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Surface Electromyogram Signal Classification for Gesture Recognition using Extreme Learning and Singular Spectrum Analysis

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CANDIDATE’S DECLARATION

I **Tanishqa Tyagi** student of MTech (Signal Processing and Digital Design), hereby declare that the project Dissertation titled “**Surface Electromyogram Signal Classification for Gesture Recognition using Extreme Learning and Singular Spectrum Analysis”** which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source withoutproper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Report titled "**Surface Electromyogram Signal Classification for Gesture Recognition using Extreme Learning and Singular Spectrum Analysis**" which is submitted by **Tanishqa Tyagi**, **2K21/SPD/16** of Electronics and Communication Department, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi **Dr. Anukul Pandey**
Date: **SUPERVISOR**

Place: Delhi **Mr. Kaustubh Ranjan Singh**
Date: **SUPERVISOR**

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Tanishqa Tyagi

ABSTRACT

Surface based gesture recognition utilizes electrical signals generated by muscles during voluntary actions to recognize human gestures. Gesture recognition has gained significant attention due to its potential application in various domains, including human-computer interaction, rehabilitation and robotics.

The primary objective of this thesis is to develop and evaluate algorithms for improving accuracy of sEMG based gesture recognition systems for systems with multiple degrees of freedom. Electromyogram (EMG) signals are crucial to record muscle activity. Several papers have been proposed about EMG signals and mostly machine learning techniques have been used to extract information from EMG signals. In this paper, a molecular-based feature extractor model has been presented. This architecture uses Singular Spectrum Analysis (SSA) to form sub-bands which are then subjected to number of statistical features extraction. The sub-bands are also used to generate textural features using the Local Graph Structure method described in this paper. The feature matrix generated using these methods has been reduced in dimensionality using the Neighborhood Component Analysis (NCA). Finally, an Extreme Learning Machine model for classification has been used for the classification of gestures into their respective classes. The model achieved an accuracy of >97% for 10 classes and outperformed its predecessors.

EMG gesture recognition holds immense potential for revolutionizing human-machine interaction. By harnessing the electrical activity of muscles, we can create seamless interfaces that enable users to effortlessly control devices, interact with virtual environments, and improve the quality of life for individuals with motor impairments. Continued research and advancements in this field will unlock exciting opportunities for the development of intuitive and immersive human-machine interfaces.

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LIST OF ABBREVIATIONS

Abbreviation		Full form
sEMG	-	Surface Electromyography
EMG	-	Electromyography
TMR	-	Targeted Muscle Reinnervation
PR	-	Pattern Recognition
DoF	-	Degree of Freedom
iEMG	-	Intrinsic Electromyography
SSA	-	Singular Spectrum Analysis
SSC	-	Singular Structure Components
SVD	-	Singular Value Decomposition
LGS	-	Local Graph Structure
NCA	-	Neighbourhood Component Analysis
ELM	-	Extreme Learning Machine

CHAPTER 1 : INTRODUCTION

1.1 Overview

The upper limb is an important part of the body that allows us to perform various activities of daily living. It has fine motor skills that help us grasp and sense objects, and it also allows us to communicate through hand gestures, sign language, and artistic expressions [1]. Losing one or both arms can severely limit a person's ability to perform tasks during daily activities, leading to a decrease in their quality of life. Amputees may also experience phantom limb pain, depression, changes in body image, and psychological burden. In some cases, upper limb loss can affect a person's stability, making them prone to falls or collisions [2].

Upper limb prostheses are commercially available to aid amputees in carrying out tasks that require their arm functions [3]. Body-powered prostheses operate by using cables to link the movement of the body to the device, enabling simple hand tasks such as opening or closing a hook or gripper. However, they are nonintuitive and require significant effort to perform simple tasks, limiting their functionality to a single degree of freedom [4]. Motorized upper limb prostheses that use electromyography (EMG) recordings to characterize upper limb movement intentions of the amputee are considered as a viable alternative for intuitive restoration of multiple DOF arm functions [4]. EMG signals are encoded in the form of control commands to the prosthetic controller, which then actuates the device accordingly. The motorized upper limb prosthetic technology has progressed over the last two to three decades, leading to the development of better control methods and designs. This article focuses on EMG-based prosthetic control methods/technologies that could help improve the overall performance and acceptability of prostheses systems [5].

1.1.1 Acquisition of sEMG signals from forearm

The forearm plays a crucial role in recording electromyography (EMG) signals for gesture recognition. EMG is the measurement and analysis of electrical activity produced by skeletal muscles [6]. When muscles contract, they generate electrical signals that can be detected and recorded using surface electrodes placed on the skin.

The relevant biology involved has been listed below:

Muscles: The forearm contains several muscles responsible for controlling hand and finger movements. These include the flexor and extensor muscles, which allow for bending and extending the wrist and fingers, as well as the muscles responsible for individual finger movements [7].

Motor Units: Muscles are composed of individual motor units, consisting of a motor neuron and the muscle fibers it innervates. Motor neurons transmit electrical signals from the brain or spinal cord to the muscle fibers, causing them to contract. When a gesture or movement is performed, specific motor units are activated, resulting in unique patterns of electrical activity [7].

EMG Signals: Surface electrodes are placed on the skin overlying the forearm muscles to detect the electrical signals produced during muscle contractions. These electrodes capture the action potentials generated by motor units and transmit them as voltage signals. The recorded EMG signals reflect the timing, duration, and intensity of muscle contractions, providing information about the underlying movements [7].

Signal Processing: Recorded EMG signals undergo further processing to extract relevant features for gesture recognition. This involves amplifying and filtering the signals to remove noise and interference. Additionally, techniques such as rectification, smoothing, and spectral analysis may be employed to enhance the desired features and make them suitable for analysis and classification [8].

Gesture Recognition: Once the EMG signals have been processed, they can be analyzed using machine learning algorithms or other pattern recognition techniques to classify and interpret the performed gestures. By training a system with a dataset of known gestures, it can learn to associate specific EMG patterns with corresponding movements or gestures, enabling gesture recognition and control of external devices or interfaces [9].

It is to be noted that the quality of EMG recordings can be influenced by various factors, such as electrode placement, signal-to-noise ratio, muscle fatigue, and individual anatomical differences. Proper electrode positioning and signal acquisition techniques are essential to obtain reliable and accurate EMG signals for gesture recognition applications [9].

1.2 Literature review

Electromyography (EMG) is the technique in which signals resulting from muscle contraction are captured by sensors mounted on the skin [1-2]. These signals can then be used for sending control commands to the prosthesis. EMG based techniques for upper-limb control have been receiving a lot of attention in recent studies.

Myoelectric control-based prosthesis was first proposed in the 1940s but significant development in that technology took place only in the late 1960s. It is this version, which is still widely used in commercial applications for upper-limb prostheses. These early myoelectric devices operated in an “on/off” mode, where the state of was decided on the basis of a threshold. The amplitude of the EMG signal was compared to this threshold and accordingly the device would be activated or deactivated [6]. Naturally, these devices limit the movements of the prosthetic as the more complex muscle contraction procedures cannot be performed. [1,2]

With the emergence of pattern recognition technologies, several improvements were made in the development of myoelectric prosthesis. The basic assumption in this is that each of the intended movement of the limb the user can be mapped to a specific EMG pattern. This is done by processing the EMG signal to extract relevant features and then classifying them to different movements for commanding the prostheses controller to perform the action. Use of Pattern Recognition based algorithms to operate upper-limb prostheses resulted in a huge improvement in the recent decades.

Another innovation that resulted in better result is the targeted muscle reinnervation [5] (TMR) that provided signals which are physiologically appropriate with the former functions of the missing arm [3,4]. This enabled using PR control in above elbow amputees as well and achieve accuracies of higher than 95%. However, these methods are still limited to lab environments and have not yet been accepted commercially.

Major reasons for clinical unacceptability of these methods are the lack of sensory feedback. The problem lies in not moving the device on command, but on the avoidance of unnecessary movements and knowing when not to move. Having multiple degrees of freedom will help in bringing the prosthetic hand movements closer to that of the human hand. In order to overcome these problems with the current prostheses the focus of research should be moved to solving these problems.

Earlier the myoelectric prostheses were controlled by the comparing the amplitude of the signal with some threshold [1,2,12]. These direct control systems could achieve high accuracies but they could achieve only on or two degrees of freedom (DoF). Here, DoF is the number of motions that the prosthesis could perform, for example, if a device can perform “hand close” and get back to “relax” types of position, it has achieved one degree of freedom. To effectively replicate the human hand function, control over multiple DoFs is desirable to perform complex actions with fingers, wrist and elbow control, especially in cases of high-level amputation.

Pattern Recognition has emerged to overcome the barrier of conventional control. These systems assume that myoelectric signals like EMG and sEMG will be the same for a given movement class, and distinct for different movement classes [2]. In PR based approaches the classification accuracy is the main measure to evaluate the performance of the system. Mostly classification accuracy remains the same in cases of different myoelectric signal like iEMG or sEMG. However, sEMG or surface EMG, is preferred more over iEMG for solving PR based myoelectric control of prostheses control because of its non-invasive nature.

The steps involved in before performing pattern analysis of a signal are signal detection, preprocessing, data windowing, feature extraction, classification, post-processing and proportional control [8-11]. The number of channels is limited because of the electrodes have to embedded in the prosthetic limb. To overcome this challenge surgical procedures like targeted muscle reinnervation are used to identify optimal points for recording the myoelectric signals for prosthesis control [3].

Analysis windows formed by segmenting the myoelectric signal data are used to extract features. The length of the analysis window versus the processing time required to reach a decision are tradeoffs. The window should be short enough to avoid long processing delays while also being long enough to make an informed decision. The maximum allowable delay between signal generation and prosthetic actuation for a reliable system must be less than 300 ms [13]. The standard window length is usually

100 to 250 ms. The windows can be separated or overlapped. About available computing capability, an overlapping analysis window capable of producing a dense decision stream is generally preferred. The pattern associated with each limb is described by features extracted from these windows. The feature mostly used are based on time domain, frequency domain and time-frequency domain methods. Post feature extraction, dimensionality reduction techniques are employed to reduce the size of high dimensional feature space. A number of classifiers have been explored to discriminate the intended movements using the features extracted. It was proved in [14-17] that if an appropriate set of features is there, different classifiers will perform in a similar way. Therefore, in the project more emphasis will be given to selecting appropriate features instead of choosing classifier.

1.2.1 Gesture recognition role in prosthetics

Gesture recognition plays a crucial role in prosthetics by enabling intuitive and natural control of prosthetic limbs. Here are some key aspects of the role of gesture recognition in prosthetics:

Control of Prosthetic Limbs: Gesture recognition allows individuals with limb loss or limb differences to control their prosthetic limbs using natural movements and gestures. By analyzing signals such as electromyography (EMG) or other sensor data from the residual limb, gesture recognition algorithms can interpret the user's intended movements and translate them into control commands for the prosthetic limb. This enables more intuitive and precise control, enhancing the functionality and usability of the prosthetic device [18].

Improved Range of Motion: Gesture recognition systems can provide users with a broader range of motion and control options for their prosthetic limbs. By recognizing different gestures or movements, users can perform various tasks and actions with their prosthetic limb, such as grasping objects of different shapes and sizes, manipulating tools, or performing delicate movements that require fine motor control. This helps individuals regain functional capabilities and improves their overall quality of life [19].

Multi-DOF Control: Prosthetic limbs with multiple degrees of freedom (DOF) allow users to perform complex movements similar to natural limbs. Gesture recognition enables users to control these multi-DOF prosthetic limbs by mapping specific gestures or combinations of gestures to different joint movements or actions. This provides users with a more natural and coordinated control of their prosthetic limbs, allowing them to perform a wide range of tasks and activities [20].

User Customization and Personalization: Gesture recognition systems can be personalized and customized to meet the unique needs and preferences of individual users. By training the gesture recognition algorithms on the specific muscle patterns or gestures of each user, the prosthetic limb can be tailored to their specific abilities and control requirements. This adaptability helps improve the accuracy and responsiveness of the prosthetic limb, leading to a more seamless integration into the user's daily life [21].

Cognitive Load Reduction: Gesture recognition can help reduce the cognitive load associated with controlling a prosthetic limb. Instead of relying on conscious effort to control each joint or movement individually, users can rely on intuitive gestures or movements that come naturally to them. By simplifying the control process, gesture recognition allows users to focus more on the task at hand rather than the mechanics of controlling the prosthetic limb, promoting greater efficiency and reducing mental fatigue [22].

Overall, gesture recognition in prosthetics empowers individuals with limb loss or limb differences to regain functional control over their prosthetic limbs, enhancing their independence, mobility, and overall quality of life. Ongoing research and advancements in gesture recognition technologies are further improving the capabilities and effectiveness of prosthetic devices

1.3 Research Gap

Gesture recognition using electromyography (EMG) signals is an active and evolving area of research. While significant progress has been made in this field, there are still several research gaps and opportunities for further investigation. The research gaps addressed here are:

Robustness to Variability: EMG signals are influenced by various factors, including electrode placement, muscle fatigue, and inter-subject variability. Research can focus on developing robust techniques that can handle these variabilities and still achieve accurate gesture recognition. This may involve investigating methods for adaptive feature extraction, model adaptation, or data augmentation techniques that account for the variability in EMG signals [22].

Multi-User Gesture Recognition: Most studies in gesture recognition using EMG signals focus on single-user scenarios. However, there is a need to explore multi-user scenarios where multiple individuals are interacting simultaneously. Research could investigate techniques for distinguishing and recognizing gestures from different users in a shared EMG signal environment [20]. This may involve developing user-specific models, signal separation techniques, or advanced machine learning approaches capable of handling multiple users.

These research gaps highlight areas where further investigation and advancements can contribute to the development of more accurate, robust, and practical gesture recognition systems using EMG signals.

1.4 Research Objective

This dissertation has the following objectives:

1. To explore the effects of different feature extraction models:

    (a) Testosterone pattern local graph structure-based method

    (b) Singular Spectrum Analysis (SSA) and statistical features

The effects of these two methods will be explored when applied on the dataset individually and in combination.

2. To evaluate the performance of the proposed model on a multiclass gesture recognition problem, and classify gestures into 10 predefined classes.

1.5 Structural organization of the dissertation

The remaining part of the dissertation is arranged in the following manner: Chapter 2, describes the feature extraction techniques in detail. It also gives the algorithm to extract testosterone structure based local graph features, and the algorithm for singular spectrum analysis (SSA). It also depicts the overview of the methodology. Chapter 3 describes the machine learning techniques and the reason for their efficiency in sEMG based classification problems. Chapter 4 describes the dataset used for study and also includes the comparative results parameters and validation of the method. It also enlists the work's advantages and limitations. Chapter 5 is the conclusion and future aspects.

CHAPTER 2: PROPOSED FEATURE EXTRACTION TECHNIQUE FOR MULTICLASS CLASSIFICATION OF sEMG SIGNALS

2.1 Introduction

This chapter is focused on the step-by-step execution of the proposed methodology in the following ways:

1. The singular spectrum analysis of sEMG signal
2. The testosterone pattern based local graph structure for feature extraction
3. Statistical features and their significance with respect to the EMG signals

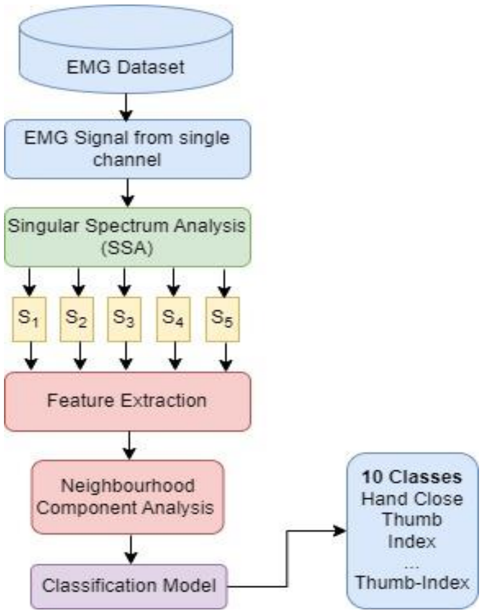

Figure 2.1 Outline of the methodology followed in this work

2.2 Singular Spectrum Analysis

Singular Spectrum Analysis (SSA) is a data analysis technique that involves decomposing a time series into a set of components called Singular Spectrum Components (SSCs). These components represent different patterns or trends present in the data and can be used for various purposes such as noise reduction, signal filtering, and forecasting [23].

The mathematical framework of Singular Spectrum Analysis (SSA) for this paper involves the following steps:

1. Embedding the time series: The time series was embedded into a trajectory matrix by concatenating successive lagged vectors of the time series. Window length, K determines the number of lags [23].

   Given a time series $X = [x_1, x_2, \dots, x_n]$, a trajectory matrix H of dimension $(N - K + 1) \times K$, where N is the length of the time series. The elements of H are given by:

   $$H(i,j) = X(i + j - 1) \tag{2.1}$$

   Where, $i = 1,2, \dots, N - K + 1$ and $j = 1,2, \dots, K$

   This forms a Hankel matrix, which is a special type of Toeplitz matrix

2. Decomposing the trajectory matrix: The trajectory matrix is decomposed using Singular Value Decomposition (SVD) [23].

   $$H = \sum_{i=1}^{L} H_i = \sum_{i=1}^{L} \sqrt{\lambda_i} v_i p_i^T \tag{2.2}$$

   Here H_i denotes the elementary matrix, λ_i is for the eigenvalues in decreasing order of magnitude and v_i are the corresponding eigenvectors of the covariance matrix defined by $C = MM^T$, and $p_i = M^T v_i / \sqrt{\lambda_i}$ are termed as the principal components.

3. Forming the singular spectrum: Singular values are used to form the singular spectrum, which represents the amount of variability in the data captured by each singular value. The singular values are typically plotted in descending order and shown in Figure 2.2

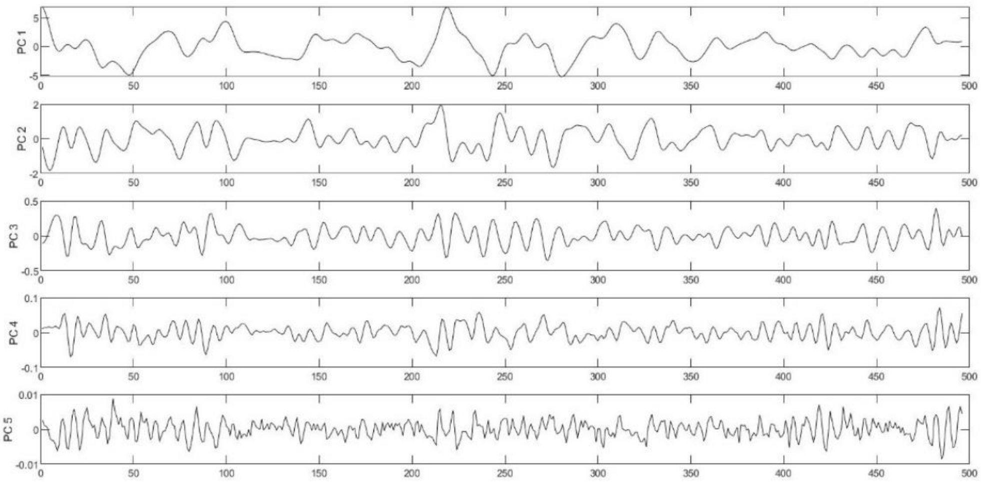

Figure 2.2 sEMG signal decomposed into 5 bands using SSA

2.3 Local Graph Structure based on Testosterone Pattern

The graph-based feature extraction method in this paper, a local graph structure (LGS) has been proposed which uses the chemical depiction of the testosterone hormone as its reference. The LGS is used in the form of a directed graph in this paper and is shown in Figure 2.3

It was found in literature that LGSs can generate discriminative features, they are low in execution time and their time complexity is also low. The directed graph implemented in this paper has a total of 24 edges which are shown in the figure. The start and end point of each arrow represent the value that will be used as input to the signum function defined by

$$f(a,b) = \begin{cases} 0, & c - d < 0 \\ 1, & c - d \geq 0 \end{cases} \tag{2.3}$$

The testosterone pattern has been overlayed on an example matrix, let it be K, to show the traversal of the directed graph.

The steps followed to generate features from an EMG signal using a testosterone pattern have been given below:

1. The signal is divided into blocks of size $b_i = 54$
2. The vector of length 54 is transformed to a matrix of size 6×9
3. In testosterone figure 3, 24 directed edges can be seen, the 24 bits from these are extracted using the signum function. The value of indices with

respect to the matrix formed from a block b_i are given below.

$$group^1 = f\begin{pmatrix} B_i(6,1) & B_i(5,2) \\ B_i(5,2) & B_i(4,2) \\ B_i(4,2) & B_i(3,3) \\ B_i(3,3) & B_i(4,4) \\ B_i(4,4) & B_i(5,4) \\ B_i(5,4) & B_i(6,3) \\ B_i(6,3) & B_i(5,2) \\ B_i(4,4) & B_i(3,4) \end{pmatrix} \tag{2.4}$$

$$group^2 = f\begin{pmatrix} B_i(4,4) & B_i(3,5) \\ B_i(3,5) & B_i(4,6) \\ B_i(4,6) & B_i(5,6) \\ B_i(5,6) & B_i(6,5) \\ B_i(6,5) & B_i(5,4) \\ B_i(3,5) & B_i(2,5) \\ B_i(2,5) & B_i(1,6) \\ B_i(1,6) & B_i(2,7) \end{pmatrix} \tag{2.5}$$

$$group^3 = f\begin{pmatrix} B_i(2,7) & B_i(3,7) \\ B_i(3,7) & B_i(4,6) \\ B_i(2,7) & B_i(1,7) \\ B_i(2,7) & B_i(1,8) \\ B_i(1,8) & B_i(2,9) \\ B_i(2,9) & B_i(3,8) \\ B_i(3,8) & B_i(3,7) \\ B_i(1,8) & B_i(1,9) \end{pmatrix} \tag{2.6}$$

These would extract 3 groups of 8 bits each, which are converted to decimal using binary to decimal conversion and added to a new vector. This would generate 3 feature maps whose length will be equal to each other, and will depend on the signal being processed. This process will be iterated for all blocks of size 54

4. The histogram of these three feature maps will be calculated with bin size 1 hence making length of each histogram extracted as $256 (= 2^8)$
5. The feature vector extracted from this method will always be of the same size because, the three histograms will be concatenated to make the feature vector as $768\ (= 256 \times 3)$

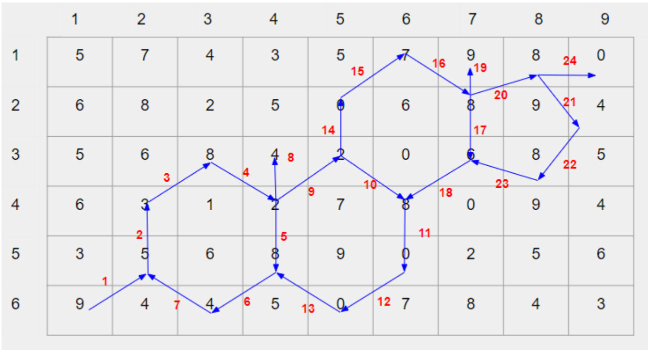

Figure 2.3 Directed graph formed using the chemical structure of Testosterone hormone (in blue) overlaid on an example matrix formed using signal of block size 54, the red numbers indicate the edge numbers

2.4 Statistical Features

Features for the analysis of EMG signals are generally of three groups, namely time domain, frequency domain, and time-scale representation or time-frequency. In this project, only the time domain features have been utilized for classification. There are a total of twenty-six time-domain conventional features out of which only eighteen have been extracted in this project. Five new features [31] were also calculated for this project. The definitions of these signals in the context of EMG signals have been listed below along with their mathematical formulations:

1. Waveform Length (WL): It is a measure of the complexity of the EMG signal. Its formula in words can be defined as the cumulative length of the EMG waveform over the time segment [33]. Mathematically:

$$\mathrm{WL} = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{2.7}$$

2. Mean Absolute Value (MAV): The most frequently used feature. It is defined as the mean of all the absolute values of all points of the EMG signal [33,34].

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{2.8}$$

3. Mean Absolute Value Slope (MAVSLP): it is a modified version of the MAV feature to establish multiple features [35]. Differences between MAVs of the adjacent segments are determined. The equation can be

defined as

$$MAVSLP = MAV_{k+1} - MAV_k; \quad (2.9)$$

4. Willison Amplitude (WAMP): Willison amplitude measures the frequency information of the EMG signal, similar to ZC. It integrates the times the difference between two segments in EMG signal exceed a given threshold [34]. This value is then representative of the firing of motor unit action potentials (MUAP) and also the muscle contraction force. The definition is as follows

$$WAMP = \sum_{i=1}^{N-1} |f(|x_n - x_{n+1}|)|$$
$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases} \quad (2.10)$$

5. Auto-Regressive Model (AR): It is a prediction model defining each sample of the EMG signal as a linear combination of the previous samples (x_{i-p}) plus a white noise error term named w_i. In the classification of the EMG signal, the coefficients of the AR model a_p have been used as feature vectors [36]. Here, p is the order of the temporal moment, in this study the order is taken as $p = 4$. The model is expressed in the following form:

$$x_i = \sum_{p=1}^{p} a_p x_{i-p} + w_i \quad (2.11)$$

6. Integrated EMG (IEMG): It is normally used as an onset detection index in EMG [31] non-pattern recognition and in clinical application. It is related to the EMG signal sequence firing point. Definition of IEMG feature is defined as the summation of absolute values of the EMG signal amplitude, which can be expressed as

$$IEMG = \sum_{i=1}^{N} |x_i| \quad (2.12)$$

7. Modified Mean Absolute Value of Type 1 (MAV1) [38]: Modified mean absolute value Type 1 (MAV1) is an extension of the MAV feature. The weighted window function w_i is assigned to the equation for improving the robustness of the MAV feature. It is calculated by

$$MAV1 = \frac{1}{N}\sum_{i=1}^{N} w_i|x_i| \tag{2.13}$$

$$w_i = \begin{cases} 1, & if\ 0.25N \le i \le 0.75N \\ 0.5, & otherwise \end{cases} \tag{2.14}$$

8. Modified Mean Absolute Value of Type 2 (MAV2): Modified mean absolute value type 2 (MAV2) is an expansion of the MAV feature which is similar to the MAV1 [38]. However, the weighted window function w_i that is assigned into the equation is a continuous function. It improves the smoothness of the weighted function. The equation is defined as

$$MAV2 = \frac{1}{N}\sum_{i=1}^{N} w_i|x_i|$$

$$w_i = \begin{cases} 1, & if\ 0.25N \le i \le 0.75N \\ \frac{4i}{N}, & elseif\ i < 0.25N \\ \frac{4(i-N)}{N}, & otherwise \end{cases} \tag{2.15}$$

9. Simple Square Integral (SSI): Simple square integral (SSI) as the name suggests, integrates the squared values of the EMG signal points and uses the scalar value as a feature [39]. The feature can also be called as an energy index, which is expressed as:

$$SSI = \sum_{i=1}^{N} x_i^2 \tag{2.16}$$

10. Variance of EMG (VAR): VAR is another power index. Generally, variance is defined as an average of square values of the deviation of that variable [34]; however, the mean value of the EMG signal is close to zero ($\sim 10^{-10}$). Hence, the variance of the EMG signal can also be defined as

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2 \tag{2.17}$$

11. Temporal Moment: Temporal moment is a statistical analysis that was proposed in the study of [40] to be used in the control of a prosthetic arm. Normally, the absolute value was taken to greatly reduce the within-class separation for the odd-moment case. The first moment and the second moment are similar to the MAV and VAR features, respectively. In this project, only the third moment has been extracted as a feature, which is defined by:

$$TM3 = \frac{1}{N}\sum_{i=1}^{N} x_i^3 \tag{2.18}$$

12. Root Mean Square (RMS): Root mean square (RMS) is another popular feature in the analysis of the EMG signal. Following the name, is the square root of the mean of squared values of EMG signal amplitude. It is representative of the constant force and the non-fatiguing contraction [34]. The mathematical definition of the RMS feature can be expressed as

$$RMS = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^2\right)^{\frac{1}{2}} \tag{2.19}$$

13. V-Order (V): It is a non-linear detector that is an estimator of the muscle contraction force m_i. It is defined from a functional mathematical model of the EMG signal generation [34] given by

$$x_i = \gamma m_i^{\alpha} n_i \tag{2.20}$$

Here, γ and α are constants, and n_i is the class of the ergodic Gaussian processes. The feature V is defined as

$$V = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^{v}\right)^{\frac{1}{v}} \tag{2.21}$$

14. Log Detector (LOG): This also provides an estimated value for the muscle contraction force [34]. It is defined as

$$LOG = e^{\frac{1}{N}\sum_{i=1}^{N}\log(|x_i|)} \tag{2.23}$$

15. Average Amplitude Change (AAC): It is similar to the WL feature with an addition of averaging the wavelength [41]. Defined as:

$$AAC = \frac{1}{N}\sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{2.24}$$

16. Difference Absolute Standard Deviation Value (DASDV): It is the standard deviation value of the wavelength [41]and looks similar to the standard deviation formula

$$DASDV = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(x(i+1) - x_i)^2} \tag{2.25}$$

17. Zero crossing (ZC): Gives the frequency information of the EMG signal that is defined in the time domain. It is the number of times that amplitude values of the EMG signal cross zero amplitude level [33]. It can be used as a noise filter by using a threshold to avoid low voltage fluctuations and background noises. The calculation is defined as:

$$ZC = \sum_{i=1}^{N-1} sgn(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geq threshold$$

$$sgn(x) = \begin{cases} 1, & if x \geq threshold \\ 0, & otherwise \end{cases} \quad (2.26)$$

18. Myopulse Percentage (MYOP): Myopulse percentage rate (MYOP) is an average value of myopulse output which is defined as one when an absolute value of the EMG signal exceeds a pre-defined threshold value [42]. It can be calculated as:

$$MYOP = \frac{1}{N}\sum_{i=1}^{N} |f(x_i)|$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases} \quad (2.27)$$

19. Slope Sign Change (SSC): Slope sign change (SSC) is related to ZC, MYOP, and WAMP features. It is another method to represent the frequency information of the EMG signal. It is the number of times that the slope of the EMG signal changes sign [33]. The number of changes between the positive and negative slopes among three sequential segments is performed with the threshold function for avoiding background noise in the EMG signal. This can be mathematically expressed as:

$$SSC = \sum_{i=2}^{N-1} f\left(x_i - x_{(i-1)}\right) \times (x_i - x_{i+1})$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases} \quad (2.28)$$

20. Integrated Absolute of Second Derivative (IASD): it behaves as a filter for noise reduction by capturing the relative changes in the second derivative of the signal [31]

$$IASD = \sum_{n=1}^{N-2} |x'[n+1] - x'[n]| \quad (2.29)$$

Here, $x'[n] = x[n+1] - x[n]$

21. Integrated Absolute of Third Derivative (IATD): Similar to IASD this feature also filters out noise and captures the relative changes of the third derivative [31]

$$IATD = \sum_{n=1}^{N-3} |x''[n+1] - x''[n]| \quad (2.30)$$

Here, $x''[n] = x'[n+1] - x'[n]$

22. Integrated Exponential of Absolute Values (IEAV): This function

amplifies the samples that are large and suppresses the samples that are small for all positive and negative samples [31].

$$IEAV = \sum_{n=1}^{N} \exp\left(|x[n]|\right) \tag{2.31}$$

23. Integrated Absolute Log Values (IALV): This function suppresses the samples that are large and amplifies the small ones. Here T is the threshold that must be empirically tuned [31]. In this project, the value of the threshold is set to 2

$$IALV = \sum_{n=1}^{N} |\log\left(x[n] + T\right)| \tag{2.32}$$

24. Integrated Exponential (IE): This feature is similar to IEAV but it also distinguishes between positive and negative samples [31], i.e. it amplifies positive samples and suppresses the negative ones.

$$IE = \sum_{n=1}^{N} \exp\left(x[n]\right) \tag{2.34}$$

The table provided below also presents a concise compilation of the features, offering a comprehensive overview of their attributes, formulae, abbreviation, and short description. These statistical features were utilized in the formation of the feature matrix.

Table 2.1 List of features extracted in this work, their abbreviations, formula and brief description

Statistical Metric	**Abbrev.**	**Formula**	**Short Description**
Waveform Length [21]	WL	$\sum_{i=1}^{N-1} \|x_{i+1} - x_i\|$	Measure of complexity of EMG signal
Mean Absolute Value [22]	MAV	$\frac{1}{N}\sum_{i=1}^{N} \|x_i\|$	Mean of all points of EMG signal
Mean Absolute Value Slope [23]	MAVSLP	$MAV_{k+1} - MAV_k$	Modified MAV, differences between adjacent segments
Willison Amplitude [22]	WAMP	$\sum_{i=1}^{N-1} \|f(\|x_n - x_{n+1}\|)\|$	Measures the frequency information
Integrated EMG [18]	IEMG	$\sum_{i=1}^{N} \|x_i\|$	Onset detection index in EMG

Simple Square Integral [24]	SSI	$\sum_{i=1}^{N} x_i^2$	Energy index
Variance of EMG [22]	VAR	$\frac{1}{N-1}\sum_{i=1}^{N} x_i^2$	Power index
Temporal Moment [25]	TM3	$\frac{1}{N}\sum_{i=1}^{N} x_i^3$	Statistical analysis tool
V-order [22]	V	$\left(\frac{1}{N}\sum_{i=1}^{N} x_i^v\right)^{\frac{1}{v}}$	Estimator of the muscle contraction force
Log Detector [22]	LOG	$e^{\frac{1}{N}\sum_{i=1}^{N}\log(\lvert x_i\rvert)}$	Gives measure of muscle contraction
Average Amplitude Change [26]	AAC	$\frac{1}{N}\sum_{i=1}^{N-1} \lvert x_{i+1} - x_i\rvert$	Similar to WL feature
Difference Absolute Standard Deviation [26]	DASDV	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(x(i+1) -}$	Standard deviation value of wavelength
Zero Crossing [21]	ZC	$\sum_{i=1}^{N-1} sgn(x_i \times x_{i+1})$ $\cap \lvert x_i - x_{i+1}\rvert$	Gives frequency information of EMG signal
Myopulse Percentage [27]	MYOP	$\frac{1}{N}\sum_{i=1}^{N} \lvert f(x_i)\rvert$	Average value of the myopulse output
Slope Sign Change [21]	SSC	$\sum_{n=1}^{N} f(x_i$ $- x_{i-1}) \times (x_i$ $- x_{i+1})$	Represents the frequency information
Integrated Absolute of Second Derivative [18]	IASD	$\sum_{n=1}^{N-2} \lvert x'[n+1]$ $- x'[n]\rvert$	Acts as a noise reduction filter
Integrated Absolute of Third Derivative [18]	IATD	$\sum_{n=1}^{N-3} \lvert x''[n+1]$ $- x''[n]\rvert$	Also acts a filter for noise reduction
Integrated Exponential of	IEAV	$\sum_{n=1}^{N} \exp\,(\lvert x[n]\rvert)$	Amplifies the samples that are large and suppresses the samples that are

Absolute Values [18]			small
Integrated Absolute Log Values [18]	IALV	$\sum_{n=1}^{N} \lvert\log(x[n]+T)\rvert$	Suppresses the samples that are large and amplifies the small ones
Integrated Exponential [18]	IE	$\sum_{n=1}^{N} \exp(x[n])$	Similar to IEAV but differentiates

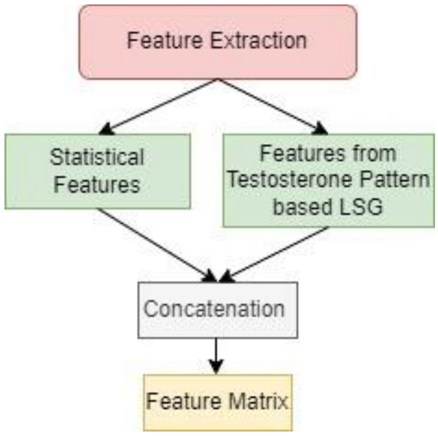

Figure 2.4 Formation of feature matrix using the methods described

The figure shows the flow of the formation of feature matrix using a combination of two feature sets. The total number of features extracted using these methods is calculated as follows:

1. The 1000-point signal was subjected to singular spectrum analysis, here the embedding dimension of 5 was selected empirically. The length of feature matrix generated using SSA and statistical features is described as follows, each signal was decomposed into 5 sub-bands which were windowed into 20 snippets. These 6 signals $(= 5\ sub-bands + 1\ original\ signal)$ were used for extraction of 21 statistical measures. Absolute values of the signal were also considered for statistical feature extraction, hence making the length of the feature matrix $5040\ (= 6 \times 20 \times 21 \times 2)$
2. The local graph structure using testosterone pattern will give a feature vector of length 768 as described in the section above

Total number of features extracted using the methods described is 5808

2.5 Conclusion

In conclusion, this thesis chapter focused on feature extraction, which is a critical step in the process of analyzing and understanding complex data. The two methods used for feature extraction in this thesis were discussed in detail. The resulting matrix from this methodology was dimensionally reduced which will be explained in the next chapter.

Feature extraction techniques provide a powerful means to extract meaningful information from complex data, enabling improved decision-making, pattern recognition, and knowledge discovery in diverse domains.

CHAPTER 3: PROPOSED METHODOLOGY FOR CLASSIFICATION

3.1 Introduction

Neighbourhood Component Analysis (NCA) and Extreme Learning Machine (ELM). two promising methodologies in the realm of machine learning, are introduced in this chapter. Using local neighbourhood relationships in the data, NCA focuses on developing a distance measure to optimise classification or regression models. ELM, on the other hand, uses random feature generation and straightforward learning models to overcome issues with massive data and real-time learning.

The goal of NCA is to find a distance measure that increases the prediction accuracy or improves the separation of data points from distinct groups. It has applications in fields such as document categorization, picture recognition, and recommendation systems. NCA offers important insights into the underlying structure of the data by learning a precise distance metric.

3.2 Neighborhood Component Analysis (NCA)

The machine learning technique known as Neighbourhood Component Analysis (NCA) is categorised as metric learning. In this technique, learning a distance metric or similarity function between data points is performed using metric learning. To enhance the precision of the closest neighbor classifiers, NCA focuses primarily on learning a distance metric that is customized to the job of classification.

The goal of metric learning algorithms is to discover a similarity or distance metric that accurately reflects the underlying structure of data. Traditional distance measures that regard all dimensions equally, such as the Euclidean distance or cosine similarity, might not be appropriate for all jobs. The NCA is a metric learning algorithm that attempts to learn a better metric that emphasizes the important dimensions of a particular activity.

For classification nearest neighbour classifier is used in this technique. Given a new data point, it classifies it based on the class label of its nearest neighbors in the training set. However, the performance of this classifier heavily relies on the choice of the

distance metric. NCA aims to improve the accuracy of the nearest neighbor classifier by learning an appropriate metric from the data.
The motivation behind NCA is to address two key challenges in this problem, (1) high number of features, so it acts as and effective way of identifying the most informative dimensions in the data in classification and (2) classification consistency, it is what aims to ensure that nearby points in the input space are assigned the same label. NCA addresses these challenges by learning a metric that optimizes a specific objective function.
Objective Function: NCA formulates the learning problem as an optimization task, where the goal is to maximize the expected accuracy of the nearest neighbor classifier. The objective function consists of two components: a neighborhood assignment probability and a classification probability. The neighborhood assignment probability measures the likelihood of a point being assigned to its correct class based on the distances to its neighbors. The classification probability quantifies the likelihood of assigning the correct class label to a point based on the distances to all other points in the dataset.

Optimization: To optimize the objective function, NCA employs a stochastic optimization technique called stochastic gradient descent (SGD). SGD iteratively updates the parameters of the distance metric based on small subsets of training data. The updates are driven by the gradients of the objective function with respect to the parameters. By iteratively adjusting the metric, NCA aims to find a distance function that maximizes the classification accuracy.

The NCA algorithm can be summarized in the following steps:

a. Initialize the distance metric parameters.
b. Select a training sample.
c. Compute the gradients of the objective function with respect to the metric parameters.
d. Update the metric parameters using SGD.
e. Repeat steps b-d for a fixed number of iterations or until convergence.
f. Use the learned distance metric to classify new data points.

Evaluation and Applications:

To evaluate the performance of NCA, various metrics such as classification accuracy, precision, recall, and F1 score can be used. NCA has been applied to various domains, including image classification, face recognition, document retrieval, and recommendation systems. Its ability to learn task-specific distance metrics makes it useful in scenarios where the underlying data structure is complex and conventional metrics may not be optimal.

Some advantages of NCA are, its ability to handle high-dimensional data, its interpretability, and its potential for feature selection. However, it also has some limitations. NCA requires labeled training data, which may not always be available.

To summarize, Neighborhood Component Analysis (NCA) is a metric learning algorithm that aims to improve the accuracy of nearest neighbor classifiers by learning a distance metric tailored to the task of classification. By optimizing an objective function using stochastic gradient descent, NCA finds a metric that emphasizes relevant dimensions and promotes classification consistency. NCA has been successfully applied to various domains and offers advantages in interpretability and feature selection. However, it also has limitations related to the availability of labeled data and computational complexity.

3.3 Extreme Learning Machine (ELM)

Extreme Learning Machine (ELM) is a machine learning algorithm that belongs to the family of feedforward neural networks. It was proposed as an efficient alternative to traditional neural networks for solving regression and classification problems.

The key idea behind the Extreme Learning Machine is to randomly initialize the input layer weights and calculate the output weights analytically in a single learning step. This random initialization makes ELM faster and simpler compared to other gradient-based learning methods, such as backpropagation.

Here are the main steps involved in the ELM algorithm:

In an ELM network, as shown in Figure, if x_j is input and o_j is output, the mathematical expression of the output of a network with a single hidden layer and the number of nodes in the hidden layer as L is defined as [30]:

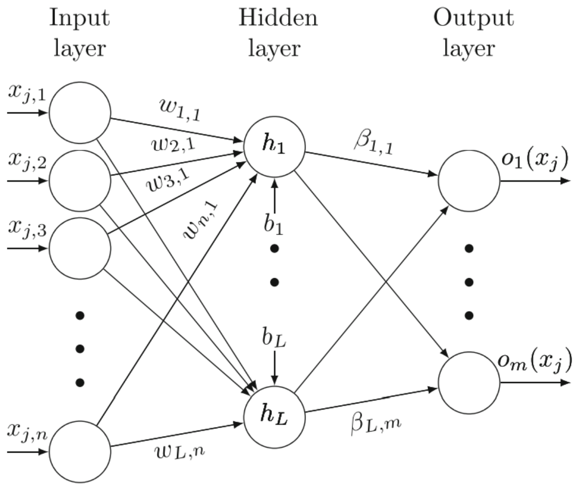

Figure 3.1 Architecture of an Extreme Learning Machine [32] with L neurons in the hidden layer

Input Layer: ELM starts by defining the input layer, which consists of a set of input nodes equal to the dimensionality of the input data.

Random Weight Assignment: Random values are assigned to the input layer weights. These weights serve as the parameters that connect the input nodes to the hidden nodes.

Activation Function: An activation function is applied to the weighted sum of inputs for each hidden node. The most commonly used activation function is the sigmoid function, but other activation functions like radial basis functions (RBF) can also be used. In this thesis, the radial basis function has been used as the activation function

Output Weights Calculation: The output weights are calculated analytically using a linear least squares approach. The hidden layer outputs and the corresponding target outputs are used to solve this system of linear equations.

$$o_j = \sum_{n=1}^{L} \beta_n h(w_n x_j + b_n), \tag{3.1}$$

Here, $k = 1,2, \dots N$, w_i are the weights between input and hidden layer and b_i are the bias values affecting the input. $h(.)$ Is the activation function. The weights between the hidden and output layer represented by β are determined analytically as explained in [31].

Training and Testing: The trained ELM model can then be used for prediction by applying the activation function and the output weights to the input data. The output is obtained by multiplying the hidden layer outputs with the calculated output weights.

The major advantages of Extreme Learning Machines are their computational efficiency and fast learning speed. They can handle large datasets and achieve good generalization performance. ELM also avoids the need for fine-tuning or iterative training processes typically associated with gradient-based methods.

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Introduction

This chapter describes the application of the methods described in former chapters on a sEMG dataset for multiple classes. It then discusses the validation of the methodology adopted for the problem

4.1 Dataset Description

The dataset used in this project was taken from [33]. It contains data recorded from eight healthy subjects, six males and two females between the ages of 20 to 35. The data was recorded using two electrodes as shown in Figure 1. The participants were asked to perform 10 finger movements, that were grouped in two i.e., Individual finger movements and combined finger movements, these two have been considered as the two classes in this study as seen in Figure 2. Each gesture was performed six times and recorded for five seconds each. Sampling frequency of the data is 4000Hz, the signals recorded were filtered with a bandpass filter (20 and 450 Hz).

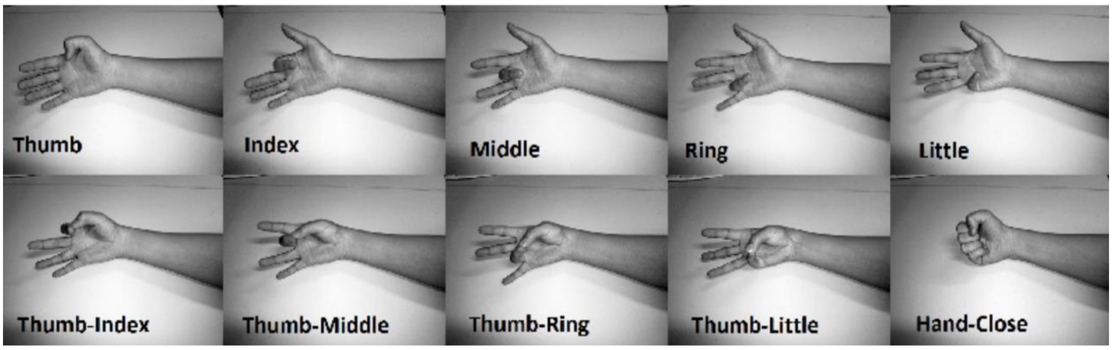

Figure 4.1 Images for the 10 classes considered in this study

Parameters Selection

The table describes the parameters selected for statistical feature extraction, the values for these were selected to be the conventional ones.

Table 4.1 Features and their specified parameters

Feature	Parameter
Willison Amplitude (WAMP)	$threshold = 0.1$
Autoregressive Model (AR)	$p = 4$, temporal moment
Temporal Moment	3
V Order (V)	3
Zero Crossing (ZC)	$threshold = 0.1$
Myopulse Percentage Rate (MYOP)	$threshold = 0.016$
Slope Sign Change (SSC)	$threshold = 0.01$

In extreme learning machine, the number of hidden neurons is an important factor to be considered for the effectiveness of the model. The figure shows the trend between hidden layer neurons and the accuracy. It was observed that with the increase in the number of neurons, the accuracy is improving correspondingly, but the increase in amplitude is very subtle and the complexity of computing nodes is getting higher. Therefore, number of neurons were set to 250.

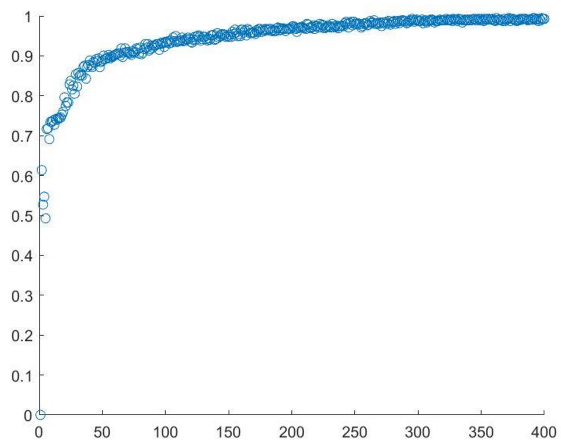

Figure 4.2 Number of neurons in hidden layer vs accuracy

Classification Results

Table 1 shows the investigative results of the comparison of performance using two distinct methods when applied individually and in combination. It was observed that the integration of SSA and LGS features yielded superior results compared to the application of either method alone. The results obtained demonstrate clearly that utilization of both methods gave improved outcomes.

Table 4.2 Accuracies achieved using the discussed feature extraction techniques

Subject	SSA features + LGS	LGS features	SSA features
Subject 1	94.04	79.0	75.4
Subject 2	91.16	70.3	67.3
Subject 4	91.34	72.5	70.2
Subject 5	95.85	81.1	**78.4**
Subject 6	95.85	76.8	69.4
Subject 8	95.49	79.9	76.6
Subject 9	**97.21**	**81.4**	73.0
Subject 10	92.96	71.4	68.7

4.2 Advantages

The proposed method attained over 95% accuracies for a classification problem with 10 classes. It used a combination of SSA features and Local Graph Structure of Testosterone based features and can successfully discriminate between different gestures. The sEMG signal acquisition technique is non intrusive and can be used in various applications like HCI, Prosthetics etc.

4.3 Limitations

The proposed method is user dependent and not tested for subject independent application of the technique, it is also susceptible to placement and calibration of the electrodes.

CHAPTER 5: CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In this project, a gesture recognition problem has been approached based on the extreme learning machine. The model could discriminate efficiently between ten classes and achieved more than 97% accuracy. For making the feature vector space, the EMG signals were windowed and decomposed using SSA. More than 5800 features were extracted using statistical metrics and Local Graph Structure of the testosterone chemical compound. These were selected using NCA and a total of 270 features were selected to be used in the classification model. The results of the project confirmed that the presented method is correct and effective.

5.2 Scope for future work

In future work, this method will be extended for recognition of more hand and finger gestures. Also, the problem of domain shifts while recording will be considered in further research, and the attempts to make gesture recognition model user independent will be made.

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RESEARCH CONTRIBUTION

1. Tanishqa Tyagi, Dr. Anukul Pandey, Mr. Kaustubh Ranjan Singh, "A testosterone pattern-based sEMG signal classification method using Singular Spectrum Analysis", International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES 2023)

2. Tanishqa Tyagi, Dr. Anukul Pandey, Mr. Kaustubh Ranjan Singh, "EMG-based Gesture Recognition using Extreme Learning Machine", 3nd International Conference on Artificial Intelligence and Signal Processing (AISP 2023)