 Sensor Isolator

3. Isolation transformer: It is used to isolate the data collection setup from the power grid, which in turns helps reduce power line interference and AC noise.

Fig. 2.3 Voltage Isolator

4. sEMG sensor: These sensors are attached on the limbs to sense and collect the sEMG signals from the subject's arm.

Fig. 2.4 sEMG sensor

2.2 Collecting Raw data from a subject

For collecting the sEMG signal from the subjects the setup shown in figure 2.5 was used. Figure 2.6 shows the connection of the sensors to a subject along with the setup used. In the setup, the sEMG sensors are connected to the flexor carpi radialis of the subject to record the data. The sensors are then connected to a sensor isolator that isolates the power supply from the sensors. The data is recorded and saved in the computer using NI-DAQ system. The power supply to all the equipments are given through a voltage isolator to prevent power line interference.

To avoid the effect of different limb position on the generated sEMG signals, subjects were seated on an armchair, with their arm supported and fixed at one position (the shoulder adducted and neutrally rotated, elbow flexed at 90◦, forearm and wrist in neutral position). All the subjects were asked to perform the following six movements, The arms of the subject were wrapped in an aluminium foil to prevent any interference and prevent any unintended noise.

1. Hand clenched in a fist,

2. Hand stretched

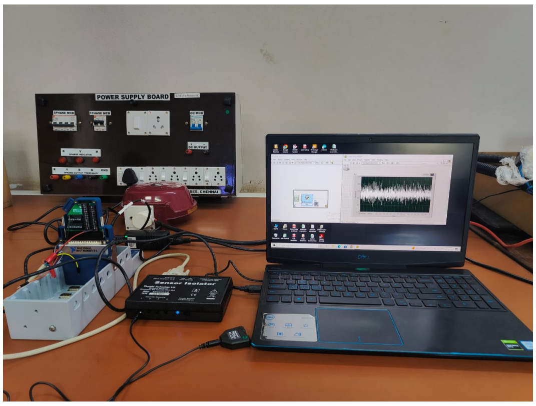

Fig. 2.5 Setup

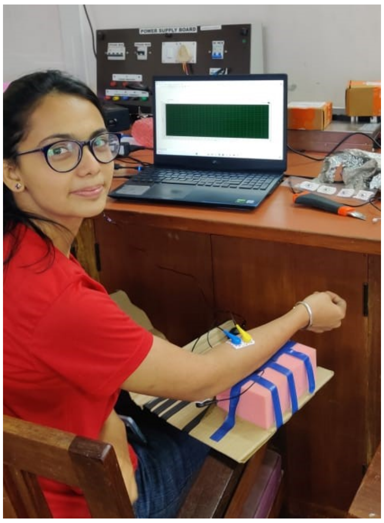

Fig. 2.6 Setup

3. Wrist flexion

4. Wrist extension,

5. Radial deviations

6. Angular deviations

All the movements were done for a duration of five seconds and a rest period of five seconds. Each movement was repeated five times and sequentially. All the data collected from the subjects were marked and labeled for further processing and feature extraction.

2.3 Summary

This chapter provides a detailed description of the data collection procedure used in the project. The data was collected from subjects who had no neurological or muscular disorders. The hardware used for collecting the data includes an NI-DAQ system, sensor isolator, isolation transformer, and sEMG sensors. The setup used for collecting the data involved connecting the sEMG sensors to the flexor carpi radialis of the subject to record the data. The subjects were asked to perform six movements, and the data was recorded and saved using NI-DAQ system. The collected data was labeled and marked for further processing and feature extraction. The chapter also provides information on the various components used in the data collection setup and the precautions taken to avoid power line interference and electrical over-voltages.

3 Data Preprocessing

3.1 Introduction

Recorded EMG signal is characterised by many interferences, such as signal acquisition noise, electromagnetic disturbances, signal instability and motion artefact due to electrodes and cables. Pre-processing is the very first step of pattern recognition techniques regarding proper signal analysis and minimizing the inherent interferences.

3.2 Filtering

To remove the dc offset and to obtain the signal in the energy band of 20–450 Hz, the signal is band passed using a Bandpass filter.

3.3 Onset offset detection

To detect the precise onset and offset timing of muscle activity, during hand-close and hand-open movements intergrated profile method is used. The integrated profile method is a commonly used technique for detecting the onset and offset of EMG signals. It involves integrating the rectified EMG signal over a moving time window and using a threshold to detect changes in the signal amplitude. The steps involved in the integrated profile method are as follows:

1.Rectify the EMG signal: This involves taking the absolute value of the signal to eliminate negative values.

2.Integrate the rectified signal: This involves summing the values of the rectified signal over a moving time window. The window size is typically chosen based on the duration of the muscle contraction being analyzed.

3.Set a threshold: A threshold is set to detect changes in the signal amplitude. The threshold can be set manually or automatically, and is typically set as a percentage of the maximum integrated value.

4.Detect onset and offset: The onset of the EMG signal is detected when the integrated signal first crosses the threshold, and the offset is detected when the signal falls below the threshold. The formula for the integrated profile method can be summarized as:

Average RMS value = (Integrated RMS value) / (Duration of EMG signal)

Threshold value = (Percentage of average RMS value)

Onset detection = (RMS value greater than Threshold value for specified duration)

Offset detection = (RMS value lesser than Threshold value for specified duration)

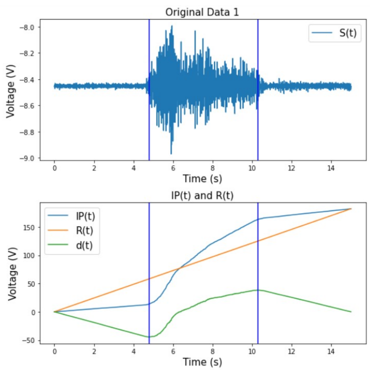

Fig. 3.1 Intergrated profile method

Fig 3.1. Illustration of the integrated profile method for onset detection using a surface EMG signal The integrated profile of the signal is plotted along in blue line with its corresponding reference line in orange line The onset was determined as the timing that generates the maximum difference between the EMG integrated profile and the reference line. The vertical dashed lines represent the detected onset/offset timing of voluntary contractions.

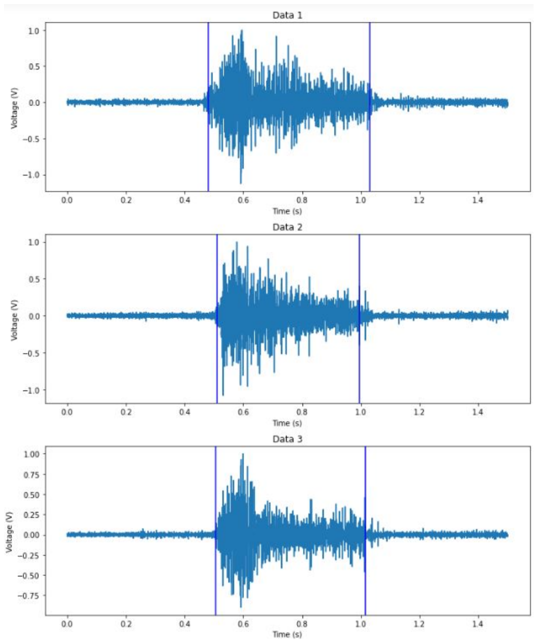

Fig. 3.2 few examples to show onset and offset detection

3.4 Summary

This chapter focuses on the initial steps required for proper signal analysis and minimizing interferences in recorded EMG signals. The chapter begins with an introduction highlighting the challenges posed by interferences such as signal acquisition noise, electromagnetic disturbances, signal instability, and motion artefact due to electrodes and cables.

The chapter then delves into the topic of filtering, where a bandpass filter is used to remove the DC offset and obtain the signal in the energy band of 20–450 Hz. The next section discusses the integrated profile method, a commonly used technique for detecting the onset and offset of EMG signals. This method involves rectifying the EMG signal, integrating the rectified signal over a moving time window, setting a threshold, and detecting the onset and offset based on the threshold. The chapter provides a formula for the integrated profile method, and includes figures that illustrate the method and show examples of onset and offset detection.

4 Feature Extraction

4.1 Introduction

Feature extraction is the transformation of the raw signal data into a relevant data structure by removing noise, and highlighting the important data. There are three main categories of features important for the operation of an EMG based control system. Those being the time domain, frequency domain, and the time-frequency domain. Eighteen feature extraction methods in time domain and frequency domain were selected .All feature extraction methods were performed using a window size of 250 ms with an increment of 125 ms (50 percent overlap), which has been shown to be suitable for use in real-time on an embedded system

4.2 Features

Features in the time domain are more commonly used for EMG pattern recognition. This is because they are easy, and quick to calculate as they do not require any transformation. Time domain features are computed based upon the input signals amplitude.

4.2.1 Time Domain Features

Time domain features are statistical measures that are calculated directly from the amplitude of a signal in the time domain. In the analysis of sEMG signals, these features are often used to extract information about muscle activation patterns and to identify abnormalities in muscle function. Some of the commonly used time domain features include:

Mean: The mean value of the sEMG signal, which represents the average amplitude of the signal.

Variance: The variance of the sEMG signal, which measures the variability of the signal around the mean value.

Root Mean Square (RMS): The RMS value of the sEMG signal, which measures the overall magnitude of the signal by taking the square root of the mean of the squared values.

Feature Extracted	Definition
Variance	$\mathrm{Var}(x_n) = \frac{1}{N-1}\sum_{i=1}^{N}(\lvert x_i \rvert)^2$
Root Mean Square	$\mathrm{RMS}(x_n) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Integrated EMG	$\mathrm{iEMG}(n) = \int_{t_0}^{t_N} \lvert x(t) \rvert \, dt \approx \sum_{i=1}^{N-1} \frac{\lvert x_i + x_{i+1} \rvert}{2} \cdot \frac{1}{f_s}$
Mean Absolute Value	$\mathrm{MAV}(n) = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$
Log Detector	$\mathrm{LogDetector}(n) = \log_{10}\left(\frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert\right)$
Waveform Length	$\mathrm{WL}(n) = \sum_{i=2}^{N} \lvert x_i - x_{i-1} \rvert$
Average Amplitude Change	$\mathrm{AAC}(n) = \frac{1}{N-1}\sum_{i=2}^{N} \lvert x_i - x_{i-1} \rvert$
Difference absolute standard deviation value	$\mathrm{DASDV}(x_n) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - x_{i-1})^2}$
Zero Crossing	$\mathrm{ZC}(n) = \frac{1}{2}\sum_{i=2}^{N} \lvert \mathrm{sgn}(x_i) - \mathrm{sgn}(x_{i-1}) \rvert$
Willson Amplitude	$\mathrm{WA}(n) = \sum_{i=1}^{N} \lvert x_i \rvert^3$
Myopulse Percentage Rate	-
Frequency Ratio	$\mathrm{FR}(n) = \frac{f_{\mathrm{high}}(n)}{f_{\mathrm{low}}(n)}$
Mean Power	$\mathrm{MP}(n) = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert^2$
Total Power	$\mathrm{TP}(n) = \sum_{i=1}^{N} \lvert x_i \rvert^2$
Mean Frequency	$\mathrm{MF}(n) = \frac{\sum_{i=1}^{N} f_i \lvert X_i(n) \rvert^2}{\sum_{i=1}^{N} \lvert X_i(n) \rvert^2}$
Median Frequency	$\mathrm{MDF}(n) = \frac{\sum_{i=1}^{N} f_i \lvert X_i(n) \rvert^2}{\sum_{i=1}^{N} \lvert X_i(n) \rvert^2} = \frac{1}{2}$
Peak Frequency	$\mathrm{PF}(n) = f_{\max}(n)$
Wavelet Energy Transform	$\mathrm{WET}(n) = \sum_{j=1}^{J}\sum_{k=1}^{2^j-1} \lvert W_{j,k}(n) \rvert^2$

Table 4.1 Features and their definition

Integrated EMG (IEMG): The IEMG of the sEMG signal, which measures the total activity of the muscle by integrating the absolute value of the signal over a specific time period.

Mean Absolute Value (MAV): The MAV of the sEMG signal, which represents the average absolute value of the signal.

Log Detector: The Log Detector of the sEMG signal, which is a non-linear transformation that compresses the dynamic range of the signal and enhances low-amplitude signals.

Waveform Length (WL): The WL of the sEMG signal, which measures the cumulative length of the waveform over a specific time period.

Average Amplitude Change (AAC): The AAC of the sEMG signal, which measures the average rate of change in the amplitude of the signal over a specific time period.

Difference Absolute Standard Deviation Value (DASDV): The DASDV of the sEMG signal, which measures the standard deviation of the differences between adjacent samples.

Zero Crossing (ZC): The ZC of the sEMG signal, which measures the number of times the signal crosses the zero axis in a specific time period.

Wilson Amplitude (WA): The WA of the sEMG signal, which is a non-linear transformation that enhances the amplitudes of high-frequency components in the signal.

Myopulse Percentage Rate (MPR): The MPR of the sEMG signal, which measures the percentage of time the signal is above a certain threshold.

Each of these time domain features provides a different type of information about the sEMG signal and can be used to analyze different aspects of muscle activation patterns. These features are often combined with other features from the frequency domain and time-frequency domain to provide a more comprehensive analysis of the sEMG signal.

4.2.2 Frequency Domain Features

Frequency domain analysis is a commonly used technique for analyzing signals in various fields, including biomedical engineering. In the context of sEMG signal processing, frequency domain features are used to obtain information about the power and frequency distribution of the signal.

The Fourier Transform is the primary tool used to convert a signal from the time domain to the frequency domain. By taking the Fourier Transform of an sEMG signal, it is possible to obtain its frequency spectrum. The magnitude of each frequency component in the spectrum corresponds to the amount of power at that frequency in the signal. The frequency domain features are then derived from the spectrum. Some common frequency domain features used in the analysis of sEMG signals are:

Mean Power Frequency (MPF): The MPF is the frequency at which half of the total power of the signal is contained below that frequency. It is an indicator of the overall frequency content of the signal.

Median Frequency (MDF): The MDF is the frequency at which half of the total power of the signal is contained above that frequency. It is an indicator of the dominant frequency content of the signal.

Peak Frequency (PF): The PF is the frequency at which the maximum power of the signal occurs. It is an indicator of the most dominant frequency component of the signal.

4.2.3 Wavelet Energy Transform

Wavelet Energy Transform (WET) is a time-frequency analysis technique that can be used to extract features from signals, including sEMG signals. It provides a multi-scale representation of the signal in both time and frequency domains. The WET algorithm involves convolving a mother wavelet function with the signal at different scales and positions. The result of this convolution produces a time-frequency map, which can be used to extract features from the signal.

In sEMG analysis, WET is used to extract features such as muscle fatigue, muscle activation patterns, and spectral characteristics of the signal. The WET can be used to decompose the signal into its constituent frequency components, and the energy distribution of these components can be analyzed to extract features such as mean frequency, median frequency, and spectral centroid.

4.3 Summary

This chapter discusses the concept of feature extraction in EMG-based control systems, which involves transforming raw signal data into a relevant data structure by removing noise and highlighting important data. The three main categories of features important for EMG-based control systems are time domain, frequency domain, and time-frequency domain. Time domain features are more commonly used for EMG pattern recognition, and this chapter lists and defines 18 feature extraction methods in time domain and frequency domain. These feature extraction methods were performed using a window size of 250 ms with an increment of 125 ms, which is suitable for real-time use on an embedded system.

5 ML Model

This chapter describes the machine learning algorithm and the machine learning model that was used to classify an EMG signal.

5.1 About the algorithm

The machine learning algorithm used in this project is random forest. Random Forest is a popular machine learning algorithm used for classification, regression, and other tasks. It is an ensemble learning method that combines multiple decision trees to produce more accurate predictions than individual trees. In a random forest, each decision tree is trained on a randomly selected subset of the data and a randomly selected subset of the features. The algorithm then aggregates the predictions of all the trees to make a final prediction. Random Forest is a powerful algorithm that can handle large datasets and high-dimensional feature spaces, making it a popular choice in a variety of applications such as image classification, fraud detection, and recommendation systems.

5.2 Random Forest model

In this project we have used a random forest classifier to classify the EMG signal. The features extracted in the previous chapter were organized into a matrix of dimensions 270 by 720, representing the 270 samples collected. Each row of the matrix corresponded to a specific feature and was associated with a label ranging from 1 to 6, indicating the 6 different classification classes. The output column was removed from the training dataset during the normalization process. The features were then normalized and split into training and testing sets.

5.3 Summary

The chapter describes the machine learning algorithm and model used to classify an EMG signal. The algorithm used is random forest, which is an ensemble learning method that combines multiple decision trees to produce more accurate predictions. The chapter explains how the random forest algorithm is trained on a randomly selected subset of the data and features, and how it can handle large datasets and high-dimensional feature spaces. The chapter also mentions that a random forest classifier was used to classify the EMG signal in the project.

6 Results

We analyzed previous semester's models and found that random forest was the best.The results of our analysis showed that the random forest algorithm achieved the highest accuracy of 77.01%, outperforming the decision tree algorithm which achieved an accuracy of 47.28%, K-Nearest Neighbours which had an accuracy of 44.85% and the Gaussian Naive Bayes algorithm which achieved an accuracy of 42.75%.

Algorithm	**Accuracy**
Decision Tree	47.28%
Gaussian Naive Bayes	42.75%
K-Nearest Neighbours	44.85%
Random Forest	**77.01%**

Table 6.1 Accuracy results of the decision tree, Gaussian Naive Bayes, and random forest algorithms.

The performance of a random forest model was evaluated using the classification accuracy metric. The model achieved an accuracy of 77.01% when trained with 1000 estimators.

In the previous semester, our evaluation of the random forest model revealed that the optimal number of estimators for preprocessed data was 7. However, our current analysis suggests that increased number of estimators leads to improved performance.

n_estimators	**Accuracy (%)**
7	54.2
100	56.98
200	60.83
500	68.86
1000	**77.10**
2000	63.24
5000	54.91

Table 6.2 Random Forest Model Accuracy with Varying n_estimators

Figure 6.1 shows the relationship between n_estimators and accuracy for the random forest model.

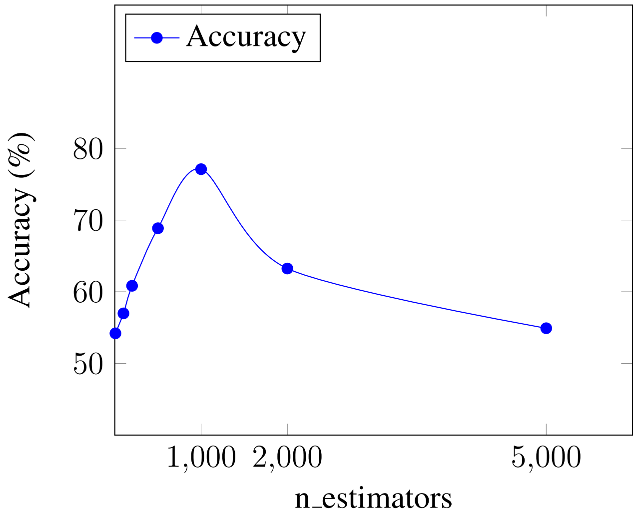

Fig. 6.1 Random Forest Model Accuracy with Varying n_estimators

Window duration (sec)	Step duration (sec)	Frame	Step	Accuracy
0.25	**0.000**	**500**	**250**	**77.10%**
0.25	0.125	500	250	73.25%
0.25	0.000	250	125	61.06%
0.25	0.125	250	125	59.1%
0.50	0.000	500	250	62.610%
0.50	0.125	500	250	58.40%
0.50	0.000	250	125	60.11%
0.50	0.125	250	125	60.27%
1.00	0.000	500	250	55.19%
1.00	0.500	500	250	62.54%
1.00	0.000	250	125	65.21%
1.00	0.500	250	125	64.90%

Table 6.3 Random Forest Model Accuracy by varying various parameters with $\mathrm{n}_e stimators$ =100

From table 6.3, we can observe that the for random forest classifier highest accuracy was observed when the windowing duration, overlap (step) duration, frame and step were 0.25 sec, 0 sec, 500 and 250 respectively. In general it can be observed that for each window duration, higher accuracy was obtained when the step duration was 0 sec i.e. no overlap in the window frames.

Classification report of the random forest classifier with the best parameters from the table 6.3 is provided in the table 6.4

The classification report tells us the precision, recall, f1-score and support for each of the 6 classes of the wrist movement. It can be observed that the recall and f1-score for class 2 i.e. Hand clenched in a fist. It can also be observed that the even thought he precision of class 3 i.e its recall and f1-score is the least among all the six classes of the action.

	precision	**recall**	**f1-score**	**support**
1	0.62	0.89	0.73	9
2	0.64	1.00	0.78	9
3	0.62	0.56	0.59	9
4	1.0	0.33	0.50	9
5	0.67	0.44	0.53	9
6	0.50	0.56	0.53	9
accuracy			0.6	54
macro avg	0.67	0.63	0.61	54
weighted avg	0.67	0.63	0.61	54

Table 6.4 Classification report

7 Conclusions

This project aimed to develop a machine learning-based classifier to classify an EMG signal into one of several wrist movement classes. We used a random forest classifier with various hyperparameters tuning and found that the best results were obtained with default parameters and $n\_estimators = 1000$. This project takes us one step closer to using a single-channel sEMG sensor for wrist movement classification for real-time applications. The limitations faced during the project include removing power line interference while collecting the data and dealing with highly sensitive sEMG sensors. The project can be improved to increase the accuracy of the classifier and to find more suitable features. Additionally, it could be implemented for real-time application using a microcontroller

8 Future Scope

There are a lot of applications to this project in real-time applications, one of the application is controlling a prosthetic arm by connecting the sEMG signals to a person's arm. In future we wish to implement a real-time hardware based prosthetic arm implementation using the machine learning model trained in this project. To do so, we would have to do the following steps:

1. Read the signal in real-time with the sEMG sensors.
2. Process and filter the input signal
3. Use the random forest classifier trained in this project as the classifier to classify the movement to one of the movement class.
4. Give suitable instructions to the prosthetic arm to perform the desired movement.

However, there are some limitations to using the current random forest classifier for real-time classification. Depending on the application of the prosthetic arm the latency in the movement of the arm is decided, which is important in deciding the input signal duration to the classifier as well as the prosthetic arm as well as the micro-controller used to process the EMG signal in real time. Changing the input duration of the signal might affect the performance of the classifier. These limitations can be overcomed by fine tuning the classifier used in project for real-time applications.

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