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NEW FRONTIERS IN EMG SIGNAL ANALYSIS FOR NEUROMUSCULAR APPLICATIONS

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ABSTRACT

The electromyography (EMG) signal is a type of biomedical signal that captures the electrical currents produced by muscles during contraction, reflecting neuromuscular activity. Muscle actions, such as contraction and relaxation, are always regulated by the nervous system. EMG records the electrical activity or muscle response when the muscle is stimulated by a nerve. The source of this electrical activity is the muscle membrane potential. The biosignal collected from a muscle or its fibers represents the anatomical and physiological characteristics of the motor system. Advanced and effective methods for detecting EMG signals are becoming increasingly important in biomedical engineering. Electromyography (EMG) signals capture electrical activity from muscles during contraction, reflecting neuromuscular activity regulated by the nervous system. These signals are essential for diagnosing and understanding various motor-related functions. Advanced methods for detecting and analyzing EMG signals have become crucial in biomedical engineering, aiding in accurate diagnostics of neuromuscular disorders. Additionally, EMG provides valuable insights into the physiological state of muscles and motor neurons, contributing to clinical research and rehabilitation. The continuous improvement of EMG techniques ensures better application in medical diagnostics and treatment.

KeyPoints: *EMG Signal, Neuromuscular Activity, Muscle Membrane Potential, Nervous System Control, Electromyography (EMG), Bio-signal Detection, Biomedical Engineering, Advanced Detection Methods*

1. INTRODUCTION

Electromyography (EMG) signals capture neuromuscular activity by detecting the electrical currents generated during muscle contraction. The voltage changes between electrodes are detected, amplified, and processed by a computer program that visually displays the voltage potential recordings. When the action potentials of motor neurons reach the depolarization threshold, the associated muscle fibers contract. This depolarization creates an electromagnetic field, which is recorded as voltage [1]. The rapid advancement in smart device industries and research is heavily focused on control systems that naturally reflect human intent. Many studies aim to develop device control systems based on human intention. One promising approach is gesture recognition through EMG signals [2]. EMG is also used to detect muscle movements, and since brain activity regulates muscle function in response to emotional states, EMG signals have been explored for emotion recognition as well [3].

In recent years, deep learning techniques have been extensively applied to EMG recognition. Numerous studies have utilized deep neural networks for processing EMG signals, particularly in human-machine interface (HMI) systems. Despite this, most research focuses on offline performance using diverse datasets. The real-time application in physical systems, such as prosthetic hand control and exoskeleton robots, requires more attention [4]. Hand gestures, being a natural and versatile form of nonverbal communication, enhance human-machine interfaces. Hand Gesture Recognition (HGR) aims to understand and interpret the intention behind hand gestures and has been applied in areas like robotics, sign language interpretation, IoT, and medical applications [5]. The raw EMG signal obtained from nerve cells is filtered to extract meaningful data without interference from mechanical disturbances, electronic noise, or ambient disruptions. The extracted data is classified using feature extraction techniques. An EMG evaluation system consists of four main phases: (1) EMG data acquisition, (2) EMG data processing (segmentation and feature extraction), (3) classification, and (4) control [6]. The characteristics of the EMG signal envelope are essential for understanding body movements but can vary significantly between individuals. This envelope may contain various artifacts, such as electrocardiographic interference, motion artifacts, and power line noise. Therefore, specialized methods are needed for more efficient EMG data processing, allowing for optimal feature extraction [7].

Muscle-Computer Interface (MCI) is a novel form of human-machine interaction (HMI) that decodes human intentions through electromyography (EMG). It has been employed in various applications such as hand gesture classification, facial gesture recognition, myoelectric prosthetics, and muscle fatigue interfaces [8]. Currently, pattern recognition techniques are widely utilized for EMG data analysis. The typical process involves extracting signal features corresponding to different upper limb movements from multiple channels. After preprocessing and noise removal, the desired movement is identified by a pattern classifier and transformed into a control command. Various methods are used for EMG analysis, including linear discriminant analysis, support vector machines, and deep learning models like random forests. Lawhem Vetal employed a nonlinear classifier to distinguish four wrist movements: wrist flexion, wrist extension, wrist internal rotation, and wrist external rotation [9]. Over the years, EMG classification accuracy has consistently improved, with state-of-the-art classifiers achieving gesture recognition precision exceeding 95%. However, most of these high-performance classifiers are computationally intensive, relying on complex learning models like Deep Neural Networks (DNNs) or Convolutional Neural Networks (CNNs). Due to this complexity, integrating these classifiers into real-time or embedded systems is costly and demands significant computational resources [10].

There are several techniques for identifying patterns in EMG signals, including time domain, frequency domain, and combined time-frequency domain methods. In time-domain methods, various techniques such as Slope Sign Changes (SSC), Mean Absolute Value (MAV), Wave Length (WL), Root Mean Square (RMS), and Zero Crossing (ZC) are commonly used to recognize patterns. Frequency-domain methods, on the other hand, include techniques like Mean Power Frequency (MPF) and Fast Fourier Transforms (FFT), along with octave bands. For a combination of time and frequency domains, methods like Wavelet and Wavelet Packet Transforms (WPT) are employed. These approaches are effective in detecting muscle signals responsible for hand movements [11].

Electromyography (EMG) has been extensively used in engineering because it reflects muscle movement responses. The signal strength of EMG varies based on muscle position and movement and is measured using electrodes. The typical EMG signal amplitude is around ±500mV, and the signal frequency usually ranges from 6 to 500 Hz, with the most effective frequency found between 20 and 150 Hz [12]. Feature extraction is crucial for EMG signal analysis and classification, as it enhances the speed and accuracy of classifiers. Time-domain features are computed as a function of time and are the most commonly used in real-time EMG hand movement recognition due to their simplicity in calculation. These features are often used to detect muscle contraction, action, and onset [13]. In order to improve wrist gesture classification accuracy, it is generally necessary to increase the number of sensors to capture more features. However, using multiple channels of EMG signals requires time to place several surface electrodes. To address this, a wearable EMG sensor system has been developed that can instantly place multiple electrodes on the forearm to capture EMG signals, exploring its effectiveness in wrist gesture classification [14].

Despite the advances in EMG pattern recognition-based control, the performance in addressing practical issues in myoelectric control remains unsatisfactory. These issues, which have been widely researched, include long-term variations in EMG signal characteristics, changes in muscle contraction effort, limb position shifts, and the non-stationary nature of signals [15]. Spastic diplegia, the most common form of cerebral palsy in children, results in symmetric impairment of the lower limbs, leading to difficulties with motor control, spasticity, and balance. Evaluating lower limb dysfunction in children with cerebral palsy using EMG signals is a complex task. This study proposed methods for processing EMG signals in the frequency domain for spastic diplegia patients [16].

There are various types of artificial neural network (ANN) algorithms, each with its own set of advantages and limitations. A shared challenge across all types of ANNs is that the complexity of the network structure increases with the number of input dimensions. In this research, the neural network was trained using a supervised learning approach [17]. Typically, users must perform repetitive, non-meaningful actions to switch control between different degrees of freedom (DOF), and the sequence of switching often follows a preset order, causing inconvenience (You, 2011). Compared to the EMG threshold-based control method, control based on the pattern recognition of EMG signals is more intuitive and user-friendly. In recent years, with advancements in pattern recognition, researchers from various countries have proposed different classifiers for EMG pattern recognition, including linear discriminant analysis, Gaussian mixture models, hidden Markov models, support vector machines, and neural networks [18].

The classification performance can be enhanced by accounting for the stochastic properties of EMG signals. Chan and Englehart explored this probabilistic approach and highlighted the effectiveness of Gaussian mixture models (GMMs) for EMG pattern classification by using GMMs to model the feature vectors of EMG signals [19]. To improve the quality of life for individuals with disabilities or the elderly, researchers emphasize the importance of creating simple and natural human-machine control interfaces. EMG-based hand gesture recognition can contribute to developing efficient interfaces, improving the quality of life for these individuals [20].

In recent years, artificial neural networks (ANNs) have gained popularity for classifying biosignals. A multilayer perceptron (MLP) can be used to classify neuro-muscular diseases by processing raw EMG data with features such as autoregressive (AR) modeling, root mean square (RMS), waveform length (WL), slope sign change (SSC), mean absolute value (MAV), and zero crossing (ZC). A classification model that employs ANN and wavelet transform to recognize three distinct hand movements is discussed in [21]. A fuzzy inference system serves as a valuable tool for analyzing the activity of muscle fibers within a single motor unit, helping to develop a robust and repeatable pattern recognition algorithm. Fuzzy logic simulates human-like decision-making processes for more accurate recognition [22].

Potential changes in skeletal muscle activity are captured through specific recording methods that monitor muscle behavior during various physiological conditions. By analyzing bioelectrical activity from neuromuscular units, EMG can evaluate muscle functionality and assist in diagnosing neuromuscular disorders, distinguishing between myogenic and neurogenic pathologies [23].

There are two common approaches to recognizing hand gestures using EMG signals: one involves utilizing multiple sensors simultaneously, while the other relies on applying classification algorithms. The subsequent section provides a review of hand gesture recognition methods using EMG sensors [24]. The research aims to use the classification results to control an anthropomorphic robotic hand that replicates human movements in real-time, with the ultimate goal of developing human-robot interfaces that assist elderly individuals and people with disabilities in daily activities [25].

Damage to the hand, particularly the thumb, significantly impairs human functionality. One notable recent advancement in prosthetic hands is the PRODIGITS, developed by Touch Bionics in Scotland. This evolved into the iLimb Ultra Revolution, which features improvements such as lighter, more anatomically precise fingers, powered thumb rotation, enhanced dexterity with up to 24 grip patterns, and even Bluetooth connectivity [26]. The quality of rehabilitation plays a crucial role in the restoration of physical function, which is why effective rehabilitation techniques are constantly being researched and new technologies are being developed. For accurate measurement of deep muscle activity, invasive electrodes like wires or needles are commonly used. In this study, we aim to separate deep muscle EMG signals from surface muscle EMG signals using non-invasive surface electrodes only [27].

Various techniques have proven effective in recognizing or classifying EMG signals, including Bayesian systems, artificial neural networks (ANN), Markov models, and fuzzy logic [28]. Age-related muscle deterioration also plays a role in strength decline. In older individuals (aged 65-83), skeletal muscles have less contractile tissue (type-II) and more non-contractile tissue (type-I) compared to younger individuals (aged 26-44). Consequently, elderly individuals may experience decreased strength. Recent reviews indicate that type-I muscle fiber size does not change significantly with age, but type-II fibers experience selective atrophy. During voluntary muscle contraction, it's essential to account for motor unit remodeling due to aging. As a result, EMG signals from younger and older individuals differ significantly because of age-related pathological and motor unit changes [29].

With the rising number of neuromuscular patients, manual testing under all conditions becomes increasingly impractical. Therefore, there is a need for a computer-assisted expert system capable of analyzing and interpreting EMG signals. These signals are typically analyzed in either the time or frequency domain [30]. Over the past decades, there has been increasing interest in EMG-based control systems as they improve the quality of life for people with disabilities and the elderly. However, one of the most challenging tasks in developing myoelectric control interfaces is the accurate classification of EMG signals based on their specific applications [31]. Neuromuscular disorders affecting the spinal cord, nerves, or muscles are common in various populations, such as athletes, elderly homemakers, artisans working with handcrafts, manual laborers, and typists. Early detection of these disorders is critical for effective treatment [32].

EMG instruments record muscle activation signals, which are difficult to interpret without proper analysis [33]. Targeted muscle reinnervation (TMR) is an innovative neural interface for enhanced myoelectric prosthesis control. High-density (HD) surface EMG studies have shown that reinnervated muscles can provide significant neural control data through EMG pattern recognition (PR). However, the large number of EMG electrodes required poses a challenge for clinical implementation of TMR techniques [34]. While cepstrum coefficients have proven effective for speech recognition, their effectiveness for classifying EMG signals remains untested. Additionally, joint angles can be estimated using linear models that relate EMG signals to joint movement. Developing a natural and intuitive human-machine interface requires continuous estimation of joint angles, with both processes designed for real-time application.

2. LITERATURE REVIEW

In their 2022 systematic review, *Methods for Analysis of EMG Signals*, Medina Herak et al. discuss various algorithms and techniques for EMG signal analysis. Their work aims to assist researchers in selecting the most suitable method for analyzing EMG signals, which is crucial for neurological diagnostics, biomedical research, and controlling prosthetic arms. Future developments will include additional features and algorithms to enhance the process. Artificial Neural Networks (ANN) is highly relevant due to their ability to recognize complex patterns, while Feed forward Neural Networks (FFNN) excels in nonlinear modeling.

In the 2021 study *EMG Based Gesture Recognition Using Noise Removal* by Kimoon Kang et al., an EMG dataset was obtained from a database to analyze gesture recognition. From 17 available gestures, the authors selected 10 based on the signal-to-noise ratio (SNR) of the raw EMG data. Similarly, they used 5 channels after filtering out those with consistently low SNR to improve accuracy. The research focuses on comparing the effectiveness of their proposed feature calibration method with a non-calibrated approach. By refining the feature set through noise removal, the authors aimed to enhance gesture recognition performance, highlighting the significance of accurate SNR assessment in the selection of both gestures and channels for improved EMG-based signal processing and classification.

In the 2021 study *Analysis of EMG Based Emotion Recognition for Multiple People and Emotions* by Shraddha A. Mithbavkar et al., the researchers explored how emotional intensity varies among individuals, leading to overlapping features in different combinations. The study employed a Long Short-Term Memory (LSTM) classifier, which selected 373 hidden nodes and utilized the 'Adam' optimization algorithm to achieve high classification accuracy. To evaluate the classifier's performance with fewer emotions, they systematically removed one emotion at a time from the dataset. This process helped enhance classification accuracy by refining the model's ability to recognize the remaining emotions. The research highlights the complexity of emotion recognition due to individual variations and the importance of optimized algorithms for improving accuracy in EMG-based emotion detection.

In their 2021 review, *Deep Learning for EMG-based Human-Machine Interaction*, Dezhen Xiong et al. conclude that while deep learning methods for EMG-based systems are still in the early stages, there is significant potential for future development. The gap between current research and its application in commercial systems suggests promising opportunities ahead. Moving forward, the focus should not only be on improving the performance of these systems but also on optimizing their practical implementation. As deep learning techniques evolve, they will enable the creation of more sophisticated and efficient human-machine interaction systems, ultimately enhancing the user's quality of life. The study emphasizes that future advancements in both algorithmic accuracy and system integration are key to realizing the full potential of deep learning in EMG applications.

In their 2021 paper, *An Open-Source Data Acquisition and Manual Segmentation System for Hand Gesture Recognition based on EMG*, Jonathan Zea et al. introduced a system designed to enhance the development and refinement of machine learning models for hand gesture recognition in various applications. One key use of the system is its ability to record EMG signals from the same individual over time, which enables the creation of more robust models that can account for physiological variations in EMG data. The authors highlight the system's potential to significantly improve recognition accuracy. They also encourage both academic researchers and professionals in related fields to adopt, utilize, and further enhance this open-source tool, fostering advancements in hand gesture recognition and EMG-based systems.

In their 2020 overview, *Prospective Synthesis for Evaluation System of EMG Information Signal*, Joslyn Benalva Gracias et al. discuss the potential of implementing artificial neural networks (ANN) and the Kalman filtering procedure for EMG signal evaluation. These methods show promise in achieving high accuracy in response while simultaneously reducing the time required for evaluation. The authors propose a partially automated system that, with further experimentation, could be refined for real-time EMG signal processing, ultimately leading to a fully automated system. Additionally, they emphasize the importance of developing an interactive human interface to enhance user experience, making the system more accessible and user-friendly. By integrating ANN, Kalman filters, and interactive interfaces, the proposed system could significantly improve the efficiency and ease of EMG signal analysis.

In the 2020 study *Removing Artifacts and Optimal Features Extraction from EMG Envelope*, Sandra Márquez-Figueroa et al. demonstrated that the use of modified filters significantly improves the smoothing of EMG signal envelopes, effectively removing many artifacts with high accuracy under the Common Mode Noise (CMN) assumption. These enhanced filters offer superior performance in cleaning up EMG data compared to traditional methods. Looking ahead, the researchers plan to implement algorithms capable of detecting a higher number of outliers than what is achievable through standard techniques. This future work aims to further improve the precision of EMG signal processing by ensuring more robust detection of anomalies, ultimately enhancing the reliability and accuracy of EMG data analysis for various biomedical and diagnostic applications.

In the 2020 study *Hand Gesture Recognition Using Instant High-density EMG Graph via Deep Learning Method*, Dezhen Xiong et al. focused on decoding human hand gestures through the use of an instant high-density electromyography (HD-EMG) graph. Their approach leverages deep learning techniques to interpret EMG signals for gesture recognition. The study highlights the potential of this method in establishing more precise and responsive human-machine interfaces. Looking ahead, the authors plan to explore additional deep neural network architectures to improve feature extraction within the instant EMG graph. These advancements are expected to yield more accurate and seamless interactions between humans and machines. The research paves the way for developing more sophisticated systems that can interpret subtle hand movements, enhancing applications in fields like prosthetics, rehabilitation, and virtual interfaces.

Gesture Recognition Algorithm Based on New EMG Representation and Convolutional Neural Network, Rui Gao et. al, 2020, This paper analyzes the impact of the input matrix on the performance of CNN, proposes a new representation for EMG signal, improves the construction of the input matrix, and usesLeNet-5 for gesture recognition. In future we use the experimental part for analysis.

Towards extending real-time EMG-based gesture recognition system, Cristina Andronache et al, 2020, This paper proposes a method to double the number of classifiable movements. This is done by employing a modified transfer learning algorithm that is usually used in image classification. In future we will compare the EMG based gesture using soft computing techniques.

Comparison EMG Pattern Recognition Using Bayes and NN Methods, Daniel Sutopo Pamungkas et al, 2020, This article shows a comparison of a system that is able to recognize human hand movements using the Naïve Bayes and the NN algorithm. This system consists of a muscle sensor, a computer, a controller, and a mobile robot. In future we will compare the different parameters using soft computing techniques.

Finger Movement Detection Based on Multiple EMG Positions, Apiwat Junlasat et al, 2019, This paper has shown the judging criteria for detecting finger movement by using multiple EMG signal analysis. This new finding is able to apply to a low processing unit to reduce the system cost. However, the experiment focuses only individual finger movement. For the future works, simultaneous finger movement is interesting to be considered.

Evaluation of EMG Signal Time Domain Features for Hand Gesture Distinction, Rim Barioul et al, 2019, In this paper, the scatter plot of features extracted from EMG signal collected from two sensor channels are used as a feature extraction evaluation method for hand gesture distinction application. In future we analysis frequency domain analysis also.

Development of wearable EMG measurement system on forearm for wrist gestures discrimination, Satoya Higashi et al, 2019, We developed the wearable system can measure multipoint EMG instantly. And the EMG signal measured by our system contained plenty information for wrist gesture classification. However, when use this system several times, the amount of noise on EMG has increased so much. It is caused by deterioration of the electrode due to elongation. In future we use the other movements in body.

Novel Features for EMG Pattern Recognition Based on Higher Order Crossings, Angkoon Phinyomark and Erik Scheme et al, 2018, In conclusion, in this work, a novel set of simple measures of frequency information inspired by the higher order crossings method was proposed. In future we will use the technique that provides better classification performance than their traditional counterparts and several other commonly used frequency information-based features.

EMG signal processing in frequency domain, Malgorzata Parfieniuk et al, 2018, It was found, that for biomechanical signals such as EMG, asymmetrical wavelets with smooth edges are needed. In future analytical part will be developed.

Feature Extraction and Real-Time Recognition of Hand Motion Intentions from EMGs via Artificial Neural Networks, Artemiy Oleinikov et al, 2018, Finally, a real-time motion recognition system showed partial sustainability. For further improvement, there is a suggestion to implement Neural Network-adaptive wavelet analysis algorithm that was utilized in. In future work also, it is suggested to implement hardware band-pass filter and to implement software optimization.

Research on the method of EMG pattern recognition based on neural networks, Peng Xu et al, 2018, EMG signals of left forearm under arm extension, inward rotating and outward rotating of wrist, fisting and opening hand were recognized using BP neural network, LVQ neural network and BP-LVQ-combined neural network into prosthesis control. In future we will use the hybrid method.

An EMG Pattern Classification Method Based on a Mixture of Variance Distribution Models, Akira Furui et al, 2018, The applicability of the proposed method to real EMG signal classification was demonstrated by the results of an EMG classification experiment. In future research, we will examine the optimal settings of the hyper parameters in the proposed method, and also conduct further evaluation experiments using different types of data.

Review on Real-Time EMG Acquisition and Hand Gesture Recognition system, Nilima Mansing Patil et al, 2017, To improve the quality of life of the disabled or aged people researchers think on the necessity of simple and natural human-machine control interface. So, the EMG based hand gesture can help to develop good machine interface that increases the quality of life of the disabled or aged people. The scope in the future for the communication through gestures has been used since early ages not only by physically challenged persons but nowadays for many other applications such as human computer interactions, robotics, sign language recognition, etc

Time Domain Multi-Feature Extraction and Classification of Human Hand Movements Using Surface EMG, Avik Bhattacharya et al, 2017, We experiment with three different set of features to raise the accuracy of four classifiers (Ensemble, k-NN, LDA, QDA) on EMG signals. Among them, for three classifiers except LDA, we observe that the highest accuracy of classification is obtained with our proposed multi-feature set. Scopes for the future work include developing modified feature sets using this study as a layout model. More sophisticated and efficient classifiers can be used for better accuracy too.

Classification of Wrist Movements through EMG Signals with Fuzzy Logic Algorithm, M.Karunaetal, 2017, In Comparison with other estimation technique based on neural network, fuzzy logic technique does not need training, So that this can be implemented for real time application with very little effort. The obtained estimated angle can fed to a robotic arm simulation and imitated human wrist movement. In future we will use the some other soft computing techniques.

Activity EMG Signal Identification Based on RadialBasis Function Neural Networks, Li Yuan and Junlin Chen, 2017, This model can predict EMG state well with the training processing within 20 seconds and an simplified neural structure of 8I-15H-1O layer settings, the model credibility is evaluated by introducing relative error, it is acceptable with the prediction error are limited within 5%for more than 98.5% cases. To improve the collection device performance, improved signal acquisition technology and filtering technology is challenging. Meanwhile, multi machine synchronization of EMG measurement technology, a comprehensive analysis of multidimensional has become an inevitable trend.

WiP Abstract: A Survey of Approaches for Recognizing Hand Gestures using EMG signal, Seongjoo Shin et al, 2016, In this paper, we survey the approaches to recognizing hand gestures using EMG sensors. Two approaches do not consider the joint angle of the elbow. In future work, we plan to use joint angle information to improve the accuracy of the detection of hand gestures and also increase the number of gestures that can be classified.

Performance Analysis of Two ANN Based Classifiers for EMG Signals to Identify Hand Motions, Rocio Alba-Flores et al, 2016, Therefore, the research team will continue developing different methods to improve the accuracy of the classification system. In future we will work for other muscular movement in different techniques.

EMG based Classification for Continuous Thumb Angle and Force Prediction, Abdul Rahman Siddiqi et al, 2015, The most appropriate feature set determined in this study, based on results from different classifiers, is MNF-MNP for angle classification and MNF-MDF-MNP for force and joint classification. In future scope research topic to pursue in classification would be to study the effect of EMG segment size on the accuracy of time-domain and frequency domain features.

Identification of Surface and Deep Layer Muscles Activity by Surface EMG, ToshikiKoshio et al, 2012, It is considered that this method can extract independent components from mixed EMG signals of surface and deep layer muscle activity. The proposed method to identify the propagation direction of EMG is available for not only viewing the flow of EMG also identifying the surface layer and deep layer muscle activity. Hence this method is expected as a new analysis method of EMG.

EMG Pattern Recognition System Based on Neural Networks, Juan Carlos Gonzalez-Ibarra et al, 2012, In conclusion, the electrode positions near muscular activity and above nerve paths provide more EMG information and notoriously facilitate the EMG pattern recognition. In future we add some other techniques so it will improve their quality.

Simulation of EMG Signals for Aging Muscle, Mohammad A. Ahad, Travis D. Orth et al, 2012, The model predicts the actual behavior of the EMG signals which has been shown in their frequency spectrum and force EMG relationship graph. In future we propose the model for real time analysis.

EMG Signal Processing and Diagnostic of Muscle Diseases, Prof. Dr. Onsy Abdul Alim et al, 2012, The rate is less in frequency domain than that in the case of time and frequency domain input vector which is attain(91%) for neuropathic signal. In future we will work for detection and analysis of diseases.

EMG Motion Pattern Classification through Design and Optimization of Neural Network, Md. Rezwanul Ahsan et al, 2012, The experimental results also show that the optimized ANN architecture can successfully classify EMG signals with correct and average classification rate of 88.4%. Furthermore, in a single trial the best overall performance has been found 89.2%. However, the designed ANN classifier has yet not been tested with the EMG signals from disable or aged people. They could have different muscle structure and different ways to move hand muscles. In that situation, redesigning of network structure through trial and error method may solve the classification performance problem.

A New Feature Selection Method for Classification of EMG Signals, SamanehKouchaki,2012, The results suggest that the proposed features might be a useful tool in the classification of these groups. Also, experimental results show that the resulted IMF components in different groups have different characteristics. In the future work, the results could be further investigated with a real data set and other features related to the structure of IMFs.

Design and Development of a Low Cost EMG Signal Acquisition System Using Surface EMG Electrode, T. S. POO et al, 2010, Developed low cost EMG acquisition system detect EMG signal from biceps muscle and obtain envelope EMG signal form the output. Besides, linear envelope of EMG signal is successfully digitized and sent into the computer through a serial communication. In future, more efforts are needed to enhance the communication between acquisitions circuit and computer for faster data transfer. Moreover, multiple types signal input need to be added in future work to enhance the variability of signal monitoring.

An Analysis of EMG Electrode Configuration for Targeted Muscle Reinnervation Based Neural Machine Interface, He Huang *et al, 2008,* This study provides evidence and tools for the clinical implementation of a multifunctional prosthetic control strategy that combines TMR and EMG pattern recognition. This study explores the configurations of electrode placement, and initial guidelines of effective electrodes placement are offered for future clinical application of TMR and EMG PR in myoelectric prosthesis control.

Real-Time Hand Motion Estimation Using EMG Signals with Support Vector Machines, Masahiro Yoshikawa, 2006, Experimental results showed that the linear models could estimate the joint angles well. Introducing posterior class probability, we improved the accuracy of the joint angle estimation. These two phases were designed so that they could be processed in real-time. In our future work, to improve the remaining classification error, we will find new effective features of EMG signals. Furthermore, we might need to increase the number of electrodes with which the activity of muscles involved in the pronation and the supination.

3. RESEARCH GAP

- In the base paper, the research focused on using a single algorithm for processing and analyzing data, which limited the scope of the study. This approach, while effective for a specific task or signal, did not account for the complexity of movements or interactions between multiple body parts. The use of only one algorithm may have provided a narrow perspective, potentially missing out on variations or patterns that could be better captured with more diverse processing techniques. This limitation leaves room for further exploration by incorporating multiple algorithms and analyzing a wider range of body movements, which can offer more comprehensive and accurate insights. In my proposed work movement of other body parts will be analyzed and compared.

- In the present work, I aim to expand the analysis by incorporating the movement of additional body parts, beyond the primary focus of the base study. By analyzing and comparing the movement of multiple body parts, the research will provide a more comprehensive understanding of body movement patterns. This approach will capture the interrelationships and coordination between different parts of the body, offering deeper insights into how they interact during specific tasks or activities. By comparing these movements, it will be possible to identify abnormalities, inefficiencies, or deviations in motion, which can be crucial for applications such as rehabilitation, sports science, or biomechanical studies. This broader scope of analysis will lead to more robust and meaningful results, enhancing the overall understanding of human movement.

4. RESEARCH OBJECTIVE:

- **Collection of data for the movement of body parts with EMG:**

Electromyography (EMG) will be used to collect data on the electrical activity generated by muscles during movement. Electrodes will be placed on the surface of the skin over targeted muscle groups to record muscle responses. These recordings will provide valuable information on the coordination and intensity of muscle contractions during various body movements. The collected EMG data will serve as the foundation for further analysis in detecting patterns or abnormalities.

- **Pre-processing & Refinement of the data:**

Raw EMG data often contains noise, artifacts, and other distortions, so pre-processing is essential to clean and refine the signals. Techniques such as filtering, signal normalization, and artifact removal will be applied to eliminate interference and baseline drift. This step ensures that only meaningful information is retained, improving the accuracy of subsequent analysis. The refined data will be prepared for more in-depth examination and comparison.

- **Analysis and comparison of the data:**

After refinement, the EMG data will be analyzed to identify movement patterns, muscle coordination, and abnormalities. By comparing data across different body parts, key relationships and interdependencies will be uncovered. Statistical and computational methods will be used to quantify the variations in movement. This comparison will provide insights into muscle function, helping to distinguish between normal and abnormal movements and uncover inefficiencies or issues.

- **Developing new soft computing technique for analysis, detection, and comparison of the data:**

A new soft computing technique will be developed to enhance the analysis, detection, and comparison of EMG data. This approach may involve machine learning algorithms, fuzzy logic, or neural networks to improve pattern recognition and interpretation. The technique will be designed to efficiently process large datasets and provide more accurate, adaptive, and intelligent detection of movement abnormalities. By leveraging soft computing, the system will offer more sophisticated insights and potential applications in areas like rehabilitation or sports performance optimization.

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5. PROPOSED METHODOLOGY:

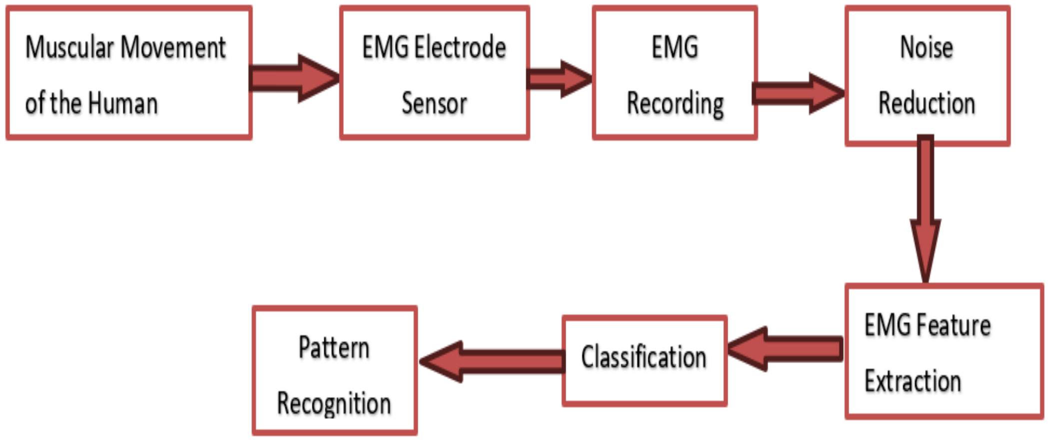

Figure: 1: Proposed Block Diagram for the EMG signal Recording

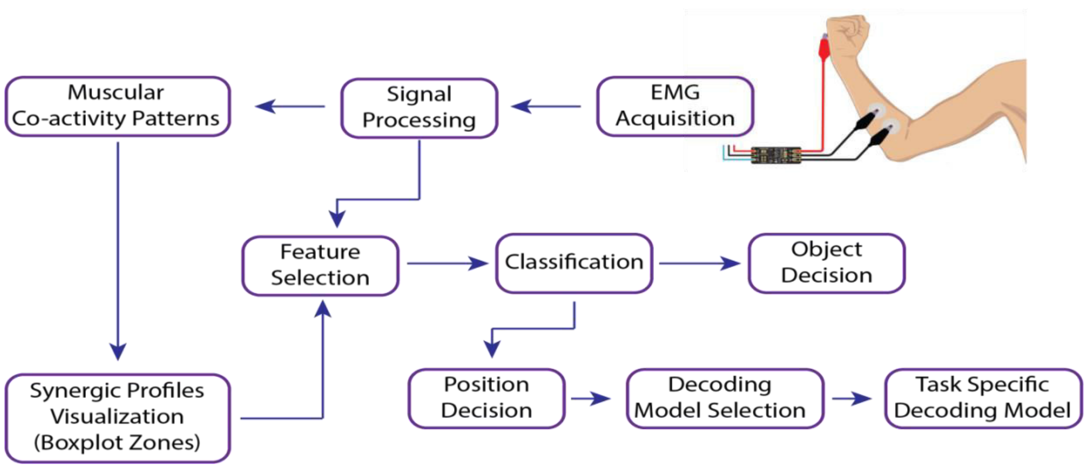

Figure: 2: Proposed Diagram for the EMG signal Procedure

6. EXPECTED OUTCOME

The present research is an attempt to improve the EMG signal analysis by using filters for noise removal as well as multiple computed methods will be used to train the data sets and a model will be suggested for enhanced signals and accurate prediction. Signals will be captured by gestures and movements of different body parts e.g., arm, forearm, wrist, hand, thigh, leg and knee etc.

Electromyography (EMG) signal analysis plays a critical role in understanding neuromuscular systems. Recent research highlights several advanced techniques that improve detection, classification, and analysis of EMG signals. These techniques include:

a. **Filtering and Preprocessing**: Filtering techniques like bandpass and notch filters are crucial in reducing noise, including powerline interference and motion artifacts, from raw EMG signals. Advanced filters enhance signal quality for accurate analysis[2].

b. **Wavelet Transform (WT)**: WT offers efficient time-frequency analysis of EMG signals, allowing better resolution across varying frequency bands. It provides better detection of transient events, making it a powerful tool for analyzing muscle activation patterns[4].

c. **Machine Learning Classifiers**: Techniques like Support Vector Machines (SVM) and Artificial Neural Networks (ANN) have shown high accuracy in classifying EMG signals for neuromuscular disease diagnosis. SVM, in particular, outperforms ANN in classification tasks when applied to selected statistical feature sets[6].

d. **Pattern Recognition**: EMG signals are increasingly used for pattern recognition in prosthetic control and neuro-rehabilitation, with the combination of machine learning algorithms and feature extraction improving outcomes[3].

These techniques represent the forefront of EMG analysis, enhancing both diagnostic capabilities and therapeutic applications in neuromuscular systems.

Focuses on advanced methods for detecting, processing, and classifying EMG signals for biomedical applications. EMG signals are critical for diagnosing neuromuscular diseases and improving human-computer interaction systems.

Key findings include:

- **Signal Processing**: The paper uses techniques such as Fast Fourier Transform (FFT) and other mathematical models like wavelet transform to enhance signal clarity and reduce noise. The primary challenge in EMG signal analysis is reducing interference from surrounding tissues and ensuring accurate detection of muscle activity.
- **Classification Techniques**: Rule-based classifiers, along with MATLAB software, are employed to differentiate between healthy and neuropathic EMG signals. These methods help distinguish between signals from different patients, contributing to accurate diagnosis.
- **Clinical Applications**: EMG signal analysis plays a crucial role in diagnosing neurological and neuromuscular disorders. The research highlights how advanced detection techniques, including artificial intelligence models such as Artificial Neural Networks (ANN), can be applied to improve diagnostic accuracy.

This research aims to enhance medical diagnostics and other clinical applications by providing better methods for detecting and classifying EMG signals.

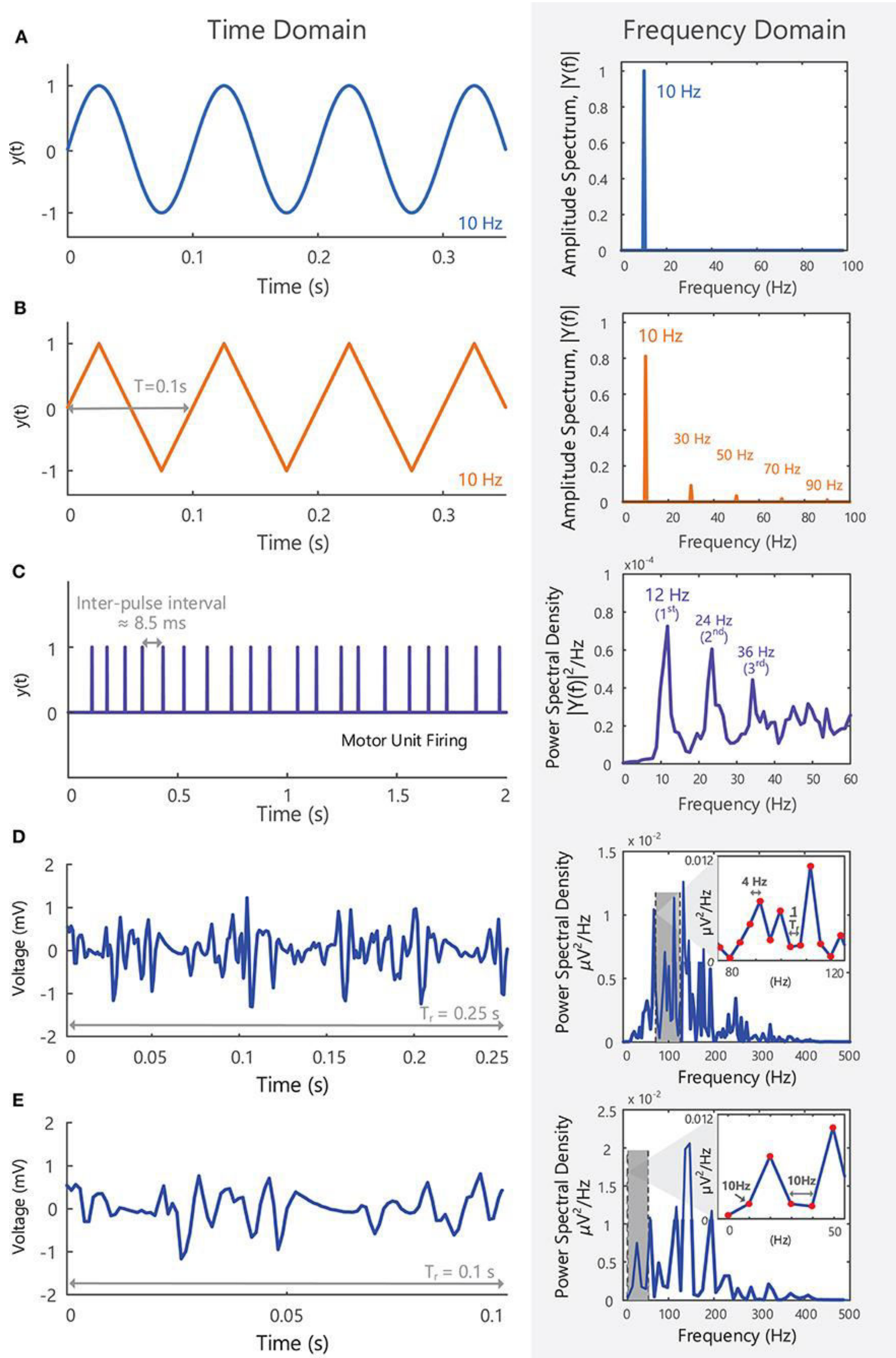

Figure 3. A, B, C, D, E Signal analysis time vs voltage and power spectral density vs frequency .

According to the above figure. A 10 Hz sine wave with an amplitude of 1 is displayed following the application of a Fourier Transform in both the frequency domain (Y(f) and time domain (y(t). The signal's whole strength is concentrated at a single frequency, often known as the fundamental frequency or first harmonic at 10 Hz. (B) A 10-Hz repetition rate triangle wave represented in the frequency domain (Y(f) and time domain (y(t)), respectively. It has frequency components at multiples of the first harmonic since it is a non-sinusoidal wave (triangle waves only have odd harmonics). Refer to Tutorial Code's Example (iii). (C) A single motor unit firing for two seconds, displayed in both the frequency and temporal domains. (D) The time-domain EMG signal lasting 0.25 seconds. The frequency resolution (1/Tr = 4 Hz) and the lowest frequency in the frequency domain that may be detected (4 Hz) are determined by the length of the signal. (E) An EMG signal that lasts for 0.1 seconds is too brief to monitor frequencies below 10 Hz; it can only identify frequency components that are multiples of 10 Hz.In [2]

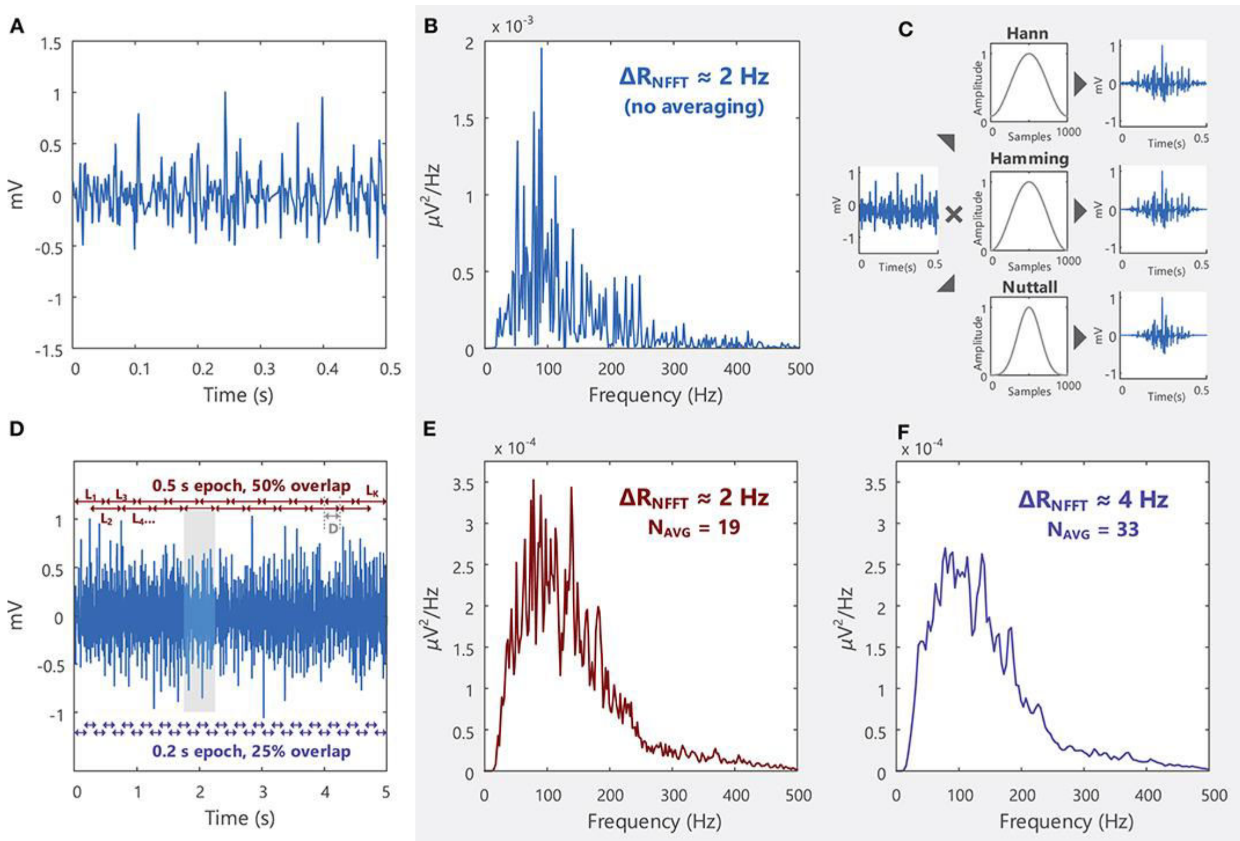

Figure 4: A, B, C, D, E. & F EMG Signal Analysis.

The aforementioned findings display: (A) an EMG signal recorded at 2,000 samples per second in the temporal domain; and (B) the signal's power spectrum in the frequency domain. The signal spectrum has multiple false highs. (C) The entire signal (5 s long, as illustrated in D) is divided into shorter segments (0.5 s) using Welch's approach. Each segment is then multiplied (convoluted) by a window function (e.g., the Hann, Hamming, and Nuttall windows) and the modified segments are then averaged. Refer to Tutorial Code's Example (viii). (D) Welch's averaging approach divides the EMG signal into many segments (K). Equation 3 in the Supplementary Material states that K is dependent on the segment's length (L) and the degree of overlap between subsequent segments. Every new section begins D samples after the ones that came before it. (E) The false peaks in (B) are diminished by calculating an average power spectral density across K segments. (F) By decreasing the length of L or increasing the overlap between segments, one can raise K (i.e., the number of averages, NAVG), which will increase the smoothness of the power spectral density function. Refer to Tutorial Code's Example (vii).[4]

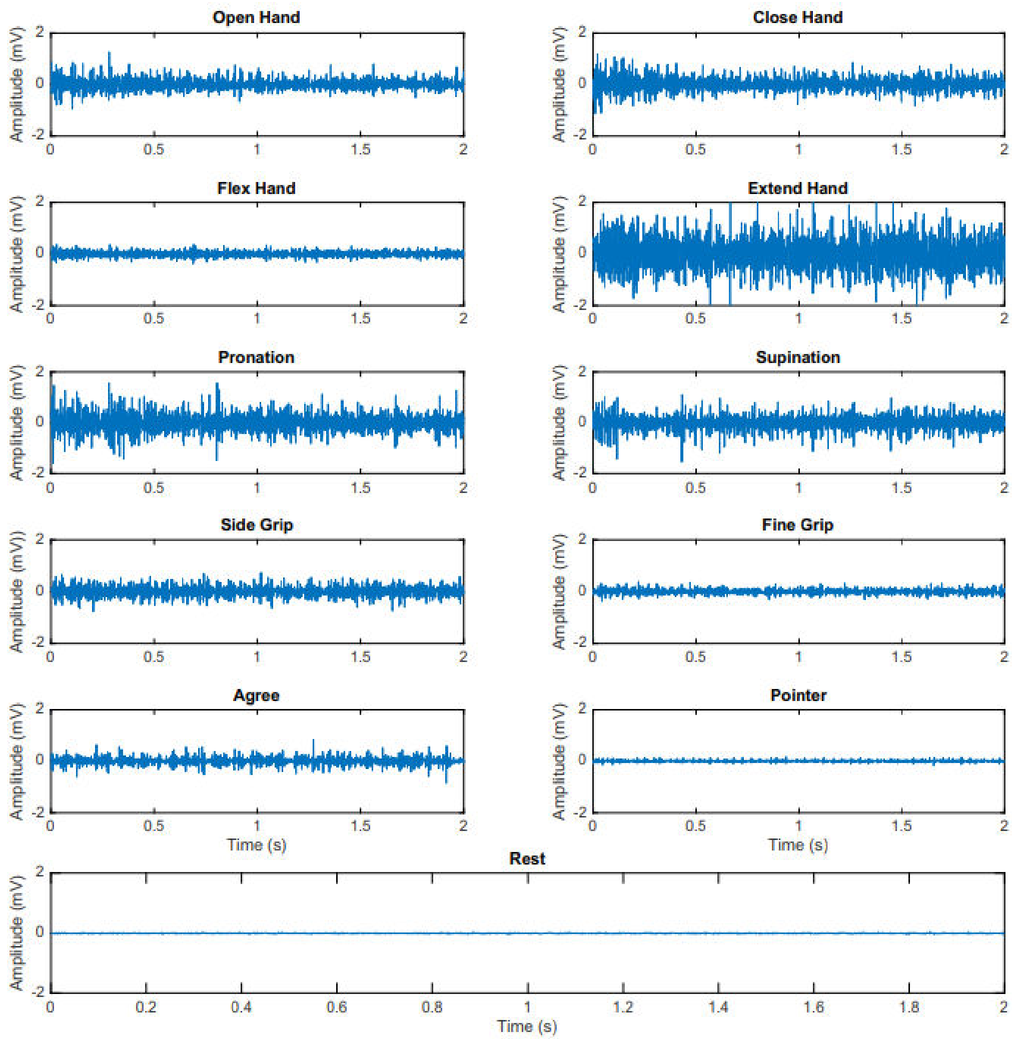

Figure 5: Two seconds of the EMG signal acquired from the first channel of one of the subjects during 10 hand motions and rest. mV, millivolt; s, second[5]

7. CONCLUSION

This research successfully demonstrates that rule-based classifiers can effectively differentiate Electromyogram (EMG) signals from various patients, which is crucial for medical diagnostics. It highlights the significance of EMG signals in providing valuable insights into the nervous system and reviews different signal analysis techniques. While discussing both the advantages and limitations of these methods, the study emphasizes continuous development in EMG signal processing to improve clinical applications. Electromyography (EMG) signals capture electrical activity from muscles during contraction, which reflects neuromuscular activity regulated by the nervous system. These signals provide crucial information about the motor system's anatomical and physiological characteristics. Advanced EMG detection methods are vital in biomedical engineering for diagnosing and analyzing neuromuscular functions effectively.

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