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A Comprehensive Review: Electromyography Signal Analysis and Classification Methods for Robotic Rehabilitation

Mohammed Laith Salim[1*], Hassan Messar Qassim[2], Wan Zuha Wan Hasan[3]

[1] Department of Medical Instrumentation Techniques Engineering, Technical Engineering College of Mosul, Northern Technical University, Mosul 41001, Iraq
[2] Department of Medical Instrumentation Technology, Polytechnic College Mosul, Northern Technical University, Mosul 41001, Iraq
[3] Department of Electrical and Electronic Engineering, University Putra Malaysia, Selangor 43400, Malaysia

Corresponding Author Email: mohammed_laith@ntu.edu.iq

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ABSTRACT

The examination of electromyography (EMG), including surface (sEMG) and intramuscular (iEMG) signals is essential for interpreting neuromuscular behaviour within diagnostic, therapeutic, and prosthetic limb control contexts. This survey explores recent research concerning comprehensive EMG signal analysis across its core phases, spanning initial signal capture and conditioning through feature derivation, probability density function evaluation, and classification. The survey emphasizes that combining conventional approaches with deep learning (DL) strategies has markedly improved classification performance, gesture identification, and assistance for rehabilitation uses and muscle fatigue assessment. It further demonstrates the expanding influence of DL instruments across multiple signal processing phases. Using a comparative assessment of more than thirty research works published between 2020 and 2025, the article particularly underscores the critical importance of intelligent rehabilitation robots, which have achieved elevated integration precision in motion encoding and system response.

1. INTRODUCTION

Electromyography (EMG) represents an essential method for investigating muscular electrical activity and interpreting its interaction with the nervous system. Its significance extends across multiple areas, including the evaluation of muscle performance, clinical treatment, physical training, and rehabilitation schemes, alongside the enhancement and assessment of sporting activities, and the diagnosis of numerous neurological and muscular disorders, including myopathy and neuropathy. It is additionally employed extensively in mechanical and kinetic investigations, where EMG signals have attracted substantial interest from researchers, while also serving as a foundation for the advancement of biomedical engineering solutions such as artificial limbs. Consequently, it integrates both medical practice and scientific research [1, 2].

Furthermore, EMG is a method employed to detect and register the electrical activity of muscles via physiological variations within muscle fibre membranes [2], delivering valuable insight into how the central and peripheral nervous systems regulate muscular function [3]. The minimal operational element used to characterise neural movement during contraction is known as a motor unit. This represents a fundamental concept for interpreting EMG signals. It defines the action of an individual neuron together with all muscle fibres that it supplies Figure 1 [2]. It comprises a nerve cell, followed by an axon which divides and connects to multiple muscle fibres, collectively forming one motor unit [2]. When the muscle fibres belonging to this unit contract simultaneously, an action potential is generated instantly, producing an electrical signal referred to as the motor unit action potential. These activated muscle fibres precisely constitute the EMG signals that are recorded [4].

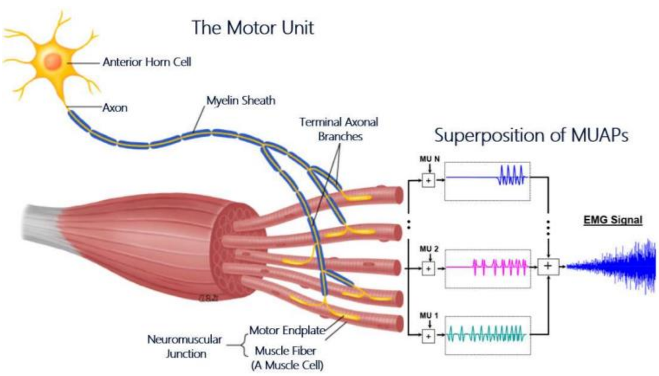

Figure 1. Schematic representation of a motor unit and electromyography (EMG) signal generation [5]

Muscular signals may be affected by numerous forms of interference, causing incorrect interpretation of the data within both temporal and spectral domains. This creates difficulties associated with signal collection and feature derivation, together with added complexity in the evaluation and understanding of muscular signals across different classification techniques [6]. One of the most notable developments within biomedical engineering involves combining EMG with robotic rehabilitation frameworks. Robotic platforms have effectively employed control driven by artificial intelligence (AI) methods to attain accurate muscle actions for rehabilitation, while also improving exercise execution, thereby increasing the reliability of pattern recognition and overall analytical performance in advanced clinical and research environment applications.

In this review, we focus on surface electromyography (sEMG) and intramuscular electromyography (iEMG) signal processing and classification techniques, especially on AI – based ones for robotic rehabilitation and prosthetic control applications. The study depicts noise reduction methods, feature extraction areas, machine learning (ML) and deep learning (DL) classifiers, and their incorporation into intelligent rehabilitation systems.

1.1 Review methodology

This review was based on EMG signal analysis as a core and inclusive component, integrating recent studies associated with processing, feature extraction, and classification. Research carried out during the period 2020–2025 was examined, and the scope of this evaluation was broadened by connecting it with specialised robots applied in rehabilitation. The review was undertaken using dependable databases such as PubMed®, IEEE Xplore®, ScienceDirect®, and MDPI®. Keywords such as "EMG signal processing," "feature extraction," "EMG classification," and "machine learning" were used with Boolean operators. Duplicate records were removed, and the retrieved articles were screened by title, abstract, and full text. Studies were included if they reported experimental results on EMG preprocessing, feature extraction, or classification. Articles not related to EMG analysis, non-research publications, or studies lacking experimental validation were excluded. The primary selection criteria were defined according to the significance of studies concentrating on noise mitigation, analytical approaches, modern integration of DL methods with conventional techniques, clarity in presenting outcomes, and signal analysis characteristics. Over thirty investigations were reviewed in the area of data acquisition techniques for sEMG or iEMG, alongside processing strategies involving key filter parameters and signal filtering approaches, progressing through feature extraction stages and reaching the most notable traditional and AI-driven classification methods. The research scope was sufficiently varied to encompass present and emerging trends, offering a comparative perspective that addresses all dimensions and intersections of the literature while identifying strengths and limitations, and emphasising the shift from classical signal processing towards intelligent models that support rehabilitation through robotic systems or prosthetic devices. Furthermore, the literature was organised into a series of thematic sections that outline the analytical and methodological framework of EMG signal research. The aim of this structure is to provide a comprehensive understanding of EMG signals from their source to their implementation in robotic rehabilitation. Every thematic category represents an analytical stage, beginning with factors affecting EMG signals, followed by successive processing and feature extraction steps, and concluding with classification approaches and robotic applications. This organisation mirrors the logical progression of EMG signal analysis and clarifies the movement from traditional processing techniques to advanced AI-based models employed in rehabilitation robotics.

2. NOISE FACTORS

EMG signals could be affected by various type of noise and distortion, making it hard to interpret the generated data, that consequently decreases the accuracy of analysis and evaluation. Typical sEMG signal amplitudes are about 10–5000 μV μV (≈ 0.01–5 mV), while the iEMG signals can be up to approximately ten millivolts, depending on the measurement settings and electrode placement. With regard to spectral characteristics, the useful energy of sEMG signals is generally distributed in 10–500 Hz frequency band. Hence, measures aimed at reducing noise or interference as well within muscular signals offer a way to retain the extracted information and control the evacuation of haunting elements to better govern variations in amplitude and frequency developed by each causal factor of disturbance. So, there are numerous methods available to efficiently remove these environmental contaminants [7]. Baseline interference is sometimes referred to as latent noise. This category explicitly comprises two forms of disturbance: chemical and thermal. Thermal interference arises when no muscular contraction occurs and is characterised as white Gaussian noise, which originates from the interaction between the electrode and the surrounding environment. Chemical interference develops as a consequence of the interaction between the skin and the electrode owing to perspiration, moisture, and cutaneous resistance, which causes a lowered signal-to-noise ratio (SNR) at frequencies exceeding 20 Hz. This category can be eliminated by cleansing the skin prior to placing the electrode and using an electroconductive gel to decrease the electrode resistance, or by applying a high-pass filter to eliminate low frequencies [7, 8]. Intrusion of undesirable signals into the EMG signal is termed interference noise, which originates from 50–60 Hz electrical power lines coupling with the muscle signal, producing impedance variations between the electrodes. It is mitigated through notch filtering or high-gain differential amplification filters techniques [8]. When measurements are taken from muscles located close to the chest, the muscular signal may be contaminated by the heart's electrical activity, referred to as electrocardiography artefacts. These are eliminated using signal processing approaches such as wavelet decomposition or fully convolutional networks to separate the EMG signal from the electrocardiography component [9, 10].

Undesired EMG activity originating from non-target muscle groups is referred to as cross-talk. Its magnitude increases with greater subcutaneous fat thickness and may be minimised by appropriate selection of electrode dimensions and inter-electrode spacing (commonly 1–2 cm) or by applying spatial filtering techniques to isolate the intended muscles [11]. Movement of either the electrode or the skin generates what is termed motion noise, which typically appears at low frequencies between 1–10 Hz. This can be addressed through the use of low-noise amplifiers or by applying a high-pass filter to suppress frequencies below 10 Hz [8] .Additional interference arises from electromagnetic radiation emitted by electronic devices like radios and TVs, contributing to environmental noise, as well as inherent noise generated by electronic components including transistors, resistors, and amplifiers, which stems from the physical characteristics of circuits across frequencies ranging from zero to several thousand hertz [9]. Such effects can be reduced through the use of low-noise components and amplifiers, shortening cable lengths, or applying digital filtering to enhance the SNR [12]. EMG recordings are also affected by low-frequency disturbances below 1 Hz caused by respiration, subject movement, or inadequate electrode contact, commonly known as baseline wander, which results in gradual baseline drift. Noise may also be present during EMG acquisition when the muscle is relaxed and no active electrical signal is produced; this is referred to as background noise [7]. In iEMG measurements using intramuscular needles, noise can occur when muscle movement produces sharp spikes that are not representative of normal muscular activity. To minimise this effect, the needle is securely stabilised during recording to limit spiking, or appropriate filtering techniques are applied to process the signal [13].

Overall, noise and interference pose a significant challenge in the analysis and processing of muscular electrical signals. To address this, each situation demands specific processing and filtering strategies to minimise or control its detrimental effects, thereby preserving the accuracy of the data extracted from the muscle signals [7].

3. SYSTEM-LEVEL ARCHITECTURE

EMG signal analysis constitutes only a single layer within a cyber-physical system that translates muscular electrical activity into robotic motion in practical rehabilitation robotics. A full-scale EMG-driven rehabilitation platform generally comprises various interdependent subsystems, which can be categorized into signal acquisition, preprocessing, feature extraction, inference, control/actuation, and feedback subsections. At first, the electrical activities of the muscle are detected by surface or iEMG sensors placed on top of specific muscles.

Next, the processed signal is separated into short time windows that allow extracting features. EMG waveform feature extraction algorithms are then applied to convert the measured EMG waveform into some representative numerical descriptor that effectively captures muscular activation patterns. The hand trajectory data can also be used as input features to either an ML or DL model to estimate what the user was trying to do. The output of the inference module is sent to the robotic control unit, which represents the movement intention prediction as control commands that will be applied to move/operate the rehabilitation device. More sophisticated control strategies may be required based on the system design, such as proportional control, impedance control or adaptive control, to guarantee safe interaction with the human patient. And actually, executes the movement to help the patient with rehabilitation. Closed-loop operation is a key aspect of such systems, in which feedback sensors (like encoders, force sensors, or position trackers) provide real-time data from the environment to the controller for improved motion accuracy. System latency is a critical design consideration for real-time rehabilitation systems. Response time refers to total response time: the signal window length + computational processing (per channel) + communication delays. Typically, in each EMG-based controller system, the range of window length is set up between 100 and 250 ms, which maximizes the responsiveness while smoothing out some noise. Typically, single channel feature extraction and classification algorithms show a consumption of a few ms on modern processors so that the end-to-end system latency stays below 300 ms which is acceptable for interactive rehabilitation applications.

4. ACQUISITION AND PREPROCESSING

EMG signal analysis relies on a set of ordered and structured stages to convert the raw signal into informative and usable data. The procedure starts with signal acquisition through EMG instrumentation. The signal is subsequently processed to filter and cleanse it of noise and distortion. This is followed by feature extraction, which captures the essential characteristics of muscular activity, thereby paving the way for classification using methods such as ML or DL. Figure 2 demonstrates the sequential stages involved in the EMG signal analysis workflow.

Figure 2. The general framework of the electromyography (EMG) signal processing analysis

4.1 Extraction of the raw electromyography signals

Signal extraction refers to acquiring the signal and transforming it into a format suitable for handling, whereas processing represents the phase of refining and examining this signal to generate meaningful information or outcomes. Emphasis is placed on initial processing methods that involve capturing the raw signal and efficiently eliminating noise introduced during acquisition, which includes choosing the recording location, obtaining the signal, and then representing, adjusting, and storing it in readiness for subsequent processing and analysis stages. Signal extraction varies in EMG applications, whether sEMG or iEMG, as sEMG employs surface electrodes positioned on the skin to record the signal, while iEMG involves inserting a fine needle electrode directly into the muscle tissue to capture activity [6, 14]. The choice of extraction technique is determined by the exact demands of the particular application area. In rehabilitation or prosthetic research, surface electrodes are generally preferred because of their simplicity, non-invasive nature, and greater comfort for patients. In contrast, needle electrodes are more appropriate in situations that require a high level of precision, as they offer an optimal solution by delivering accurate measurements of muscle activity at specific depths within the muscle tissue [6].

Once the raw, untreated signal has been acquired through electrodes, differential amplifiers are applied to raise the signal level, since the original muscle signal is extremely weak (10–5000μV). Consequently, a clearer signal is produced without sacrificing fine detail. Commonly, amplifiers such as instrumentation amplifiers (INA128) with a gain factor of 1000x are employed, because this device helps minimise electromagnetic interference from power sources (50/60Hz). Following amplification, the signal moves to the cleaning stage, where filters are applied to remove noise generated by electrode motion. A high-pass filter is typically set between 10–20Hz. To eliminate unwanted high-frequency components, a low-pass filter is applied at 400–500Hz. For suppressing electrical interference, a notch filter is implemented at 50/60Hz. The signal is subsequently passed to digital processing once it has been amplified and purified, during which an analogue-to-digital converter transforms it into a digital format. The signal is then stored, and feature extraction is performed as part of the early processing of the raw data. In most cases, the signal amplitude or peak value is first extracted to assess the intensity of muscular activity. Ultimately, the waveform structure allows detailed analysis and a clearer understanding of the main objective of the extraction process within experimental and clinical contexts [6, 15, 16].

4.2 Electromyography signal processing

This section addresses the methods, parameters, and filtering approaches applied in EMG signal processing. Traditional analytical models remain the most widely used among researchers, whereas DL approaches offer higher efficiency and accuracy, in spite of requiring substantial computational resources. The primary aim is to enhance the SNR of various noise sources before feature extraction. The signal undergoes multiple phases, including normalization, segmentation, and filtering, reflecting the diversity of tool selection across studies. For instance, Sevim [16] applied a band-stop filter (BSF) within a frequency range of 45–55 Hz to remove power line interference, using a window duration of 250 ms and a skip length of 64 ms. This approach was essential for ensuring stability and temporal precision, while maintaining an appropriate balance between these factors. Choi et al. applied a conventional high-pass filter with a cut-off frequency of 10 Hz alongside a BSF set at 50 Hz. This stage was further complemented by the use of a Savitzky–Golay filter as a smoothing method to minimise noise and enhance overall signal quality [17]. Toledo et al. [18] implemented a band-pass filter (BPF) spanning 15–500 Hz to suppress interference while retaining the most critical frequency components of muscular activity. This approach aligns with the established frequency range reported in the existing research literature (20–500 Hz).

While Benavides-Álvarez et al. [19] scaled each sample within a range of -1 to +1, the muscle signals were subsequently transformed into spectrogram representations, then normalised once more and combined into a matrix to serve as sequential inputs for the classification stage. This work concentrated on an alternative preprocessing strategy which depends on normalisation as a critical step within DL based signal processing workflows [19]. In a separate investigation, EMG signals were acquired wirelessly using Bluetooth technology, and the signals were amplified to a range of 0–3 V as supplied by the Myo armband. To remove electrical power line interference, a fourth-order Butterworth band-pass filter with cut-off frequencies of 20–500 Hz was applied, with the objective of minimising the influence of unintended finger movements [20]. Sul et al. [6] adopted a similar methodology to acquire precise data suitable for controlling prosthetic limbs. Lundsberg et al. [21] extended this approach by employing a BPF with a high-pass range of 0.7–4400 Hz to capture the full spectrum required for high-density EMG applications. Principal component analysis was performed, and a third-order Butterworth filter was applied using bidirectional filtering at cut-off frequencies of 49–51 Hz, alongside a BSF set between 5–500 Hz to reduce signal noise. The careful selection of these two filters was crucial to avoid waveform distortion, ensuring that the temporal accuracy of EMG signals was preserved during the analysis of muscle control [21].

According to the literature, EMG signals contain useful frequency content approximately in the range of 10–500 Hz. Yet many studies examine narrower frequency bands (20–450 Hz or 25–350 Hz) depending on the filtering approach, recording setup and the application in mind. In a study examining muscle fatigue, Hassan M. Qassim et al. employed a second-order Butterworth IIR BPF with a non-zero time delay and a cut-off range of 25–350 Hz to isolate relevant frequencies, along with a BSF of the same type set at 47–53 Hz to remove 50 Hz power line interference. The Butterworth filter was selected due to its maximally flat response between the cut-off frequencies [22]. In another investigation by Xiang et al. [23], focusing on image processing via DL, the window length was configured at 150 ms with a step size of 75 ms, and the signal values were converted to grayscale to analyse time-varying transformations. Bao et al. [24] applied a similar procedure, using a 2 Hz band-pass filter and recording the signal digitally, with an additional 20–450 Hz filter to suppress noise. The extracted data was divided using sliding windows of 102 ms with a 51 ms overlap to process images for gesture recognition in stroke patients. More recently, Anastasev et al. [25] adopted a comparable method to study the kinematics of weak muscles in stroke survivors, implementing a BPF spanning 20–300 Hz followed by signal normalisation. Their processing did not require feature extraction, enhancing the overall efficacy of the model. Mesin et al. [26] selected a band-pass filter spanning 5–350Hz, after which motor unit action potential patterns were derived from the EMG signal through monopolar channels. The DEMUSE® algorithm was subsequently applied for analysis. In contrast to earlier investigations, this work concentrated on the motor unit scale to isolate the fundamental fine-grained signal patterns precisely. Donati et al. [27] employed sixteen negative electrodes for signal acquisition. They eliminated power line interference before applying a ten-stage 50 Hz notch filter, together with a fifteen-stage band-pass filter ranging from 1–2 kHz to suppress direct current offset and high-frequency interference. In a separate investigation done in 2020, Olmo et al. advised applying a low-pass filter (LPF) with a cut-off frequency spanning 400–500Hz, alongside a BPF operating between 20–450Hz. He noted that window duration influences overall system performance, since it defines the volume of information obtained, which consequently governs the direction and precision of the classification procedure used in practice [28]. Ashraf et al. [29] addressed both surface and needle electrode approaches for signal acquisition, allocating a frequency range of 4–50Hz for sEMG signals, whereas needle EMG signals covered a broader range between 10–1500Hz, with a 60Hz notch filter implemented to suppress power line interference. The researchers subsequently introduced white Gaussian noise to assess system performance and emulate noisy conditions, and proposed a technique to remove this Gaussian noise using variational mode decomposition, which decomposes and separates the signals without adversely influencing the sampling frequency [29]. In a study comparing sEMG and iEMG signals, the researchers applied a frequency band of 30–450Hz for sEMG and 100–4400Hz for iEMG, using a second-order Butterworth filter with zero phase lag. To estimate joint torque, two signal acquisition methods surface and needle electrodes were evaluated. Due to the reduced interference observed with the invasive technique, the findings demonstrated the superior performance of iEMG signal recording [30]. Surface electrodes are prone to low-frequency interference. To address this, the signal was processed using a low-pass filter at 400 Hz, combined with a 50 Hz band-stop filter to suppress power line noise. The signals were then normalised to zero mean and unit variance. Finally, a 293-ms time window was applied to compute the signal envelope. These procedures demonstrate the researchers' prioritisation of signal clarity over preserving temporal dynamics [31]. Parashuram et al. employed a 600-ms sliding window with 50% overlap and applied a band-pass filter to eliminate undesired frequencies. The extended window length enhanced signal stability by capturing more consistent muscle contractions, but it came at the cost of decreased temporal resolution [32]. In a separate study, noise caused by muscle movement was mitigated using a fourth-order Butterworth filter set between 49.5–50.5 Hz. The signals were segmented into overlapping 200-ms windows and smoothed, allowing for a more precise assessment of muscle activity during rapid, transient changes [33]. In a research on hemiplegic stroke patients, Thomson et al. [34] applied high-pass and low-pass Butterworth filters with cut-off frequencies at 60, 120, and 180 Hz, demonstrating effectiveness for the weak and noisy signals typical of this patient group while preserving the primary signal components. Signal extraction was performed using a 300-ms sliding window, and 34 surface electrodes were employed to support processing and achieve more accurate signal capture. At the same time, Aviles and colleagues applied a 10–500 Hz band-pass filter using a second-order Butterworth design, then segmented the filtered signal into 250 ms frames with 190 ms overlap, subsequently enhancing classification accuracy [35].

However, with the aim of enabling practical implementation of EMG-based analysis systems, we can derive a few guidelines based on the approach most commonly found in literature. Skin sEMG signals are non-stationary and susceptible to numerous noise sources such as electrical artifcats, power lines and electronic input noise. Hence, the preprocessing phase is a key factor towards the dependability and robustness of extracted features and consequently classification or analysis stages.

The EMG signal contains relevant components that contain physiological information, as well as disturbances (move noise being one of them), and to extract the physiologically relevant information and minimise unwanted disturbance we set to apply an appropriate filtering process. The majority of sEMG studies apply a band-pass filter with bandwidth of around 20–450 Hz, capturing the major frequency components associated with muscle fiber activity while attenuating motion artifacts at low frequencies and noise at high frequencies. Further, a band-stop filter centered around the local power-line frequency (50 Hz or 60 Hz depending on the electrical system) is often applied to reduce power-line artifacts. If motion artifacts are prevalent, an additional high-pass filter with a cutoff frequency of 10 to 20 Hz can be applied to undisturb the effects of low-frequency noise from electrode movement or skin impedance fluctuation [7].

Second, segmentation of the EMG signal into short analysis windows is a more common approach for performing time-resolved feature extraction. Various studies report window lengths, typically from 150 ms to 300 ms, which serve as a compromise between a acceptable temporal resolution and feature stability. In real-time control applications, such as human–machine interfaces or prosthesis control, windows in the range of 150–250 ms and overlapping rates between 25% and 50% are usually suggested to ensure quick system response while retaining sufficient feature estimation reliability see Table 1 [36]. Third, normalization of EMG signal is often needed to reduce variability between subjects, muscles and recordings sessions. Common amplitude normalization techniques like z-score normalization or min–max scaling are performed before the feature extraction step, especially in ML-based systems. Revolutionizing classification algorithms, this step guarantees that extracted features become comparable across trials improving their generalization capability.

Table 1. Typical parameter ranges for sEMG and iEMG signal acquisition

Parameter	sEMG	iEMG	References
Amplitude	10–5000 µV (0.01–5 mV)	50 µV – 10 mV	[37]
Bandwidth	10 Hz – 500 Hz	10 Hz – 1000 Hz	[17, 38]
Sampling Rate	1000–2000 Hz	2000–5000 Hz	[38]
Common Filters	Band-pass: 20–450 Hz, Notch: 50/60 Hz	Band-pass, Notch	[30, 38-40]
Timing Window	100-250 ms with 50 ms overlap	25 ms to 500 ms, in 25 ms steps	[36, 41]

Note: sEMG = surface electromyography; iEMG = intramuscular electromyography

Table 2. Datasets summary

Dataset	Task	Subjects	Channels	Sampling Rate	Classes	Common Baselines	Ref.
GrabMyo	Hand gesture recognition	43	28	2048Hz	16 hand gestures	LDA, SVM, K-NN	[42]
CabgMyo	Hand gesture recognition	23	16	N/A	8 and 12 hand gestures	LDA, SVM, K-NN	[16]
FORS-EMG	Finger movement recognition	19	8	985 Hz	12 different wrist and finger motions	CNN-based models: ResNet50, DenseNet121, MobileNetV3, EfficientNetB0, Traditional classifiers: SVM, k-NN, LDA	[43]
(Myo Armband21 (MA21)	Hand gesture recognition	13	8	200 Hz	21 hand gestures	SVM, K-NN, RF, ETC	[44]
UC2018 Dual Myo (UC8)	Hand gesture recognition	1	20	200Hz	8 hand gestures	SVM, K-NN, RF, ETC	[44]
JJ Datasets	Lower limb human	15	16	1000Hz	10 gait phases	SVM, CNN, ANN, ResNet-18	[45]

	motion intention pattern recognition

Lastly depending on the properties of the recorded signal further techniques for signal conditioning can also be implemented. Such methods can include smoothing or averaging algorithms to remove random fluctuations in low SNR recordings, as well as wavelet-based denoising or adaptive filtering techniques when highly non-stationary EMG signals are present. Such methods can increase the robustness of the signal processing pipeline and make sure that the extracted features are reliable [37].

Overall, the combination of appropriate filtering, window-based segmentation, normalization, and optional denoising techniques provides a practical framework for preprocessing EMG signals in both research and real-world applications. Adhering to these recommendations can enhance the quality of the recorded signal, stability of features, and the overall performance of EMG-based analysis systems.

4.3 Datasets

In this section, we provide an overview of the datasets used in upper and lower limb EMG signal classification studies. Table 2 highlights the key characteristics of these datasets, including the tasks assigned, the number of participants, the channels used, the sampling rate, the target groups, and the primary classification methods employed.

5. FEATURE, CLASSIFICATION AND ROBOTICS

5.1 Feature extraction

Feature extraction represents a core step in signal processing and is essential for attaining high accuracy when classifying movement-related patterns. During this phase, raw signal data are converted into a structured feature vector suitable for analysis. In most signal-processing frameworks, extracted features are categorised into three main domains: time-based, frequency-based, and time–frequency–based representations. In addition, statistical measures—such as the probability density function (PDF) are often employed to examine the signal's statistical characteristics, offering deeper insight into muscle activation behaviour. Each feature domain contributes unique information that assists in recognising muscle activity characteristics, including motion intent and fatigue levels, which are particularly important in clinical and biomedical applications.

5.1.1 Time domain features

Time-domain features are extensively employed by researchers because they are straightforward to understand and closely reflect underlying muscle activity, allowing key characteristics to be derived directly from the signal. A substantial body of research has leveraged this domain to detect variations in EMG signal amplitude, offering important perspectives on neuromuscular function. As an illustration, Chen and co-authors applied the root mean square (RMS) method in combination with analysis of variance to characterise EMG-derived features, while also using Pearson correlation and chi-square testing to enable real-time EMG monitoring and evaluate statistically significant differences in classification performance [46]. In a comparable approach, Choi employed the maximum overlap discrete wavelet transform (MODWT) for feature extraction implemented on a field-programmable gate array (FPGA), highlighting both its efficiency and accuracy. This was largely attributed to the straightforward extraction of features well suited for FPGA deployment, enabling effective use in edge-based systems while preserving strong time-domain performance [17]. Likewise, Al-Jubouri examined muscle signal behaviour and variations through the application of the discrete wavelet transform (DWT), demonstrating how decomposing time-domain signals into multiple components can significantly enhance classification accuracy [47]. Similarly, Etana et al. [48] utilised DWT techniques to isolate and extract the most informative components of muscle signals within the time domain, improving feature clarity and separability.

A study at the University of Central Florida examined time-domain feature extraction by analysing the SNR and signal quality index from lower limb muscles using dry electrodes. The processing pipeline included filtering, normalisation, and envelope extraction in the time domain. Despite this approach, EMG signals remain vulnerable to motion artefacts, representing a major limitation and indicating the need for further advancements in this area [49]. In contrast, Chang et al. [50] faced challenges from electrocardiographic noise contamination. Among the extracted features, the integrated electromyogram (I-EMG) was least impacted by high noise levels. The researchers also employed a similarity index to compare actual and simulated signals, reinforcing both the reliability and precision of their feature analysis. Moreover, novel, previously unreported or unique features were derived by Azhiri et al. [51], including integrated absolute second derivative, integrated absolute third derivative, integrated absolute logarithmic value, integrated exponential absolute value, and integrated exponential. These features enabled multiple approaches for enhancing the signal, suppressing noise, and scaling samples up or down, while separating and prioritising positive and negative elements within those sample sets effectively and consistently overall performance.

Anastasiev et al. [52] concentrated on time-domain feature extraction and selection by employing brute-force and semi–brute-force search strategies to identify the optimal combination from eight extracted feature groups for hand movement classification in stroke patients. Their proposed approach produced a notable enhancement in both classification accuracy and overall system performance, yielding improvements of approximately 10–17% when compared with conventional techniques. Likewise, a 2022 investigation adopted a hybrid approach that integrated conventional signal-processing techniques with DL methods, utilising wavelet transformation alongside a convolutional neural network (CNN) for gesture classification. Key extracted features included zero-crossing (ZC) rate, RMS, mean absolute value (MAV), and waveform length (WL). In this approach, signals were first converted into image representations, after which feature extraction was performed using a CNN architecture [53]. The principal time-domain features are summarised in Table 3.

Table 3. Time domain features

Features	Abbreviation	Description	Ref.
Root Mean Square	RMS	Measures overall muscle activity intensity.	[6, 54, 55]
Mean Absolute Value	MAV	Calculates the average absolute value of the EMG signal to measure the muscle activity level.	[6, 54, 55]
Waveform Length	WL	Quantifies signal complexity by calculating total WL.	[6, 54-56]
Zero Crossing	ZC	Counts the ZC in the signal, indicating changes in muscle contraction direction.	[6, 54, 55]
Variance	VAR	Measures signal dispersion around the mean.	[6, 51, 54]
Standard Deviation	SD	Measures signal spread and muscle variability.	[54-56]
Sample Entropy	SampEn	Measures the regularity of the signal.	[52, 54]
Skewness	SKEW	Measures the asymmetry in the EMG signal distribution.	[54-56]
Kurtosis	KURT	Quantifies the peakiness or flatness of the signal distribution.	[54-56]
Slope Sign Change	SSC	Counts sign changes in the EMG signal slope.	[54-56]
Mean Absolute Deviation	MAD	Measures the average absolute deviation from the mean.	[54]
Willison Amplitude	WAMP	It counts the number of times the changes in the sEMG signal amplitude.	[6]
Integrated EMG	iEMG	Measures total signal energy over time for muscle activity.	[6, 51, 53]

5.1.2 Frequency domain features

In frequency-based analysis, the energy of the EMG signal is examined across the spectral domain rather than over time in order to characterise muscle behaviour during fatigue or exhaustion and to assess overall muscular performance. Commonly extracted frequency-domain features include median frequency (MDF), mean frequency (MNF), power spectral density (PSD), and spectral moments, as these parameters effectively represent how signal energy is distributed across different frequency components. Among these, mean power frequency has received particular attention for its sensitivity to spectral shifts, notably the reduction of high-frequency components accompanied by a slight rise in lower-frequency content, which is indicative of muscle fatigue. To improve the precision of fatigue monitoring, modified versions of MNF and MDF have been proposed and utilised by researchers. Nevertheless, several studies have reported that certain frequency-domain features like MNF, total power, MDF, peak frequency, and mean power frequency often yield limited classification performance [11]. Using the fast Fourier transform (FFT), Al-Khashab et al. derived frequency-domain features such as mean power (MP), MNF, dominant frequency, and power ratio to analyse spectral energy distribution for gesture recognition in stroke patients [57]. In a separate 2022 study, MDF and MNF were extracted alongside cross-entropy from the entropy domain to capture signal complexity and nonlinearity under high-noise conditions, thereby improving muscle signal discrimination. Feature selection was performed using the Relief algorithm, which considerably enhanced classification accuracy and feature relevance [58]. Conversely, Alkan, Zeyn, and Roggio, in their review of spectral analysis methods, noted that several frequency parameters such as MNF, total power, power frequency, and frequency ratios are derived from PSD within the Fourier domain, while highlighting MDF and MNF as particularly informative indicators of muscle activity [3]. Conversely, Aji and Rajan investigated muscle strength estimation and fatigue evaluation. They determined that frequency-domain markers, notably MDF and MP, proved superior to time-domain variables regarding feature extraction efficacy. Nevertheless, limitations were imposed by high computational complexity. Thus, their work emphasised the functional success and physiological relevance vital for interpreting muscle activity across multiple studies [59]. Kim et al. reasserted the Fast Fourier Transform's merit in effectively translating EMG signals from time to frequency domains, yet flagged its specific inability to trace spectral components over time. To counter this, they proposed the Short-Time Fourier Transform (STFT). Providing spectral-time analysis by splitting signals into narrow overlapping windows, this approach allows for an exact representation of muscle activity across both time and frequency realms [57]. Research by Qassim et al. derived frequency-domain metrics, including MDF and MFD, by monitoring elbow flexion and extension. Employing affordable sensors on biceps and triceps muscles, they produced consistent findings applicable to robotic control systems and rehabilitation tasks [60]. The findings revealed that frequency-domain indices, notably MNF, MDF, and PSD, serve as pivotal markers for defining muscle fatigue. This approach blends quantitative power spectrum examination with the decoding of physiological shifts, including stamina and muscle power. Moreover, this development influenced broader analytical facets, addressing the substantial difficulty of unifying time and frequency domain studies. Consequently, this may motivate investigators to adopt hybrid time-frequency strategies offering distinct resolutions and multi-scale dimensions. Table 4 outlines the primary frequency-domain attributes.

Table 4. Frequency domain features

Features	Abbreviation	Description	Ref.
Mean Frequency	MNF	It is defined as the total sum of the product of the power spectrum and the frequency, normalized by the total power of the spectrum.	[55, 56]
Median Frequency	MDF	The frequency value that splits the sEMG power spectrum into two regions of equal power.	[51, 52, 54, 56]
Spectral Moment	SM	It is utilized to examine the spectral frequency distribution of the EMG signal.	[6, 61]
Power Spectrum Deformation	PSD	A meter used to measure spectral distortions caused by interference or noise in an EMG signal by comparing the power spectrum of the original and distorted signal.	[6, 7, 53]

5.1.3 Time-frequency domain features

Shifting attention to the time–frequency domain, which represents a more advanced framework for EMG signal analysis, this approach enables a detailed and evolving representation of muscle activity over time. By integrating the strengths of both temporal and spectral analyses, it becomes a powerful method for identifying movement patterns and assessing muscle fatigue. Mengying et al. described the use of empirical mode decomposition (EMD) for extracting and evaluating features within the time–frequency domain. Their methodology is based on the Huang–Hilbert transform, through which the signal is decomposed into intrinsic mode functions. The combined use of EMD and these intrinsic components plays a critical role in suppressing noise within EMG recordings, thereby preserving and highlighting the dominant characteristics of the original signal [62]. Liu et al. [63] leveraged the Continuous Wavelet Transform (CWT) to derive time-frequency spectral attributes for optimising motion gesture identification. They demonstrated that this methodology increased accuracy by 4%, whilst simultaneously mitigating specific problems which negatively impact classification performance. In the same vein, Rattani and Aarotale employed time-frequency methodology to discern gestures from muscle cues. They utilised STFT to derive spectrograms ; meanwhile, the CWT technique enabled the successful isolation of the signal's dominant frequencies [43]. Sbargoud et al. [64] demonstrated that time–frequency analysis techniques are the most appropriate approach for processing EMG signals. In their work, features were derived using both the wavelet packet transform (WPT) and the DWT. The application of WPT enabled certain researchers to focus on the fusion of EMG and electroencephalogram signals, as it allows signal decomposition across multiple frequency bands with high precision, thereby improving the precision of the final integrated analysis. Di Nardo et al. [65] utilised CWT methodology to derive time-frequency characteristics from EMG signals to spot muscle co-activation. Moreover, they included cross-spectral power analysis, which refined the exact timing of contraction initiation, promoting improved real-time functionality. Table 5 depicts the time-frequency domain properties.

Table 5. Time frequency domain features

Features	Abbreviation	Description	Ref.
Continuous Wavelet Transform	CWT	Calculating the correlation coefficients between the signal and the mother wavelet to analyze the non-stationary signal.	[6, 64]
Discrete Wavelet Transform	DWT	An effective approach to analyzing non-stationary signals involves decomposing them into multiple scales.	[6, 65]
Wavelet Packet Transform	WPT	To analyze non-stationary signals by dividing the signal into coarse and detailed components across multiple levels.	[6, 47]
Empirical Mode Decomposition	EMD	To analyze non-stationary signals by decomposing the signal into recurring components.	[6, 66]
Short-Time Fourier Transform	STFT	The FT converts a time-domain signal into a time–frequency representation by segmenting it into overlapping windows and applying the transform to each window.	[67]

5.1.4 Statistical features and distribution modeling

During feature extraction, the PDF is employed to examine the statistical distribution of EMG signal values and to reveal patterns linked to muscle activity. The signal amplitude plays a central role in PDF-based analysis, as it directly reflects the level of muscle contraction [68]. Jou et al. investigated muscle fatigue in older adults, with a particular emphasis on handgrip exercises and the feasibility of real-time fatigue detection. They noted that accurate interpretation of muscle behaviour depends largely on the features derived from EMG signals. To characterise the PDF shape, the study extracted statistical descriptors using skewness and kurtosis, which were computed through data-processing techniques defined in Eqns. (1) and (2), respectively

$$Kurtosis = \left[\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^{n} \left(\frac{Xi-\bar{X}}{S}\right)^4\right] - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (1)$$

$$Skewness = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{Xi-\bar{X}}{S}\right)^3 \quad (2)$$

where, *n* is the total number of sample points used to estimate the probability coefficient, and *xi* is the value of the PDF, while ($\bar{X}$) is the mean value of the probability coefficients in the sample.

Beyond the previously discussed methods, the study introduced a novel metric for evaluating muscle fatigue, referred to as temporal mean kurtosis, which served as a quantitative indicator for identifying the onset of fatigue. This measure was subsequently assessed using analysis of variance to evaluate its effectiveness and performance. Although the researchers faced several data-related challenges because of the dataset being restricted to elderly participants, the findings demonstrated encouraging potential for clinical applications related to muscle fatigue assessment [69].

A 2023 investigation introduced a Laplace–Gaussian mixture model for analysing EMG signals collected from upper-limb muscles, demonstrating superior performance compared with standalone modelling approaches. The proposed model was dependent on varying levels of muscle contraction force (MCF). Consequently, a PDF was employed to characterise and interpret the statistical distribution of the recorded EMG signals [70].

Navallas et al. [71] observed that at low muscle contraction force (MCF) levels, the PDF of the EMG signal approximates a Laplace-like distribution, particularly under degenerate conditions. Through analytical derivation of the signal amplitude's PDF, they demonstrated that as muscle activation persists and MCF increases to higher levels, the distribution gradually shifts towards a Gaussian form. Their analysis was grounded in the use of the EMG signal filling factor, which served as a key parameter for characterising changes in signal behaviour across varying contraction intensities [71]. A year later, Rodríguez Falces adopted a comparable methodology, investigating a progressive rise in muscle contraction force (MCF) from 0 to 10% of maximum voluntary contraction, whereas Navallas et al. focused on a gradual increase ranging from 10 to 100% of maximum voluntary contraction. This variation in the MCF range represented one of the most notable distinctions between the two investigations The PDF of the surface electromyogram and its dependence on contraction force in the vastus lateralis [68, 71]. At Northeast China University, a study proposed a system to identify fine hand and finger movements using two EMG signal channels. The researchers applied quadratic discriminant analysis and linear discriminant analysis (LDA) for classification, utilising probability density functions (PDFs). Nine subtle movement types, including grasping and tapping, were evaluated, achieving recognition accuracies of 95.79% with quadratic discriminant analysis and 95.01% with LDA [72]. In a study investigating motor neuron loss, Navallas et al. employed three metrics negative entropy, kurtosis, and the signal fullness factor to characterise the shape of the EMG signal's PDF in participants with neurological impairments versus healthy controls, while progressively increasing muscle contraction force from low to high levels [73]. Regarding the statistical features used to analyze EMG signals, PDF features can be more sensitive to noise and require higher computational costs compared to traditional features. Table 6 compares PDF-based and traditional features across several criteria.

Table 6. Comparison of probability density function (PDF) features and traditional features

Feature Category	Main Tasks	Noise Sensitivity	Computational Cost	Real-Time Suitability	Ref.
PDF Shape Features	Fatigue, force estimation	High	High	Low–Medium	[68]
Time-Domain	Monitor Muscle Fatigue	Medium	Low	High	[56, 74]
Frequency-Domain	Fatigue and muscle condition analysis	Medium–High	Medium	Medium	[59, 75]
Time–Frequency Domain	Complex gestures and rehabilitation analysis	Low–Medium	High	Medium	[56]

Overall, PDF-based analysis is particularly useful in studies focused on muscle fatigue assessment, contraction force variation, and the statistical characterization of neuromuscular behavior, especially when distribution shape and higher-order statistics provide clinically relevant insight. However, in DL based frameworks where features are automatically learned from raw or minimally processed signals, PDF-based statistical descriptors may contribute limited additional improvement compared with time-domain, frequency-domain, or time–frequency features. Therefore, its effectiveness depends strongly on the application context and the selected classification strategy. Ultimately, the limited number of studies in this domain underscores a significant research gap, in spite of the critical relevance and potential of this area for assessing neuromuscular function and performance.

The selection of feature domains depends on task complexity and computational constraints. Time-domain features are widely used in real-time rehabilitation and prosthetic systems due to their low computational cost. Frequency-domain features are mainly applied in fatigue analysis and muscle condition monitoring. Meanwhile, time–frequency methods such as wavelet transforms provide richer representations of non-stationary EMG signals and are often used in complex gesture recognition tasks. However, their higher computational cost may limit their use in wearable systems.

5.2 Electromyography classification

Recent research has explored a range of techniques for EMG signal classification across applications, including rehabilitation and muscle control, with each approach employing distinct strategies to differentiate feature sets. In a study by Toledo-Perez et al. [18], a support vector machine (SVM) was implemented as the classifier to evaluate the ZC feature both with and without an applied threshold. The findings demonstrated that introducing the threshold improved classification accuracy by approximately 40%, while also reducing computational processing time in comparison with alternative methods. Two years later, Sevim [16] introduced a feature extraction framework that employed SVM classifiers alongside a newly defined feature derived from autoregressive modelling and spectral transformation within the time domain. This approach achieved exceptionally high classification accuracy, exceeding 99%. The study also evaluated alternative classifiers, including LDA and k-nearest neighbours (KNN); however, these methods demonstrated lower effectiveness than SVM. The findings suggested that combining suitable features with appropriate classification algorithms can significantly enhance system performance compared with using classifiers in isolation. Conversely, the results also showed that feature combination does not always lead to improvement, as evidenced by the reduced accuracy observed when applying KNN with combined features [16]. A 2023 study showed that applying the maximum overlap MODWT to compress a lightweight neural network led to test-phase accuracies reaching approximately 95%. This reduction in model complexity made the approach well suited for implementation on wearable platforms, including hardware such as field-programmable gate arrays (FPGAs) [17]. While Aviles et al. [76] identified the multilayer perceptron (MLP) as a principal classification approach for EMG signal processing and enhanced its performance by integrating the Grey Wolf Optimisation (GWO) algorithm. Results from two experimental phases indicated that, in the first phase, the optimised MLP achieved an accuracy of 93%, outperforming the SVM method. However, a slight reduction in accuracy was observed during the second experimental phase. A 2025 study investigated the classification of muscle spasticity in stroke patients using the KNN algorithm, finding that analyses based on multi-channel EMG signals consistently achieved higher average accuracy compared with those using a single-channel configuration [77]. Donati et al. [27] employed canonical correlation analysis to enhance SVM classification. This approach mitigated performance degradation across multiple days of data collection, reducing the dependence on extensive datasets and prolonged training periods. A 2025 study reported a remarkable milestone, attaining 100% accuracy in the recognition of hand and finger movements by employing DL techniques, specifically through the use of convolutional neural networks (CNNs) [19]. Cai et al. [78] applied a genetic algorithm to optimise the parameters of an SVM classifier, achieving a classification accuracy of 94.14%, which represented an improvement over the lower accuracy obtained using the default parameter settings. Kok et al. [42] employed LDA for dimensionality reduction prior to classification with a SVM. This process effectively isolated the most relevant features, resulting in an improved accuracy of 90.69%. The combination of LDA and SVM produced notable outcomes, demonstrating strong potential for applications in prosthetic limb control and rehabilitation systems. One study initially applied a one-dimensional convolutional neural network (1D CNN) in the time domain, achieving the highest accuracy on the GRABMyo dataset for hand gesture recognition. However, classification performance was lower when evaluated on the forearm orientation based EMG (FORS-EMG) dataset in the spatio-temporal domain. In contrast, a 2022 study classified EMG signals derived from scalogram images using a least squares support vector machine (LS-SVM). The signals were first transformed via the CWT, enabling classification of hand movements into six primary gesture categories [79]. A 2023 investigation centred on the classification of epileptic seizures for clinical management using a ML approach built on an artificial neural network (ANN). The ANN-based model outperformed alternative classifiers, including decision tree methods, KNN, and random forest (RF) algorithms, by achieving the highest classification accuracy [57]. In a separate line of research, Sun et al. [45] utilised a large-scale dataset known as the JJ dataset, consisting of approximately 13,350 clean EMG signal segments, to classify gait phases using a ResNet-18 DL architecture. This work established an important foundation for future investigations, as such extensive datasets are uncommon within DL studies focused on recognising human movement intention. A 2024 study introduced a transfer learning-based model employing a prototypical network to classify post-stroke hand movements, with classification accuracy further enhanced through the selection of K-best features and optimisation of the signal window length [80]. In the same year, a study evaluated four ML classifiers SVM, extra trees classifier (ETC), KNN, and RF. Among these, the ETC achieved superior performance on the UC8 dataset, attaining an accuracy of 99.77% in EMG-based hand gesture classification. In a more recent study conducted this year, researchers introduced XMANet, a DL architecture incorporating inter-layer attention mechanisms to enhance gesture recognition performance. The findings showed that when STFT representations were used, XMANet outperformed existing models such as MobileNetV3, EfficientNet B0, and DenseNet121. Additionally, when wavelet transform (WT) features were applied, the network consistently delivered improved results, demonstrating a positive effect on signal processing effectiveness [43]. Table 7 encapsulates the recent research works on EMG signal classification, specifying the classifier types, accuracies, datasets, and main references across various experimental conditions.

Table 7. Summary of electromyography (EMG) signal classification methods

Groups	Year/Ref.	Classifier	Accuracy	Number of Subjects	Type of Tasks	Channels	Evaluation Protocol	Metric Type
Subject-dependent	2019 [78]	SVM	Default parameters: 78.53%, parameters optimization: 94.14%	5 healthy subjects	Shoulder Movements	8	5-Fold Cross-Validation (CV)	Accuracy, Recall, F1-Score
	2020 [18]	SVM	40% improvement with the proposed method and 13.5% better accuracy compared to threshold methods	5 subjects	Hand Movements	2	5-Fold Cross-Validation (CV)	Accuracy, Sensitivity, Precision, Specificity
	2022 [16]	SVM	99.57%	CapgMyo dataset 23 healthy subjects	Hand Movements	16	10-Fold Cross-validation	Accuracy
	2022 [79]	LS-SVM	95.33%	5 subjects	Hand Movements	3	10-Fold Cross-validation	Accuracy, Recall, F1-Score
	2023 [17]	1D Convolution Layer (Light-weight Neural Network)	Training: 96%, Validation: 96%, Testing: 95%	5 subjects	Hand Movements	2	Train-Validation-Test Split	Accuracy
	2025 [19]	CNN	100%	5 healthy subjects	Hand Movements	2	Train-Test Split	Accuracy
	2024 [44]	SVM, ETC, RF, KNN	UC8 dataset: ETC (99.77%), SVM (99.08%), RF (97.60%), KNN (97.50%);77.50%) MA21 dataset: ETC (97.33%), SVM (90.35%), RF (93.55%), KNN (77.50%).	MA21 dataset: 13 subjects, UC8 dataset: 1 subject	Hand Movements	8 and 20	subject-dependent 5-Fold Cross-Validation	Accuracy, Recall, F1-Score, Precision
	2025 [77]	KNN	78.70%	45 stroke patient	Arm Movements	3	Subject-dependent 10-Fold Cross-validation	Accuracy, Recall, F1-Score, Precision

Subject-dependent + Subject-independent	2025 [43]	XMANet (Cross-layer Mutual Attention Learning Network)	XMANet (ResNet50):99.60% XMANet (DenseNet121):99.61% XMANet (MobileNetV3):99.61% XMANet (EfficientNetB0):99.4%	Grabmyo dataset with 43 healthy subjects, FORS-EMG dataset with 19 healthy subjects	Hand Movements	8	Subject-dependent Train-Validation-Test Split	Accuracy, Recall, F1-Score, Precision
	2024 [45]	ResNet-18	95.34%	JJ Dataset, 15 subjects	Gait Phases	16	Subject-dependent Trail-Test Split, Subject-independent (LOO)	Accuracy
Cross-Day and Cross-Session	2023 [27]	SVM	95%	3 subjects	Hand Movements	8	Cross-Day and Cross-Session	Accuracy
	2024 [35]	RNN (LSTM, GRU, Bidirectional)	First stage 100%, Second stage LSTM: 98.46%, GRU: 96.38%, Bidirectional RNN: 97.63%	9 subjects	Arm and Hand Movements	4	Train-Test Split	Accuracy
	2023 [57]	Artificial Neural Network (ANN)	99.95%	20 healthy subjects	Muscular Seizure Movements	8	Train-Validation-Test Split	Accuracy, Recall, F1-Score, Precision
	2024 [32]	CNN	Grabmyo dataset:97%, FORS-EMG:94.95%	Grabmyo dataset with 43 healthy subjects, FORS-EMG dataset with 19 healthy subjects	Hand Movements	8	Train-Test Split	Accuracy, Recall, F1-Score, Precision
	2024 [42]	SVM	SVM with LDA:90.69%	CapgMyo dataset, 43 subjects	Hand Movements	28	Train-Validation-Test Split With 5-Fold Cross-Validation	Accuracy, F1-Score, Precision, Sensitivity
Subject-Independent	2024 [80]	Prototypical Networks (PN)	82.20%	20 subjects	Arm and Hand Movements	6	LOSO	Accuracy, Recall, F1-Score, Precision

Classification performance depends not only on the learning algorithm but also on the signal representation and application scenario. Traditional classifiers such as SVM, LDA, and KNN remain effective for small datasets and real-time systems due to their low computational requirements. In contrast, DL models such as CNNs and RNNs achieve higher accuracy when large datasets and image-based representations (e.g., spectrograms or wavelets) are used. However, their higher computational cost may limit their implementation in wearable rehabilitation devices.

5.3 Robotic rehabilitation systems in the electromyography space

Advancements in rehabilitation technologies based on robotic systems have significantly enhanced treatment effectiveness and patient outcomes following stroke, establishing robots as essential tools in contemporary research [81]. These rehabilitation programmes, which integrate AI – driven robotic platforms, seek to improve the accurate interpretation of human movement intention [82, 83]. A range of innovative robotic solutions has emerged in this area, including soft robotic systems, exoskeletons, and end-effectors, each designed to address specific patient requirements. For instance, Cisnal et al. [84] employed the RobHand platform to support finger extension and flexion while monitoring hand states such as opening, closing, and resting, utilising an externally mounted hand structure. In contrast, Devittori's work [85] concentrated on upper-limb motor and sensory rehabilitation through the Rehapticknob device, which applies sensory and motor stimulation techniques to enhance hand and arm movement training. Meanwhile, Abdallah et al. [86] explored real-time reduction of muscle fatigue using neuromuscular electrical stimulation delivered through a hybrid remote-control system based on a 3D-printed robotic hand. Robotic rehabilitation strategies typically depend on repetitive training frameworks or direct neuromuscular stimulation to restore movement. Additionally, Jiang et al. [87] applied an LSTM model to analyse spatiotemporal data for identifying robotic movement patterns during therapy, alongside federated joint learning methods to enhance collaborative robot training and movement performance. Abdullah designed the prosthetic hand using the SolidWorks CAD platform and applied a Butterworth filter operating within the 10–500 Hz range, along with a gain of 1000, for enhancing the SNR. This approach aimed to minimise user effort while improving the reliability and stability of control [86]. Extracting the most relevant information from the signal is critical for accurately interpreting different movement patterns. In a study examining forearm muscle activity during robotic finger motion, researchers applied a sliding window of 200 ms with a 170 ms overlap. This processing approach enabled the extraction of five principal features, which were subsequently used as input variables for movement decoding [88]. Perez utilised a multilayer neural network to derive three features corresponding to distinct voluntary contraction patterns, along with an additional feature capturing involuntary muscle activity, with a five-second rest interval separating each contraction. This approach enabled a precise representation of muscle contraction dynamics during exercise [89]. Each feature vector contains distinctive attributes associated with a particular class, which are collectively used to identify the activated muscle movement and assess classification performance across different algorithms. In research carried out by Kim et al. [90], a novel classifier based on a convolutional recurrent neural network (CRNN) was introduced, integrating CNNs with recurrent neural networks. Trained on data collected from 11 subjects performing 10 distinct gestures, the proposed model achieved an overall classification accuracy of 96%. By comparison, Liu et al. [91] described the use of the Bronson model as the foundation of a stroke rehabilitation programme based on electrical stimulation. Their protocol comprised three sequential stages. The initial stage was passive, in which the patient's limb was guided between two points at a regulated speed without active effort. In the second stage, assistive support was provided to aid muscle activation during targeted movements, with this assistance being progressively withdrawn as therapy advanced. The final stage required the patient to actively push the limb forward over a distance of 30 cm while external resistance was applied, enabling assessment of the maximum force the patient was capable of generating. Table 8 provides a summary of recent EMG-driven robotic rehabilitation systems.

In EMG-based robotic rehabilitation systems, the output of the classifiers need to be mapped into specific control commands for robotic devices. After applying signal filtering and extracting features (e.g., RMS, MAV, MNF), the models of machine learning (SVM, CRNN or fuzzy logic) classify the movement intended. In several rehabilitation systems, the classification results are utilized to produce control actions. For instance, within the upper-limb exoskeleton rehabilitation domain, changes in the detected level of muscle activation are used to modulate robotic assistance while performing therapeutic exercises. In EMG-based hand gesture robot control systems, hand gestures are recognized via an EMG classifier and then mapped to a command for the robot (e.g. grasping or moving its arm). A similar principle is used in hybrid bionic hand systems, where classified muscle patterns are mapped into motor commands that actuate the fingers and feedback signals can be used to monitor muscular fatigue and guarantee safe interactions. The EMG-based robotic rehabilitation system is presented in Figure 3, where the data read from the sensors go through several processing stages such as signal processing, feature extraction, intent detection and ends with the robot itself. There is also a feedback mechanism incorporated that allows for system updates based on kinematic data points in real time.

In rehabilitation robotic systems, the output of the EMG classifier is used as an input to the robot control strategy rather than only as a performance indicator. For example, when the classifier detects a hand-closing intention from EMG features, the output is translated into a command that activates the robotic actuator to assist the grasping motion. The controller regulates the assistance level according to muscle activation, and the system performance can be evaluated using metrics such as task completion time, response delay, and fatigue reduction.

Similarly, in upper-limb rehabilitation, the classifier may identify elbow flexion or extension intentions. Based on this output, the controller generates a trajectory command that guides the robotic joint to assist the intended movement using an assist-as-needed strategy. In this case, the effectiveness of the system is evaluated using control-oriented metrics such as trajectory tracking error, response time, and improvements in clinical scores such as the Fugl–Meyer Assessment (FMA).

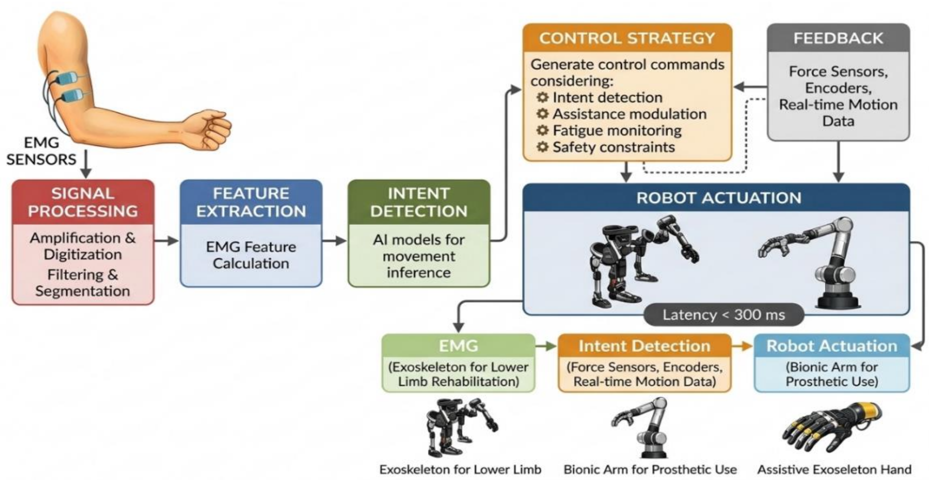

Figure 3. Electromyography (EMG)-based robotic rehabilitation

Table 8. Summary of electromyography (EMG)-based robotic systems

Name of Robot	System Type	Control Pipeline	Timing (Window Length / Latency)	Control Objective	Evaluation Metric	Ref.
Dual-arm Rehabilitation Robot	Hybrid rehabilitation system	EMG acquisition → fourth-order Butterworth band-pass filter (20–450	Signal window with a step size of 100ms / low-latency	Detecting muscle fatigue	Range of Motion (RoM), Active Torque, and	[82]

		Hz) → Extraction (RMS, MAV, ZC, MF, MP) → SVM (95%)			Passive Torque	
ReoGo-J	Robotic system for motor rehabilitation	Item Response Theory (IRT), Graded Response Model (GRM) → Predicted Ability(θ), Fugl-Meyer Assessment (FMA) → patient grouping based on θ	Task duration adjusted based on predicted ability (θ) and real-time adjustments based on the patient's ability	Improving upper limb mobility in stroke patients	FMA (Fugl-Meyer Assessment)	[92]
Exoskeleton Robot	Robotic system for upper limb rehabilitation and electrical stimulation	sEMG signals are acquired using e-health sensor shield V2.0 → Butterworth band-pass filter ranging from 20 to 400 Hz → Extract (RMS) → Activation of electrical stimulation from extracted EMG signals	A period of 1 ms, with an offset of 0, a priority of 100, and a deadline and timeout of 1 ms	Activating electrical stimulation modes (pain relief, massage, relaxation)	Joint Range of Motion (RoM)	[93]
UR3 Robot, Robotiq 2F-140 Gripper	A dynamic hand gesture-based industrial robot control system using the edge AI platform	Myo gesture control armband EMG sensor with notch filter 50Hz, Receiving EMG signal data to the NVIDIA Jetson Nano motherboard → CRNN (96.04%)	low latency	Dynamic control of robots using Edge AI.	Accuracy of Hand Gesture Classification using EMG Signals	[90]
Bionic hand with 5 Independent Servomotors	A hybrid bionic control system based on EMG and NMES.	EMG signal → 10–500 Hz Butterworth band-pass filter → Extract (MNF, MNP, RMS, MAV) → SVM, Fuzzy logic (95.4%)	The average delay (140–150 ms)	Reduce Muscle Fatigue	Accurate Classification, Improved Muscle Fatigue Performance, and Strength Stability	[86]
Thor 3D-printed robotic arm (6-DoF)	Myoelectric control system	A wireless Myo motion armband → Extract (RMS, MAV, WL, ZC, SSC, AR) → (SVM, K-NN, LDA) SVM achieved 95.04% accuracy for gestures with the dominant hand and 99.55% accuracy in elbow extension and flexion.	The window size was adjusted from 30 to 120 milliseconds, increasing the size by half.	Hand Gesture Control	Accuracy of Classifying Hand Gestures	[94]
Dexterous Robotic Manipulator	A robotic system for recognizing human hand movements (HIM)	EMG signal → Ensemble Empirical Mode Decomposition (EEMD) algorithm and Multivariate Autoregressive (MVAR) method → Gradient Boosting Decision Tree (GBDT) (92.78%)	N/A	Human In-Hand Motions – HIMs	Classification Accuracy	[95]
Exo-Glove Power (EGPO)	Robotic control system using ERG signals	fourth-order Butterworth filter between 20 and 450 Hz, sampled at a frequency of 1,000 Hz → Extract (MAV, ZC, WL, SSC) → SVM with True Positive Rate for Grasping (TPRG) and True Negative Rate for Grasping (TNRG)	Data with a window length of 250 ms and a step time of 50 ms	Power Grasp Intention	Sensitivity (TPRG) Specificity (TNRG)	[96]
Pepper Robot	Human-Robot Interaction	EMG Extract by the MYO EMG Armband (Thalmic Labs) → RF,	A sliding window of length 1s at an overlap of	Recognizing thumb gestures	Classification Accuracy	[97]

	SVM by applying Transfer Learning	0.5s divides the data into short-wave segments

6. DISCUSSION

Conventional signal processing techniques, including Butterworth and notch filters, continue to play a critical role in denoising and stabilising EMG signals. At the same time, the adoption of DL models such as CNNs, recurrent neural networks, and hybrid frameworks has markedly enhanced classification accuracy, gesture recognition, and resilience in noisy conditions. Comparative studies suggest that time–frequency domain methods, including continuous wavelet transforms (CWT) and DWT, are superior to purely temporal or spectral approaches for capturing the non-stationary nature of EMG signals. Additionally, iEMG offers greater spatial and temporal resolution for assessing deep muscle activity, whereas sEMG remains the preferred non-invasive choice for wearable devices and rehabilitation applications.

In spite of advancements in EMG signal analysis through AI and DL integration, several research gaps remain. Challenges persist in signal acquisition and processing, including variations in algorithm performance and applicability, noise interference particularly in rehabilitation settings and the substantial computational demands of DL models for clinical signal interpretation. Moreover, there is a notable lack of studies exploring the role and potential of AI in advancing EMG technologies. Future investigations should address diverse muscle groups, consider the nuances of pathological conditions across varied clinical contexts, and position AI as a central component in developing technologies which combine EMG signal analysis with intelligent robotics to enhance understanding of human–machine interaction.

6.1 Challenges and open issues

This review examined recent progress in EMG signal analysis by combining conventional processing techniques with advanced AI-based approaches. The adoption of DL models has led to notable improvements in classification performance when compared with conventional methods. Nevertheless, signal noise and the challenge of effective denoising remain major issues, directly influencing signal quality and classification reliability. In addition, the high computational and resource demands of AI-based models represent a significant limitation, especially for real-time implementations. These constraints highlight the need for continued efforts to overcome existing technical challenges and optimise system performance. Although AI has significantly transformed EMG signal analysis, there remains a clear gap in the effective integration of AI techniques with classical signal processing methods and EMG-driven robotic control mechanisms. Future studies should aim to close this gap by advancing classification strategies and incorporating more comprehensive analyses of pathological conditions and clinical use cases, thereby enhancing the flexibility and scope of this domain. Ultimately, the convergence of AI-driven methodologies with EMG signal processing and robotic applications holds substantial promise for developing innovative solutions in medical treatment, particularly in areas like stroke rehabilitation, and for driving further progress in this rapidly evolving field.

DL approaches necessitate large_training sets along with well-annotated samples in order to obtain reliable performance, but dataset rarity and lack of experimental redundancies are major barriers still dominating the EMG field. A huge limitation remains in the fact that EMG signals share substantial inter-subject variability, and intra-session variabilities due to changes by electrode displacement or muscle fatigue as well as signal drift from day-to-day recording. Additionally, the human effort necessary to annotate data accurately a problem that is especially relevant in clinical settings makes practical implementation even more challenging. Embedded deployment constraints such as latency, memory size, and power consumption restrict the applicability of computationally-heavy models in real-time rehabilitation and wearables systems even more.

7. CONCLUSIONS

The present review has introduced a detailed overview of recent advances in the acquisition, processing, feature extraction and classification of EMG signals as well as in robotic rehabilitation applications. Overall, the results show that the traditional filter such as Butterworth and notch filters are still plays an important role in effectively suppressing noise while sophisticated AI and DL models provide a huge lift on accuracy performance for classification and hand gesture recognition.

New methods in time–frequency domain have outperformed traditional techniques as they are better suited for the description of non-stationary nature of EMG signals, while integrating EMG-driven intelligent robotic systems in rehabilitation and assistive technologies revealed great potential.

However, challenges remain regarding noise interference, computational complexity and real-time implementation. Overall, although some trends can be noticed, there is no consensus on the fusion of classifiers in EMG-based rehabilitation systems that separates better from classical signal processing methods and AI-derived robotic controls, which future research may deepen to leverage synergies towards more effective, adaptive and clinically translatable solutions.

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