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# Machine Learning Methods for sEMG-based Motion Intention Classification in Upper-Limb Exoskeletons

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**Abstract:**

Surface electromyography (sEMG) provides a crucial non-invasive method for early assessment of motor intent, essential for the control of upper-limb exoskeletons operating under stringent real-time constraints. This review compares three prominent classifiers—support vector machine (SVM), linear discriminant analysis (LDA), and random forest (RF)—in the context of sEMG-based motion intention recognition. Employing a standardized methodological framework, this paper analyze performance metrics such as accuracy, latency, robustness, and computational efficiency, while addressing challenges like non-stationarity, inter-subject variability, and class imbalance. Results indicate that LDA is suitable for fast inference in control loops at 50–100 Hz, while SVM offers high accuracy for complex decision boundaries at a greater computational cost. RF stands out for its robustness to noise and cross-user variance, making it viable for real-time applications, albeit with trade-offs in model complexity and interpretability. Overall, LDA and compact RF models present practical options for embedded systems, whereas SVM is preferable for scenarios prioritizing peak accuracy. Future research should focus on compact feature fusion, domain adaptation, and hybrid learning models to enhance applicability in real-world settings.

**Keywords:** Surface Electromyography (sEMG); Upper-Limb Exoskeleton; Motion Intention Recognition; Machine Learning; Rehabilitation Robotics.

## 1. Introduction

Upper-limb dysfunction is a prevalent consequence of limited motor function arising from various central or peripheral nervous system disorders, including stroke, traumatic brain injury, spinal cord injury, cerebral palsy, multiple sclerosis, and peripheral nerve injury [1]. Patients often exhibit muscle weakness, joint stiffness, impaired fine motor skills, decreased coordination, and difficulties with motor intention

expression, significantly hindering their ability to perform essential activities of daily living (ADLs) such as dressing, eating, and writing. In post-stroke populations, approximately 70% experience upper-limb motor impairment after the acute phase, with less than 15% regaining near-normal function within six months [1].
Research indicates that neurological recovery is contingent upon neuroplasticity activation, necessitating intense, high-frequency, repetitive training during rehabilitation. Traditional physiotherapy, however, faces challenges including insufficient training intensity, high subjectivity, and difficulties in quantifying outcomes. Thus, there is an urgent need for innovative assistive rehabilitation technologies to enhance the standardization, personalization, and traceability of rehabilitation training [2].
As a wearable intelligent rehabilitation device, the upper-limb exoskeleton robot offers multi-degree-of-freedom motion capabilities, facilitating both passive and active motion training by simulating natural human motion trajectories. These exoskeletons differ from conventional rehabilitation devices through their significant human-computer interaction, high adjustability, and real-time feedback. The conceptual origins of exoskeleton technology can be traced back to the Cybernetic Anthropomorphous Machine (CAM) proposed by General Electric in the 1960s [3], which enabled external mechanical expression of human intention via a master-slave arm structure and force-position feedback mechanism. Initially intended for industrial and military applications, this control principle has profoundly influenced the design of medical rehabilitation exoskeletons and remains a theoretical foundation for modern rehabilitation robotics [3].
Accurately discerning users' movement intentions is pivotal in the control of exoskeleton robotics. Surface electromyography (sEMG) has emerged as a prominent method due to its non-invasive characteristics and its ability to provide real-time insights into neuromuscular activity[4][5].
The precision of movement-intention recognition becomes increasingly significant as upper-limb exoskeletons gain traction in both support and rehabilitation contexts. Recent advancements in machine learning methodologies have markedly improved the application of sEMG in intention recognition, motion classification, and the modeling of control strategies. These technological developments are essential for enhancing the efficacy and responsiveness of exoskeleton systems in real-world applications [6].
The sEMG signal can generally be detected 50-100 ms prior to movement [5]. It offers advantages such as early detection and non-invasive application. However, its effectiveness is impacted by physiological and environmental factors like perspiration, electrode displacement, and muscle fatigue [5]. Inter-subject variability and the difficulty of non-invasive parameter acquisition hinder model-based approaches and degrade cross-person recognition [7]. The high-dimensional, nonlinear nature of sEMG raises feature-extraction and computation demands; real-time systems must maintain stable conditions to avoid recognition delays that jeopardize control and rehabilitation effectiveness [4].
The implementation of exoskeleton robot control through electromyographic signals involves a methodical process, including signal preprocessing, feature extraction, classification, and control. Machine learning techniques enhance system adaptability and recognition capabilities [4]. Rule-based strategies lack flexibility for inter-individual variability and often yield suboptimal accuracy [5].
Machine learning methods, particularly supervised learning classification algorithms like Support Vector Machine (SVM) and Random Forest (RF), improve precision and robustness in recognizing action intention by autonomously learning from data [7]. Recent advancements in deep learning, such as CNN, LSTM, and Transformers, exploit automatic feature extraction, reducing reliance on manual selection [6]. Furthermore, researchers have introduced methodologies like domain adaptation and incremental learning to address the challenges of temporal and inter-user variability in sEMG, enhancing model generalization and stability for long-term use [7].
This study reviews the use of sEMG for upper-limb exoskeleton control, with emphasis on three widely used classifiers—SVM, Linear Discriminant Analysis (LDA), and RF. Methods are compared across signal preprocessing, feature extraction, classification accuracy, and suitability for embedded real-time control. Strengths and limitations are contrasted, and implementation challenges (e.g., non-stationarity, inter-subject variability, latency) are identified to clarify conditions under which each method is preferable. Potential directions include multi-feature fusion, compact feature selection, hybrid models, and adaptive learning to enhance accuracy, robustness, and generalizability in sEMG-based intention recognition.

## 2. Machine Learning–Based sEMG Processing and Classification Methods for Upper-Limb Exoskeletons

### 2.1 SVM in Upper-limb Exoskeleton Classification and Processing

sEMG is utilized for the recognition of movement intention in upper-limb exoskeleton applications, employing SVM to facilitate real-time movement classification. The method unfolds through the following specific steps:

#### 2.1.1 sEMG Signal Acquisition

Atzori et al. provided a comprehensive overview of the

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electrode arrangement and acquisition parameters in the protocol for the NinaPro dataset [8]. The experimental setup involved eight electrodes equally spaced around the circumference of the forearm, just below the elbow at the level of the radio-humeral joint. Additionally, one electrode was positioned at each of the principal activity points of the flexor digitorum superficialis and extensor digitorum superficialis muscles. In a subsequent configuration, the researchers incorporated one electrode each at the main activity points of the biceps brachii and triceps brachii muscles. The identification of these major activity points was conducted through palpation to ensure the capture of signals from the principal muscles.

Data acquisition was executed using the Delsys Trigno Wireless EMG system, where each electrode was powered by an individual battery and affixed to the skin surface using standard adhesive tape along with an external latex-free elasticated fixation band to mitigate electrode displacement during physical activity. The signal sampling frequency was set at 2000 Hz, ensuring a baseline noise level below 750 nV RMS, thereby providing high-quality EMG data for subsequent motor intention recognition.

**2.1.2 Signal Pre-processing**

The sEMG signal has low amplitude and is easily affected by motion artefacts, changes in electrode-skin impedance, and power line interference. Rigorous pre-processing is required before feature extraction and classification. Raw signals are processed with a Butterworth band-pass filter (10–500 Hz) to remove unwanted frequency components. A 50 Hz notch filter reduces power supply interference [4]. Multichannel sEMG signals are normalized, often by Z-score, to reduce individual variance [4][5]. After filtering, signals are segmented with a sliding window. A 200 ms window and 50% overlap help ensure stable features under real-time conditions [5]. Outliers and incomplete segments are discarded before feature extraction. [4].

**2.1.3 Feature Extraction**

To effectively represent motion intent from preprocessed sEMG signals, feature extraction using a sliding window approach is essential. Recent studies classify features into three categories: time-domain, frequency-domain, and time-frequency-domain features, each with distinct significance and classification capabilities.

In the time-domain analysis, certain features provide direct indicators of muscle contraction. Key features include:

Mean Absolute Value (MAV): This metric averages the absolute values of the signal within a specific window, reflecting the intensity of EMG activity.

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

Root Mean Square (RMS): This feature calculates the square root of the mean energy, effectively reducing incidental noise while indicating muscle contraction strength.

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

Zero Crossing Count (ZC): This measures the number of times the signal crosses zero, offering insight into the frequency change of the signal.

Waveform length (WL) and Willison amplitude (WAMP): describing the signal complexity and sensitivity to amplitude variations, respectively [4][5].

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

$$WAMP = \text{count}\left(|x_{i+1} - x_i| > T\right) \tag{4}$$

In terms of frequency domain characteristics, the power spectrum of the signal is obtained by Fourier transform and can be further calculated:

Mean Frequency (MNF) and Median Frequency (MDF) for characterizing muscle fatigue regarding the signal spectral distribution.

$$MNF = \frac{\sum_i f_i P(f_i)}{\sum_i P(f_i)} \tag{5}$$

where $f_i$ is the frequency component and $P(f_i)$ is the power spectral density of the spectrum at frequency $f_i$.

$$\sum_{f=0}^{f_m} P(f) = 0.5 \times \sum_{f=0}^{f_{\max}} P(f) \tag{6}$$

where f_m is the frequency corresponding to when the total energy of the spectrum reaches half, and $f_{\max}$ is the maximum frequency of the spectrum.

Spectral Power (SP) and Spectral Entropy (SE), which can reflect the energy distribution of the signal in a specific frequency band [4].

$$SP = \sum_{f=f_1}^{f_2} P(f) \tag{7}$$

In relation to time-frequency domain features, for non-stationary sEMG signals, techniques such as Short Time Fourier Transform (STFT) or Wavelet Transform (DWT, WPT) may be employed to acquire both time and frequency information, thus enhancing differentiation in complex action patterns [4][5].

The previous features can be utilized independently or in conjunction, contingent upon the specific task requirements. Research has proved that time-domain features, particularly, offer significant advantages in classification scenarios.

Cai et al. created a method for recognizing upper-limb intentions using SVM, designed for mirror-type rehabilitation on the ReRobot platform. Their system utilized 16 channels of sEMG data at a frequency of 1 kHz, capturing signals from nine different muscles. It applied baseline correction, 20–500 Hz band-pass, 50 Hz notch, full-wave rectification, and amplitude normalization with 4th-order Butterworth filters. Sample entropy identified activity segments. Feature extraction included RMS, waveform length, variance, absolute mean, short-term energy, and 4th-order autocorrelation, using 128 ms Hanning windows and 64 ms steps. A genetic algorithm optimized the RBF-SVM, raising accuracy from 78.53% to 94.18%. With five healthy subjects and five motions, 10×5-fold cross-validation gave a 93.34% ± 0.59% recognition rate (F1 = 0.9368). In robot tests, 92% actions were recognized, and the sEMG-based emergency stop worked in all 25 trials [9].

## 2.2 LDA in Upper-limb Exoskeleton Classification and Processing

LDA, a fundamental linear classification technique, is extensively employed in the domain of motion intention recognition for upper-limb exoskeletons. In comparison to SVM, LDA offers notable advantages, including a simpler structural framework, reduced computational demands, and enhanced real-time performance. These characteristics render LDA particularly advantageous for exoskeleton control systems that feature stringent real-time operational requirements [4][5][8].

### 2.2.1 Feature Input and Data Processing

The input for LDA is analogous to that of SVM, wherein preprocessed multi-channel sEMG feature vectors are utilized. Frequently employed input features include time-domain characteristics (e.g., MAV, RMS, ZC, WL, WAMP), as well as frequency-domain and time-frequency-domain features. These features effectively capture the intensity and frequency fluctuations of muscular activities, as well as the complexity inherent in the signals [4][5][8].
Typically, these features are concatenated into a singular multidimensional feature vector and subjected to computation and input in real time, utilizing a consistent sliding window length of approximately 200 ms with a 50% overlap.

### 2.2.2 LDA Classifier Design

The foundational premise of LDA is to maximize the projective separation among distinct classes of samples by identifying the optimal linear projection direction within the feature space. To articulate this, one defines the intra-class scatter matrix $S_w$ and the inter-class scatter matrix $S_b$:

$$S_w = \sum_{j=1}^{C} \sum_{x_i \in D_j} \left(x_i - \mu_j\right)\left(x_i - \mu_j\right)^T \tag{8}$$

$$S_b = \sum_{j=1}^{C} N_j \left(\mu_j - \mu\right)\left(\mu_j - \mu\right)^T \tag{9}$$

where $C$ denotes the number of categories, $\mu_j$ represents the mean vector of the $j$-th category, $\mu$ signifies the overall mean vector for all samples, $N_j$ indicates the number of samples in the $j$-th class, and $D_j$ denotes the set of samples corresponding to the $j$-th class. The optimal projection matrix $W$ is subsequently deduced by optimizing the corresponding criterion function:

$$W^* = arg\,\max_{W} \frac{\left|W^T S_b W\right|}{\left|W^T S_w W\right|} \tag{10}$$

where $S_b$ is the between-class scatter Matrix and $S_w$ is the Within-Class Scatter.
This optimal projection direction effectively maps the feature space to a lower-dimensional linear discriminant space, facilitating optimal classification [8][10].

### 2.2.3 Real-Time Classification Decision and Implementation

In practical exoskeleton control applications, the trained LDA projection matrix is employed for real-time classification. When the feature vectors for a new window are extracted, they are initially mapped to the discriminant space through the matrix W. Subsequently, the system makes decisions based on the distance between the feature vector and the mean vectors of each category. This method employs a nearest neighbour strategy to identify the current motion intent. [4][5].

### 2.2.4 Examples of LDA Applications and Recent Advances

Several studies have confirmed the suitability of LDA for intention recognition in upper limb exoskeletons [10]. Duan et al. employed three-channel temporal domain features to achieve real-time recognition of nine hand gestures with 91.7% accuracy. Subsequent work combined LDA with features such as MAV and ZC for classifying shoulder-elbow coordinated movements. This approach supports real-time control with high accuracy and low latency [4][5][6].
Another notable example is the fully wearable soft hand exoskeleton, “RELab tenoexo.” This device uses surface EMG signals for grasp intention recognition. It captures multi-channel sEMG signals via a wireless Myo armband during a 30-second calibration. Subsequently, standard time-domain features train an LDA classifier, achieving ~92.9% average online classification accuracy (individual accuracies 95.5% and 90.3%) along with low-latency recognition of ‘open’ and ‘closed’ intentions [11][12]. The

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wearable system features lightweight design, multiple compliant grasp modes, and automatic customization [12]. Post-training, LDA outputs directly drive the exoskeleton actuator, translating muscle signals into corresponding hand assistance. In functional tests, users, including spinal cord injury patients, demonstrated significant improvements in hand function, enabling tasks such as pinching marbles and using cutlery that would not have been possible without the device.

In conclusion, despite the growing interest in deep learning, LDA remains a pivotal and widely adopted method for real-time motion intention recognition in upper-limb exoskeletons. Its ease of implementation, low computational cost, and real-time performance make it well-suited for embedded systems with demanding operational requirements [4][5][8].

## 2.3 Random Forest in Upper-limb Exoskeleton Classification and Processing

RF is an ensemble learning method introduced by Breiman, which significantly enhances the accuracy and robustness of classification tasks by constructing a multitude of decision trees and aggregating their results through a voting mechanism [13]. RF has been widely used for upper-limb exoskeleton motion intention recognition. This method is particularly well-suited for real-time processing and classification of multi-channel, high-dimensional feature sets [4][5].

### 2.3.1 Feature Input and Data Processing

RF employs the same preprocessed multi-channel sEMG features as SVM and LDA. The signals are band-pass filtered between 10–500 Hz and notch filtered at 50 Hz, followed by Z-score normalization. The data is segmented into 200 ms windows with a 50% overlap [4][5]. For each segment, standard time-domain metrics and frequency-domain features, including mean frequency, median frequency, and spectral power, are extracted. Additionally, time–frequency features such as wavelet packet energies are incorporated. These features are then concatenated into a high-dimensional vector, which serves as the input for the RF model [4][8].

### 2.3.2 Random Forest Classifier Design

Random Forest employs an ensemble of $M$ decision trees, each trained on $M$ bootstrap replicas of the training set. For each tree, splits are determined by a random subset of features (“feature bagging”), selecting the split that minimizes Gini impurity, defined as

$$Gini\left(D,a\right)=1-\sum_{k=1}^{C}p_k^2 \tag{11}$$

Where $D$ represents the node’s data, $a$ is the candidate feature, and $p_k$ denotes the fraction of class $k$ within the node. During inference, each tree casts a vote on the label of a new vector $X$, with the prediction being the majority class:

$$\hat{y}=\mathrm{mode}\{h_1\left(X\right),h_2\left(X\right),\ldots,h_M\left(X\right)\} \tag{12}$$

This ensemble methodology reduces variance and mitigates overfitting compared to a single tree, demonstrating robust performance against inter-subject variability and noise in sEMG signals [13].

### 2.3.3 Real-time Classification and Control

In real-time applications, feature windows are continuously input into the trained Random Forest (RF). Each tree requires a limited number of split nodes to generate outcomes, with majority voting concluding within tens of milliseconds. This latency aligns with the demands of embedded exoskeleton control loops operating at 50–100 Hz [4][5]. Model outputs are swiftly converted into control commands, such as flexion/extension states or assist levels. Compared to single decision trees, RF exhibits enhanced robustness to intricate movements and unstable or noisy sEMG signals, along with superior generalization performance.

### 2.3.4 Application Examples and Recent Advances

Atzori et al. introduced the NinaPro dataset, comprising over 50 hand/wrist gesture classes, establishing a standard benchmark for random forests (RF) and other classifiers in high-dimensional, multi-class surface electromyography (sEMG) recognition [8]. Xie et al. demonstrated that RF outperforms single decision trees in multi-channel sEMG, exhibiting greater resilience to inter-subject variability [5]. Zhao et al. highlighted RF’s ability to mitigate overfitting while maintaining high accuracy and real-time performance in complex upper-limb intent recognition for exoskeletons [6]. Zhou et al. applied RF to NinaPro DB4, which includes 12 basic finger movements across 10 subjects with 12-channel sEMG. They extracted nine time-domain features (e.g., RMS, MAV, WL, SSC, ZC) and utilized scikit-learn, achieving an average accuracy of 84.11% (SD 3.99%), with the best subject reaching 92.94%. Among the features, MAV was the most effective (~81.10%), while ZC showed lower performance (~48.49%). These findings underscore RF’s efficacy in multi-feature fusion and its robustness against overfitting, which is advantageous for myoelectric control in upper-limb exoskeletons [14]. Overall, RF is a robust choice for upper-limb intent recognition, adept at handling high-dimensional features and noisy signals while generalizing well across users, thereby facilitating complex control and personalized rehabilitation [4][5][6].

# 3. Comparative Discussion and Analysis

## 3.1 Real-Time Classification Decision and Implementation

The three methods—SVM, LDA, and RF—utilize the same sEMG acquisition, preprocessing, and feature set; however, they differ in their learning mechanics and computation costs. SVM, a large-margin method, employs kernels to project features into higher-dimensional space, effectively identifying a separating hyperplane. While it adeptly models complex multi-class boundaries, it is sensitive to hyperparameter tuning and may exhibit high computational demands in settings with elevated dimensionality [4][5][8].

Linear Discriminant Analysis (LDA) serves as a linear classification method that aims to maximize inter-class variance while minimizing intra-class variance. Its straightforward structure and efficient execution render it particularly suitable for real-time applications in embedded exoskeleton systems. Yet, LDA assumes Gaussian distributions with equal covariances, limiting its efficacy with nonlinear data [4][5][10].

RF utilizes ensemble learning, training multiple decision trees on diverse feature and sample subsets. This method is resistant to noise and overfitting, and it handles high-dimensional features well, often achieving high accuracy in complex scenarios. However, RF models can be relatively large in scale, and ensemble-level interpretability is limited [4][5][8].

The choice of classification method depends on specific application needs. For example, the EksoUE by Ekso Bionics and MyoPro by Myomo both require high classification accuracy to guide patient movements safely. In contrast, exoskeletons for daily assistance prioritize smooth control over absolute accuracy to prevent user discomfort [15][16].

Many commercial exoskeletons have limited computational capacity, necessitating classification algorithms with low complexity and small memory footprints. In this context, LDA and optimized RF methods are advantageous.

## 3.2 Performance Analysis and Practical Implications

Existing studies highlight the differing performance of SVM, LDA, and RF in sEMG-based motion intention recognition for upper-limb exoskeletons. Hassan et al. (2020) conducted a gesture recognition study using a Myo armband, extracting RMS, MAV, WL, AR(4), ZC, and SSC features from seven gestures and six subjects, with 240 ms windows and 120 ms overlap. SVM (RBF kernel) achieved the highest accuracy of 95.26%, outperforming LDA (92.58%). SVM demonstrated strong generalization for complex boundaries, while LDA's efficiency favors embedded real-time control despite slightly lower accuracy [17].

Atzori et al. evaluated classifiers on the NinaPro dataset. RF, trained on multi-channel time-, frequency-, and wavelet-domain features, achieved average accuracies of 75.3% (DB1) and 75.27% (DB2) over 50 gesture classes. Although less accurate than SVM or LDA, RF showed greater stability and resistance to overfitting in high-dimensional, noisy conditions, helping manage inter-subject variability [8]. These results reflect task difficulty (large class set, early feature engineering, heterogeneous cohort) rather than an inherent RF limitation [8].

Building on these accuracy results, real-time constraints are considered next. Exoskeleton control demands strict real-time performance, with motion classification latency below 100 ms and ideally 50–80 ms [4][5][10]. LDA excels in processing speed, RF adapts well to noise, and SVM is suitable for managing nonlinear boundaries. These latency profiles align with the accuracy–complexity trade-offs in Section 3.1.

In terms of real-time performance, LDA exhibited the lowest computational complexity. SVM incurred slightly higher delays due to kernel complexity but remained feasible (<100 ms). RF required voting across multiple trees, increasing computational effort, but offered robustness against noise and variability. Table 1 shows the performance comparison of different classification methods.

**Table 1. Performance comparison of different classification methods [8, 17].**

| Classification | Literature sources | Average accuracy (%) | Advantages | Limitations |
|---|---|---|---|---|
| SVM (RBF) | Hassan et al. | 95.26 | Strong ability to handle nonlinear boundaries, highest accuracy | Parameter tuning is complex and computationally intensive |
| LDA | Hassan et al. | 92.58 | Simple structure, good real-time performance, embedded friendly | Assumes Gaussian distribution, insensitive to nonlinearity |
| RF | Atzori et al. | 75.3 / 75.27 (DB1 / DB2) | Strong noise resistance, can handle high-dimensional redundant features | Large model, poor interpretation, slightly lower accuracy |

Note: RF accuracy in [8] is affected by task difficulty (50+ classes), early feature engineering, and cohort heterogeneity.

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## 4. Conclusion

This study evaluates SVM, LDA, and RF for sEMG-based motion intention recognition in upper-limb exoskeletons. In brief, SVM has strong nonlinear modeling and achieves the highest accuracy on complex actions, making it well suited for rehabilitation and fine manipulation. Conversely, LDA has a simple architecture, low computational cost, and solid real-time performance, making it a preferred choice for real-time control in embedded systems. Recent studies report competitive accuracies for RF when features and parameters are carefully optimized.

Choosing the right algorithm requires consideration of accuracy, real-time performance, and available computational resources. For devices like EksoUE and MyoPro, high accuracy and low latency are critical. In assistive exoskeletons, a balance between computational complexity and control stability is essential. Future work should emphasize feature fusion, compact feature selection, hybrid models, and adaptive learning to enhance accuracy, reduce latency, and improve cross-user adaptability.

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