Data Driven Control of Intelligent Hand Exoskeleton

MTP Phase 1 Report

Submitted By

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Declaration

I hereby declare that the submitted report represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the sources. I affirm that I have adhered to all principles of academic honesty and integrity, ensuring that this work is an accurate reflection of my research and understanding. I recognize the importance of maintaining ethical standards in academic writing and research and have diligently worked to uphold these standards throughout the preparation of this submission.

Date: 19 November 2024 Harshit Paramhans

Place: IIT Guwahati Roll No. 234103420

Certificate

This is to certify that the project report entitled “Data driven control of intelligent hand exoskeleton” being submitted to the Indian Institute of Technology Guwahati, India, by Mr. Harshit Paramhans (Roll. No. 234103420) for the fulfilment of the requirement for the degree of Master of Technology is a record of Bonafide research work carried out by him under my supervision and he fulfils the requirement of the regulations of the same. The results embodied in this report have not been submitted to any other University or Institute for the award of any degree.

Dr. Shyamanta M. Hazarika
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Abstract

The development of intelligent exoskeletons for hand rehabilitation and assistance requires sophisticated control systems that respond reliably to user intent. This study presents a data-driven approach to control an intelligent hand exoskeleton, employing electromyography (EMG) data to classify a range of hand gestures. The analysis leverages Rami Khushaba's dataset, which includes signals from eight EMG channels during fifteen distinct hand gestures, focused on the individual and combined finger movement. To maximize information extraction, we derived three time-domain features (Root Mean Square, Mean Absolute Value, and Waveform Length), two frequency-domain features (Mean Frequency and Median Frequency), and two statistical features (skewness and kurtosis), offering a comprehensive representation of the muscle activity patterns associated with each gesture.

The extracted features were then compiled into a feature matrix through data flattening, enabling a structured and efficient input for classification. A random forest classifier was subsequently applied to the feature matrix, yielding accurate classification of the fifteen gestures based on the EMG signals. The classifier's performance underscores the suitability of these feature sets for EMG-based gesture recognition and highlights the potential of machine learning methods in developing reliable, responsive controls for wearable exoskeletons. This approach also suggests that, with minimal computational requirements, a practical, real-time implementation in exoskeletal devices may be feasible.

Contents

Nomenclature

ML = Machine Learning

EMG = Electromyography

RF = Random Forest

NMF = Non-Negative Matrix Factorization

RMS = Root Mean Square

MAV = Mean Absolute Value

WL = Waveform Length

PSD = Power Spectral Density

MNF = Mean Frequency

MDF = Median Frequency

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CHAPTER 1

Introduction

1.1 Background and Motivation

The human hand is a marvel of biological engineering, capable of performing a vast array of intricate movements with precision and dexterity. However, injuries, neurological disorders, and age-related conditions often impair hand functionality, significantly affecting an individual's ability to perform daily tasks. To address these challenges, hand exoskeletons have emerged as a promising solution in rehabilitation and assistive technologies. These devices are designed to aid in restoring motor functions, assisting with movement, and enabling users to regain independence.

A critical aspect of hand exoskeleton development lies in understanding and replicating the complex neuromuscular signals that govern hand movements. Electromyography (EMG) signals, which capture the electrical activity of muscles during contraction, offer a direct interface for controlling exoskeletons. By analysing EMG signals, it is possible to infer user intent and translate it into specific hand gestures or movements. This capability makes EMG-based systems particularly valuable for creating intuitive and responsive control mechanisms.

Machine learning has emerged as a powerful tool for addressing these challenges by enabling the classification of EMG signals into distinct hand gestures. However, traditional approaches often rely on complex models with extensive computational requirements, limiting their real-time applicability. Furthermore, identifying the most relevant features from raw EMG data to improve classification accuracy is an ongoing area of research

The motivation for this study stems from the need to develop a data-driven approach that balances accuracy, robustness, and computational efficiency. By leveraging machine learning techniques this research aims to classify hand gestures based on EMG signals effectively.

1.2 Introduction to Machine Learning

Machine learning (ML) is a branch of artificial intelligence research that focuses on the creation and analysis of statistical algorithms that can effectively generalize and complete jobs without explicit instructions.

Mitchell [1] describes ML as "*A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E*".

The great flexibility of machine learning algorithms enables them to process a variety of data types such as text, image, audio, numerical, and time series data. Machine learning is therefore finding use in many different domains. From the study of medicine to speech and picture recognition to problem-solving in engineering.

There are three broad categories into which machine learning can be divided which are as the following:

1. **Supervised Learning**: In supervised learning, models are trained on labelled datasets, where each input is paired with an output label. The model learns to map inputs to the correct outputs by finding patterns in the data. This approach is commonly used for tasks like classification (e.g., identifying images) and regression (e.g., predicting prices).

2. **Unsupervised Learning**: Unsupervised learning deals with unlabelled data, where the model is not given specific output labels. Instead, it learns to identify patterns and relationships within the data itself. This is useful for tasks like clustering (e.g., customer segmentation) and dimensionality reduction (e.g., feature extraction).

3. **Reinforcement Learning**: In reinforcement learning, an agent learns by interacting with an environment, receiving feedback through rewards or penalties for its actions. The goal is to maximize the cumulative reward by developing a policy that selects optimal actions over time. Reinforcement learning is widely used in applications requiring sequential decision-making, such as robotics, game playing, and autonomous driving.

The basic functioning of a machine learning algorithm is depicted in Figure 1.1. The training set, validation set, and test set are separated from the original data set. The training data set is used to train the model. The validation set is used to verify the outcomes of the training process. Various model parameters are fine-tuned based on the validation data set results. Using the revised set of parameters, training is repeated on the training data set. The purpose of the test data set is to evaluate the model's performance after the complete training.

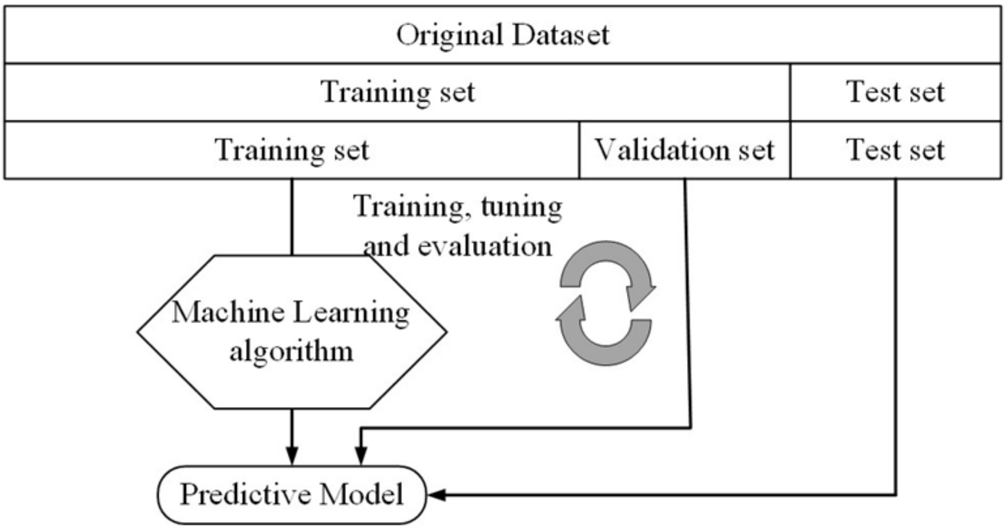

Figure 1.1: Overall working of a ML model

Through advanced algorithms, machine learning models can analyse signals from electromyography (EMG) or other sensors, allowing prosthetic hands to better interpret user intentions and provide more natural and precise movements. This adaptability helps in restoring motor function, improving user comfort, and enhancing the quality of life for amputees. Additionally, machine learning enables continuous learning and customization of prosthetic devices, ensuring they evolve with the user's needs over time, which is essential for long-term rehabilitation.

1.3 Supervised Classification in ML

One of the main areas of machine learning is supervised learning, which allows models to predict future outcomes after they have been trained using historical data. In supervised learning, input-output pairs or labelled data are used to train the model in order to generate a function that is sufficiently approximate to predict outputs for new inputs when they are introduced.

A classification algorithm is one that learns from the training set and then assigns new data point to a particular class. A classification model concludes some valid mapping function from training dataset and predicts the class label with the help of the mapping function for the new data entry. A classification model can be built by following steps [2]:

1. Collect and clean the dataset or data preprocessing.
2. Make the classifier model initialized.
3. Split the dataset using cross-validation and feed the classifier model with training data. Python-based scikit-learn package has inbuilt methods named fit-transform (X, Y)/fit (X, Y) that map the input data member set X and corresponding label set Y to prepare the classifier model.
4. Predict the label for a new observation data. There is also a method predict (X) that returns the mapped label Y for the input instance X.
5. Evaluate error rate of the classifier model on the test dataset

1.4 Objectives

The primary objective of this study is to develop a data-driven framework for the classification of hand gestures using electromyography (EMG) signals, with a focus on enabling precise and reliable control of an intelligent hand exoskeleton. By leveraging Rami Khushaba's publicly available dataset, which contains EMG data from eight channels for 15 different hand gestures, this research seeks to bridge the gap between raw EMG signal acquisition and gesture recognition. A critical component of this study is the systematic extraction and evaluation of features from the raw EMG signals. The features are selected to capture both the temporal and spectral characteristics of the signals, along with statistical measures to enhance the differentiation between gestures. Specifically, three time-domain features two frequency-domain features and two statistical features are extracted and integrated into a feature matrix.

To achieve the classification of these gestures, the study employs a Random Forest classifier, known for its ability to handle high-dimensional data, robustness to overfitting, and effectiveness in capturing complex nonlinear relationships. The classifier is trained and evaluated to determine its accuracy in distinguishing between the fifteen gestures.

Beyond the immediate focus on gesture classification, this research also aims to lay the groundwork for future advancements in intelligent exoskeleton control. The study envisions leveraging Non-Negative Matrix Factorization (NMF) to derive muscle synergies from the EMG data, simplifying the control strategy by reducing the dimensionality of the input space. Additionally, the integration of reinforcement learning is proposed to enable adaptive, real-time control, ensuring that the exoskeleton can dynamically adjust to variations in user input and environmental conditions.

In summary, the objective of this study is twofold:

1. To design and validate a feature-based machine learning approach for accurately classifying hand gestures from EMG signals.

2. To explore future directions that enhance the practical utility of the framework, such as dimensionality reduction and real-time adaptability using reinforcement learning, thereby contributing to the development of intelligent, user-centric hand exoskeletons.

1.5 Structure of the Thesis

The thesis is organized into five chapters.

Chapter 1 is introduction which introduces the topics of machine learning (ML), supervised classification in ML and outlines the objectives of the thesis.

Chapter 2 is the literature survey on existing research on EMG signal processing, feature extraction methods, and machine learning techniques for gesture recognition.

Chapter 3 covers the methodology used to describe the dataset, including details of the EMG signals and hand gestures. Explains the feature extraction process, data preprocessing steps, and the implementation of the Random Forest classifier for gesture classification.

Chapter 4 presents the results of gesture classification, evaluates the Random Forest model's performance, and discusses the implications of the findings. It concludes with a summary of contributions made by the research.

Chapter 5, the final chapter explores future directions, including using Non-Negative Matrix Factorization (NMF) for muscle synergy analysis and reinforcement learning for adaptive real-time control of the hand exoskeleton.

CHAPTER 2

LITERATURE REVIEW

2.1 Rehabilitation and Hand Exoskeletons

The field of hand exoskeletons, particularly for rehabilitation, has gathered significant attention due to the increasing need for effective assistive devices. These exoskeletons are designed to restore motor functionality, assist with daily tasks, and improve the quality of life for individuals with motor impairments. **Du Plessis et al.** [3] conducted a comprehensive review of advancements in active hand exoskeleton technologies over the past decade, categorizing their applications into rehabilitation, assistance, augmentation, and haptics. They highlighted that the complex anatomy of the human hand, coupled with engineering constraints like size, weight, and ergonomics, presents significant challenges in device design. Their study also emphasized the critical role of intelligent control systems, such as those based on electromyography (EMG) and electroencephalography (EEG), for intention detection and robotic assistance estimation.

Similarly, **Noronha et al.** [4] analyzed 97 active hand exoskeletons, categorizing them based on design features and readiness levels. Their findings revealed a preference for underactuated devices due to their simplicity and robustness, alongside a growing adoption of soft robotics technologies for improved flexibility. However, the review also identified a gap in translating these devices from laboratory settings to real-world applications. Most devices remain at the prototype stage or in early clinical trials, with only a handful achieving commercialization. These insights underscore the need for multidisciplinary collaboration and long-term clinical evaluations to bridge the gap between research and practical deployment.

2.2 EMG-Driven Control Systems for Hand Exoskeletons

Electromyography (EMG)-based control systems have become a cornerstone of modern hand exoskeletons, enabling intuitive interaction and precise control. These systems leverage electrical signals generated by muscle activity to drive robotic mechanisms, making them particularly useful for rehabilitation and assistive purposes. **Leonardis et al.** [5] introduced a bilateral EMG-driven hand exoskeleton for stroke rehabilitation, emphasizing its free-palm and free-fingertip design, which preserved residual sensory perception. Their real-time control mechanism utilized the non-paretic hand to guide the paretic hand, providing robotic assistance that closely mimicked natural movements. Experimental evaluations demonstrated the device's potential in improving motor function in stroke patients.

Wege et al. [6] proposed an EMG-based control system tailored for rehabilitation after hand injuries or strokes. Their device featured integrated safety mechanisms to prevent abrupt movements, ensuring its suitability for patients with limited mobility. Force sensors embedded within the exoskeleton allowed users to control hand movements, facilitating tasks such as muscle training and trajectory learning. This approach highlighted the importance of incorporating feedback and safety features into EMG-driven systems to enhance their reliability and user experience.

Advancements in EMG signal processing have significantly contributed to the development of these systems. **Reaz et al.** [7] reviewed various EMG signal analysis techniques, including decomposition, classification, and feature extraction, focusing on their applications in prosthetic control and human-computer interaction. Their findings emphasized the need for robust algorithms capable of handling the variability and noise inherent in EMG signals. Similarly, **Phinyomark et al**. [10] evaluated 37 time-domain and frequency-domain features, identifying the most effective ones for classification tasks. Their work streamlined the feature selection process, providing a foundation for developing computationally efficient control algorithms.

Despite these advancements, challenges remain in improving the robustness and adaptability of EMG-driven systems. Factors such as muscle fatigue, signal interference, and variations in electrode placement can affect performance. Addressing these issues requires the integration of adaptive algorithms and machine learning techniques to enhance real-time signal interpretation.

2.3 ML Approaches for EMG Signal Classification

Machine learning (ML) techniques have revolutionized EMG signal classification, enabling more accurate and efficient control of hand exoskeletons. These methods facilitate the extraction of meaningful patterns from complex, high-dimensional EMG data, translating them into actionable commands for robotic systems. **Seyidbayli et al.** [12] demonstrated the effectiveness of ensemble models, particularly Bagged Trees, in classifying hand gestures. Their study achieved an impressive accuracy of 98.55%, highlighting the potential of ensemble methods to handle the variability and non-linearity of EMG signals. Random Forest (RF) algorithms have also gained prominence in EMG signal analysis. **Jaiswal et al.** [13] showcased the utility of RF in feature selection, classification, and regression, particularly for datasets with numerous variables. By identifying the most relevant features, RF algorithms enhance model accuracy while reducing computational complexity. Building on this, **Chaudhary et al.** [15] developed an improved RF classifier that incorporated attribute evaluation and instance filtering, achieving superior performance in multi-class classification tasks.

Beyond traditional ML algorithms, researchers have explored advanced ensemble methods for EMG signal processing**. Ren et al.** [16] reviewed various ensemble techniques, including bagging, boosting, and deep learning-based approaches. Their findings underscored the versatility of ensemble methods in addressing diverse classification challenges, from motion recognition to clinical diagnosis.

While these methods have significantly improved classification performance, challenges such as overfitting, computational efficiency, and scalability persist. Future research should focus on developing hybrid models that combine the strengths of multiple algorithms to achieve greater robustness and adaptability.

2.4 Synergy-Based Analysis Using Non-Negative Matrix Factorization (NMF)

Non-Negative Matrix Factorization (NMF) has emerged as a powerful tool for analyzing muscle synergies, offering insights into the underlying coordination patterns of human motor control. By decomposing EMG signals into non-negative components, NMF provides a biologically interpretable representation of muscle activation patterns. **Ajiboye et al.** [18] applied NMF to predict untrained static hand postures using a minimal training set, achieving over 90% accuracy. Their findings revealed two distinct synergy types: subject-specific synergies, characterized by balanced coactivation of multiple muscles, and population synergies, dominated by single-muscle activation. These results demonstrated the potential of NMF in simplifying control strategies for prosthetic and robotic applications.

Tresch et al. [19] evaluated the robustness of various matrix factorization methods, including NMF, in identifying muscle synergies. Their study highlighted the superiority of NMF over other techniques, such as Principal Component Analysis (PCA), in capturing non-negative activation patterns. This makes NMF particularly suitable for applications requiring biologically plausible interpretations, such as rehabilitation and prosthetic design.

In addition to EMG signal analysis, NMF has been applied to other domains, such as facial image recognition and semantic text analysis. **Lee et al.** [17] demonstrated the versatility of NMF in providing parts-based representations, contrasting it with holistic approaches like PCA. These applications underscore the adaptability of NMF as a dimensionality reduction technique.

Future research should explore the integration of NMF with real-time control systems, enabling dynamic adaptation to user-specific requirements. This approach could enhance the functionality and user experience of EMG-driven hand exoskeletons.

CHAPTER 3

METHODOLOGY

3.1 Description of the Dataset

The raw EMG signal data is taken from the online bio signals repository provided by Dr. Rami N. Khushaba. In the experiment he conducted for his paper [20], eight subjects, six males and two females, aged between 20-35 years were recruited to perform the required finger movements. The subjects were all normally limbed with no neurological or muscular disorders. All participants provided informed consent prior to participating in the study. Subjects were seated on an armchair, with their arm supported and fixed at one position. The datasets were recorded using eight EMG channels (DE 2.x series EMG sensors) mounted across the circumference of the forearm and processed by the Bagnoli desktop EMG system from Delsys Inc. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick them to the skin. A conductive adhesive reference electrode, dermatrode reference electrode, was placed on the wrist of each of the subjects during the experiments.

The collected EMG signals were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software. The EMG signals were then bandpass filtered between 20-450 Hz with a notch filter implemented to remove the 50 Hz line interference. Fifteen classes of movements were collected during this experiment including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L), and the combined Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (TL), Index-Middle (I-M), Middle-Ring (M-R), Ring-Little (RL), Index-Middle-Ring (I-M-R), Middle-Ring-Little (M-R-L), and finally, the hand close class (HC) as shown in Fig.3.1. These were labelled from number 1 to 15 in the same order as above.

The subjects were asked to perform each of the aforementioned fifteen movements, and hold that movement for a period of 20 seconds in each trial. Only first 10 seconds from each trial used in this study. So, in summary, the raw data consists EMG signals for fifteen hand gestures for eight subjects conducted over three trials.

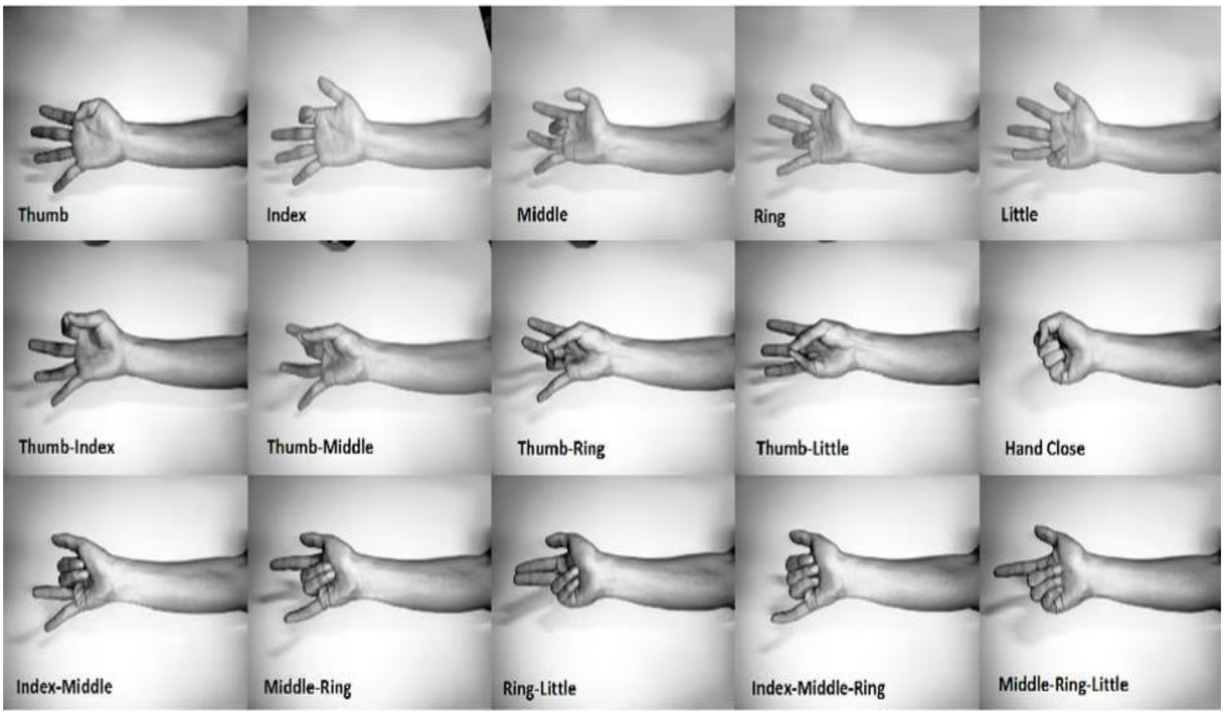

Fig.3.1 Different classes of individual and combined fingers movement [20]

3.2 Feature Extraction

Feature extraction from EMG signals is a critical step in the development of machine learning models for tasks such as gesture recognition, prosthetic control, and neuromuscular disorder diagnosis. EMG signals, which are inherently complex and noisy, contain valuable information about muscle activation and coordination. However, directly using raw EMG data for machine learning is challenging due to its high dimensionality and variability caused by physiological, environmental, and electrode placement factors. Feature extraction transforms these raw signals into a lower-dimensional, meaningful representation that captures the most relevant patterns and characteristics for the task at hand. The extraction of well-chosen features reduces the computational complexity of the machine learning model, improves classification accuracy, and enhances generalization by focusing on the most discriminative attributes of the data. Thus, feature extraction is a vital preprocessing step that ensures the reliability and efficiency of EMG-based machine learning systems.

3.2.1 Time-Domain Features

Time-domain features are derived directly from the raw EMG signal in the time domain and provide insights into the signal's amplitude and variability.

Root Mean Square (RMS):

The RMS feature represents the square root of the average of the squared values of the signal. It reflects the power content of the EMG signal and correlates with the contraction level of muscles. Mathematically, it is expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

where x_i represents the signal amplitude at each time point and N is the total number of samples.

Mean Absolute Value (MAV):

MAV calculates the average of the absolute values of the EMG signal. It provides an estimation of the signal's overall activity level and is computationally simple to implement:

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i|$$

Waveform Length (WL):

WL is the cumulative length of the waveform over the analysis window. It measures the complexity and variability of the signal and is calculated as:

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i|$$

This feature is sensitive to both amplitude and frequency changes in the signal.

3.2.2 Frequency-Domain Features

Frequency-domain features are computed from the frequency spectrum of the EMG signal, providing information about the frequency content and energy distribution. Power Spectral Density (PSD) quantifies the power distribution of the signal across various frequency components. It is derived using Fourier Transform and provides insights into the energy concentration in specific frequency bands, which can distinguish between different muscle activations.

Mean Frequency (MNF):

MNF is the weighted average frequency of the power spectrum and represents the center of gravity of the spectral power distribution. It is defined as:

$$MNF = \frac{\sum f . PSD(f)}{\sum PSD(f)}$$

where f is the frequency, and $PSD(f)$ is the power at that frequency. MNF is sensitive to muscle fatigue and motor unit recruitment patterns.

Median Frequency (MDF):

MDF is the frequency that divides the power spectrum into two equal halves, where 50% of the signal's total power lies below this frequency and 50% lies above. It provides insights into muscle fatigue, as a shift in MDF is often observed with prolonged muscle contractions:

$$\int_0^{MDF} PSD(f)df = \int_{MDF}^{f_{max}} PSD(f)df$$

Where $PSD(f)$ is the power at frequency f, and f_{max} is the maximum frequency.

3.2.3 Statistical features

Statistical features capture the distributional properties of the EMG signal and provide additional discriminative information.

Skewness:
Skewness measures the asymmetry of the signal's amplitude distribution around the mean. It is computed as:

$$Skewness = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3}{\sigma^3}$$

where μ is the mean and σ is the standard deviation. Positive skewness indicates a distribution with a longer tail on the right, while negative skewness indicates a longer tail on the left.

Kurtosis:
Kurtosis quantifies the tailedness of the distribution, describing the sharpness of the signal's amplitude peaks. It is given by:

$$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^4}{\sigma^4}$$

A high kurtosis value indicates sharper peaks, often associated with bursts of muscle activity in EMG signals.

These features collectively encapsulate the amplitude, frequency, and statistical properties of EMG signals, enabling effective differentiation of hand gestures. The combination of time-domain, frequency-domain, and statistical features ensures robustness and enhances the classification accuracy of the machine learning models.

The raw EMG signals were processed and analyzed using Python, a versatile programming language widely used in data analysis and scientific computing. Feature extraction was implemented using specialized Python libraries, which provided efficient and reliable tools for signal processing and statistical computation.

Metrics such as Root Mean Square (RMS), Mean Absolute Value (MAV), and Waveform Length (WL) were calculated directly from the raw signal using numerical computation libraries like NumPy and pandas. Custom functions were developed to ensure accurate implementation of these formulas.

Power Spectral Density (PSD), Mean Frequency (MNF), and Median Frequency (MDF) were derived using the Fast Fourier Transform (FFT), leveraging the scipy.signal library for spectral analysis. These libraries facilitated robust and efficient frequency-domain computations.

Skewness and Kurtosis, which describe the statistical properties of the signal distributions, were computed using Python’s scipy.stats module.

The entire process of feature extraction was automated within a pipeline, ensuring consistency across all data samples. The use of Python not only streamlined the workflow but also enabled the reproducibility of results.

3.3 Organizing the extracted features

The seven features (Root Mean Square, Mean Absolute Value, Waveform Length, Mean Frequency, Median Frequency, Skewness, and Kurtosis) were calculated for all eight muscles for a given hand gesture, resulting in a feature matrix of size 8×7 for each hand gesture. Since there were eight subjects, each performing fifteen hand gestures for three trials, therefore the total number of trials were 360 $(8 \times 15 \times 3)$. The features for hand closed gesture for the first trial of subject 1 is shown in the Fig.3.2.

feature_matrix_S1HC1

	RMS	MAV	WL	MnF	MedF	Skew	Kurt
M1	0.000496	0.000363	2.825458	108.745083	82.03125	-0.507230	3.328739
M2	0.000275	0.000208	1.577894	101.411414	82.03125	-0.232099	1.477972
M3	0.000095	0.000072	0.678409	122.804061	97.65625	0.085067	1.183536
M4	0.000192	0.000137	0.997684	96.108328	82.03125	0.759377	3.816475
M5	0.000695	0.000511	3.943219	108.264834	89.84375	-0.377707	2.902550
M6	0.000441	0.000313	2.538971	110.450317	93.75000	-0.615495	4.422357
M7	0.001769	0.001299	11.918374	143.657432	121.09375	-0.618228	1.115376
M8	0.000929	0.000680	7.027085	143.013852	117.18750	-0.389537	2.195681

Fig.3.2 Features of subject 1 for hand closed gesture

To prepare the data for compatibility with machine learning algorithms requiring a vectorized input, the 8×7 matrix of features for each gesture was flattened into a one-dimensional vector of size 56 (8×7). This transformation ensured that the feature data for each hand gesture was represented as a single feature vector. The above process was repeated for all hand gestures in the dataset, resulting in a set of feature vectors corresponding to each hand gesture. The flattening step allowed for seamless integration of the feature data into the machine learning pipeline while preserving the contribution of features from all muscles. Lastly, to complete the feature matrix, a label column was added corresponding to each hand gesture. This preparation enabled consistent analysis and classification of hand gestures based on their EMG signal patterns.

3.4 Classification using Random Forest classifier

The extracted feature matrix X of size 360×56, containing features for all eight muscles across all hand gestures, along with the corresponding labels vector y of size 360×1 was used for classification. A Random Forest (RF) classifier was implemented to classify hand gestures based on the extracted features. The implementation was performed using Python and the Scikit-learn library.

3.4.1 Data Preprocessing

To ensure the classifier performs optimally, the dataset was split into training and testing subsets using a stratified train-test split with 70% of the data allocated for training i.e. $252 \text{ out of } 360$ data points and 30% for testing i.e. $108 \text{ out of } 360$ data points. This stratification preserved the proportion of labels in both subsets. The features were then standardized using the StandardScaler function from Scikit-learn to normalize their values, which is critical for algorithms sensitive to feature scaling.

3.4.2 Model Training

A Random Forest classifier with 100 decision trees (n_estimators = 100) was trained on the standardized training set. The classifier was initialized with a fixed random seed (random_state=42) to ensure reproducibility of the results.

3.4.3 Model Evaluation

The trained model was evaluated on the test set. Predictions were made for the test set samples, and the model's performance was quantified using accuracy, a confusion matrix, and a detailed classification report. The Random Forest classifier achieved an accuracy of $\mathbf{81}\%$ on the test set.

CHAPTER 4

RESULTS

4.1 Model Performance and Classification Report

The Random Forest Classifier achieved an accuracy of **81.48%**, indicating its effectiveness in classifying hand gestures based on the extracted EMG features. The model's performance was evaluated using several metrics, including precision, recall, F1-score, and support for each gesture class, as detailed in Table 4.1.

Label	Precision	Recall	f1-score	support
1	0.85714	0.85714	0.85714	7
2	0.83333	0.71429	0.76923	7
3	0.87500	1.00000	0.93333	7
4	0.87500	0.87500	0.87500	8
5	0.66667	0.85714	0.75000	7
6	1.00000	1.00000	1.00000	7
7	1.00000	0.75000	0.85714	8
8	1.00000	0.85714	0.92308	7
9	0.70000	1.00000	0.82353	7
10	0.62500	0.71429	0.66667	7
11	0.85714	0.85714	0.85714	7
12	0.71429	0.71429	0.71429	7
13	0.71429	0.62500	0.66667	8
14	0.66667	0.57143	0.61538	7
15	1.00000	0.85714	0.92308	7
Accuracy	0.81481	0.81481	0.81481	0.81481
macro average	0.82563	0.81667	0.81545	108
weighted average	0.82668	0.81481	0.81501	108

Table 4.1 Classification report of the model

The classification report (Table 4.1) highlights the performance of the model across each gesture class. The F1-score is a critical metric in evaluating machine learning models, particularly in cases where the class distribution is imbalanced. It is the harmonic mean of precision and recall, combining both metrics into a single number that balances their trade-off. Figure 4.1 represents the f1-score of the model in a graphical manner.

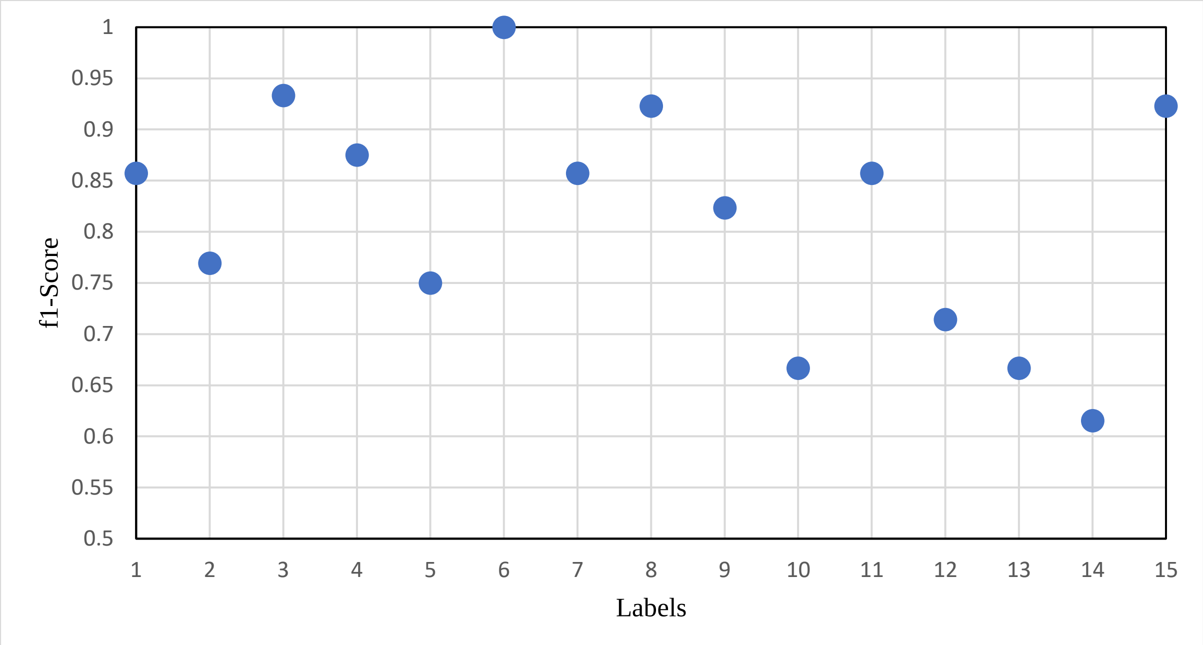

Fig.4.1 f1-score of each label

The macro average precision, recall, and F1-score are 0.82563, 0.81667, and 0.81545, respectively, suggesting a balanced performance across all labels. The weighted average metrics (precision: 0.82668, recall: 0.81481, F1-score: 0.81501) account for the support of each label and confirm that the model performs well on classes with more data points.

Labels 6 and 15 achieved a perfect F1-score of 1.0 and 0.92308, respectively, indicating the model's ability to accurately predict instances of these gestures. Labels 3, 7, and 8 also performed well with high precision, recall, and F1-scores above 0.85. Labels 2, 5, and 10 have moderate F1-scores (between 0.66 and 0.77) due to imbalances between precision and recall. For instance, label 2 has a precision of 0.83333 but a slightly lower recall of 0.71429, meaning it occasionally misses positive instances. Labels 13 and 14 showed relatively low F1-scores (0.66667 and 0.61538) due to reduced recall values (0.62500 and 0.57143, respectively), suggesting the model struggles to capture all instances of these gestures.

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Each label has an equal support of 7-8 instances, indicating a balanced dataset for evaluation, which ensures that metrics are not biased toward any particular label.

4.2 Confusion Matrix

The confusion matrix (Fig 4.2) provides a visual representation of the classifier's predictions compared to the true labels. It highlights the correctly classified instances along the diagonal and the misclassified instances elsewhere. Notably, the model showed high accuracy for gestures 3, 4, 6, and 9, while struggling to classify gestures 10, 12, 13 and 14, as evidenced by a higher frequency of misclassifications between these classes.

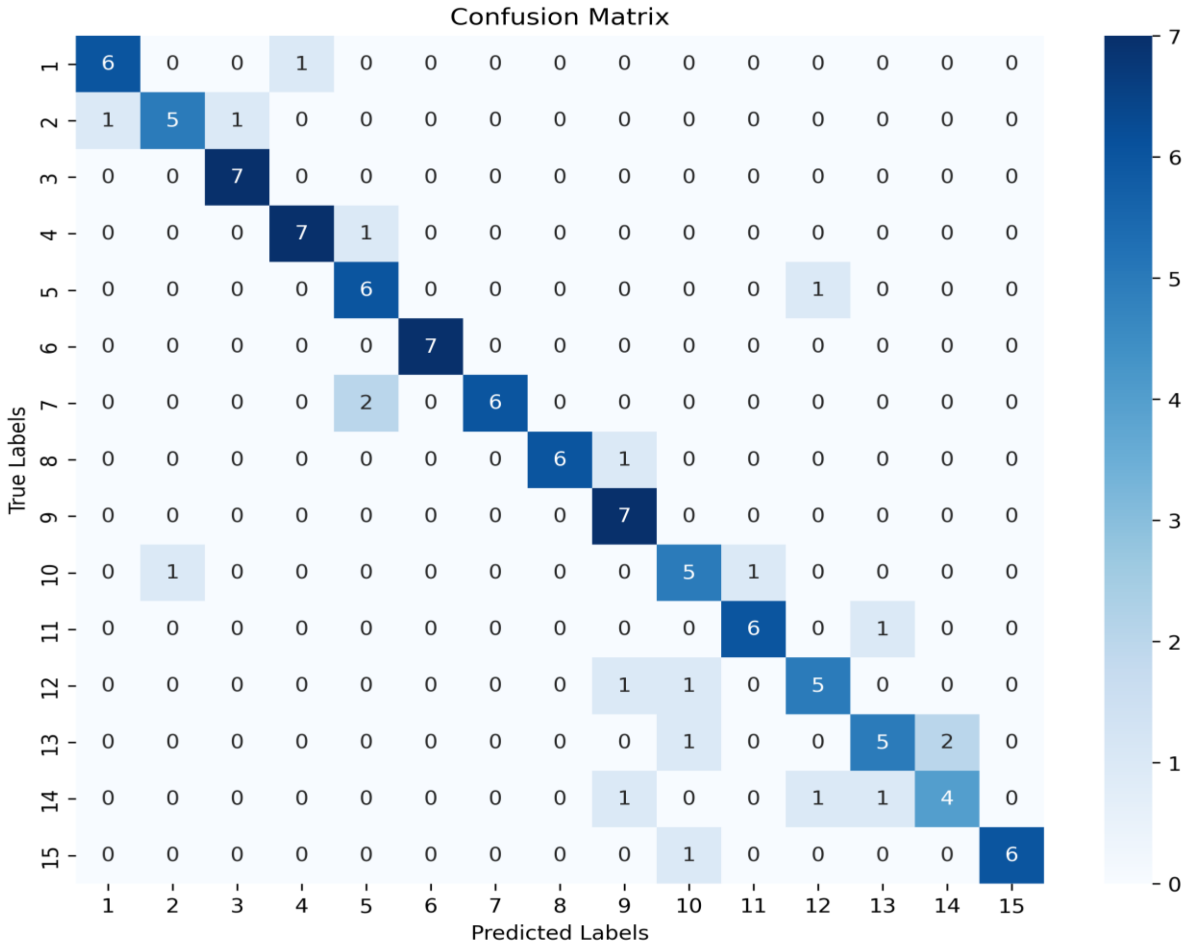

Fig 4.2 Confusion matrix of the model

The Random Forest classifier performs well on most labels, achieving high precision, recall, and F1-scores for gestures such as **3, 6, 7, and 15**. However, the model faces challenges with labels **13 and 14**, which have lower recall and F1-scores. Improving feature selection or model optimization may help address these specific challenges. Overall, the results indicate that the classifier is robust and capable of accurately distinguishing between most hand gestures.

CHAPTER 5

CONCLUSION AND FUTURE WORK

The research presented in this thesis lays the foundation for gesture classification using EMG signals and demonstrates the efficacy of a random forest classifier on the extracted feature set. While the achieved classification accuracy is promising, there is significant scope for enhancing the current methodology, broadening its applications, and exploring innovative techniques to better model muscle activation patterns.

Building upon the progress made so far, the upcoming semester will focus on integrating advanced techniques into the current framework to enhance the performance and capabilities of the intelligent hand exoskeleton. Specifically, two key methodologies will be explored: **Non-Negative Matrix Factorization (NMF)** for extracting muscle synergies from electromyographic (EMG) signals and **Reinforcement Learning (RL)** for optimizing the control and classification tasks.

The first phase will involve acquiring a deep understanding of NMF, a dimensionality reduction technique that can reveal underlying patterns in EMG data. This will enable the extraction of meaningful muscle synergies, potentially providing a more compact and interpretable feature representation. The insights gained from NMF will be leveraged to refine feature extraction methods, which could significantly improve the classification accuracy of hand gestures.

In the second phase, Reinforcement Learning will be employed to develop adaptive control strategies. RL, with its ability to optimize decision-making in dynamic environments, will be utilized to enhance the functionality of the hand exoskeleton by learning efficient policies for gesture classification and movement prediction. By designing a simulated environment for training and testing, the integration of RL will aim to create a robust, real-time control framework.

The work plan is structured to systematically progress from theoretical exploration to practical implementation, with clear objectives and milestones. A detailed timeline has been established to ensure efficient use of the semester, covering literature reviews, algorithm implementation, experimental evaluation, and final integration. This structured approach is expected to yield significant contributions to the thesis while addressing key challenges in the development of intelligent hand exoskeletons.

The objectives of the future work to be done are:

Understanding and Implementing NMF:

- Gain proficiency in applying NMF to Khushaba's dataset to extract meaningful muscle synergies.
- Interpret the synergies to assess their utility for controlling a hand exoskeleton.

Controller Design Using Synergies:

- Develop a control strategy (in hardware or simulation) driven by the identified muscle synergies.

Incorporating Reinforcement Learning:

- Apply RL algorithms to optimize the control strategy, ensuring adaptive and efficient performance in real-time applications.

The following timeline outlines the planned progression of the project. It highlights the key objectives and tasks to be completed in each month, focusing on learning and implementing Non-Negative Matrix Factorization (NMF) for muscle synergy extraction, as well as incorporating Reinforcement Learning for controller optimization.

Task\Month	Dec 2024	Jan 2025	Feb 2025	March 2025	April 2025
Learning NMF					
Implementing Synergies					
Learning RL					
Simulation and Testing					
Finalization and Documentation					

Table 5.1 Proposed timeline for future work

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