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Myoelectric Control for Robotic Exoskeletons: A Comprehensive Review from Signal Processing to Future Directions

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Abstract: Electromyography (EMG) control technology would be used to realize natural human-robot interaction in exoskeletons. The presented work gives a systematic literature overview of the EMG signal processing and control algorithms to be used in exoskeletons. To begin with, it describes how surface EMG signals are generated and acquired and what the benefits and drawbacks of various types of electrodes and sensors are. Secondly, it discusses the detailed process of signal processing, such as preprocessing, filtering, feature extraction (especially the Root Mean Square (RMS) within the time domain), and pattern recognition methods. Based on this, it groups and examines threshold control, proportional control, and control strategies based on machine learning and describes their appropriate areas of application. Lastly, it recaps the main issues at stake today (variability of signals, real-time constraints, and barriers to clinical translation) and envisions future research perspectives like multimodal fusion, edge computing, and personalized adaptive control. The purpose of the present review is to offer an organized body of knowledge about EMG-controlled exoskeletons to those who are new to electronics and information-related disciplines.

Keywords: Surface electromyography signal; Exoskeleton robot; Signal processing; Feature extraction; Pattern recognition; Human-machine interaction

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1. Introduction

Exoskeleton robots are wearable mechatronic devices that help improve or assist in moving humans. Because the first exoskeleton, the Hardiman, was developed by the General Electric Company in the 1960s, this technology has diversified in its development, starting with military enhancement and moving into medical rehabilitation. In the last few years, due to the increase in population aging and the increase in rehabilitation medical demands, exoskeletons have shown a significant application perspective in the field of stroke rehabilitation, spinal cord injury, as well as in elderly walking support, etc.

The key to exoskeleton control lies in the accurate and real-time perception of the user's movement intentions. Traditional physical input methods (such as buttons and joysticks) lack naturalness and make it difficult to achieve "human-machine integration" collaborative control. In contrast, surface electromyographic signals directly reflect neural and muscle activities and can detect movement intentions 50–100 milliseconds before the actual human movement, making them the preferred biological signal source for exoskeleton control [1].

Most of the existing reviews focus on a single technical aspect and lack an end-to-end system overview for exoskeleton applications. This paper, targeting beginners in the field of electronic information, presents the complete technical chain of myoelectric exoskeletons from signal generation, acquisition, and processing to control strategies.

2. The basics of myoelectric signals and acquisition technologies

2.1.The generation principle of myoelectric signals

Myoelectric signals are the temporal and spatial superposition of the action potentials of the motor units during muscle contraction. As can be seen in **Figure 1**, when the brain issues a movement command, it is transmitted through the spinal cord motor neurons to the neuromuscular junction, causing the depolarization of the muscle fiber membrane and generating action potentials. The single motor unit potential lasts for 3–15 ms and has an amplitude of 20–2000 μV. The superposition of multiple motor unit potentials in time and space forms an interference waveform that can be detected on the skin surface.

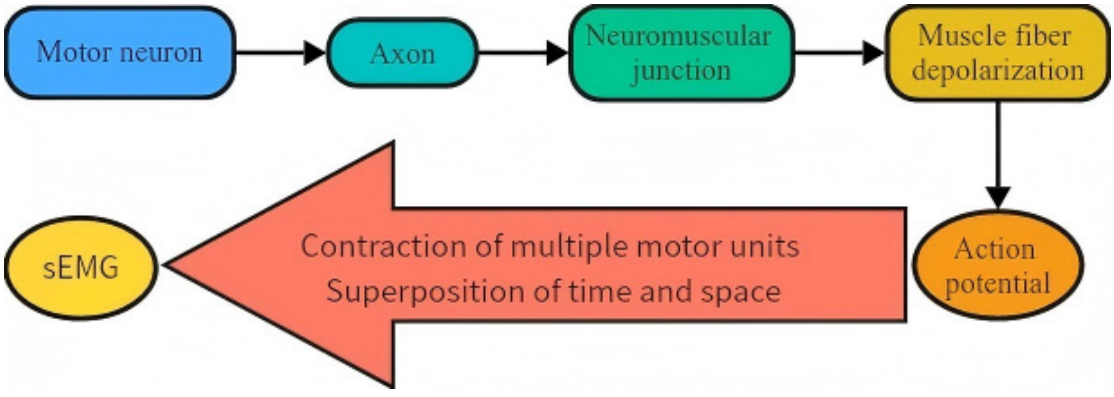


Figure 1. Schematic diagram of sEMG(Picture credit:Original).

2.2.The characteristics of myoelectric signals

The surface electromyographic signals have several important characteristics as shown in **Table 1**.

Table 1. Electromyographic signal characteristics

Character	Typical value	Illustration
Amplitude range	0.1–5 mV	It depends on the size of the muscles and the intensity of the contraction.
Frequency range	20–500 Hz	The main energy is concentrated in the range of 50–150 Hz.
SNR	3–10 dB	Susceptible to interference and contamination
Leading time	50–100 ms	Preceding the mechanical action

2.3.Electrode types and selection

The electromyography signal collection electrodes can be classified into three categories as shown in **Table 2**.

Table 2. Electrode category

Category	Operation principle	Advantages	Disadvantages	Suitable condition
Wet electrode	Ag/AgCl+ Conductive gel	High signal quality and low impedance	Gel drying, skin irritation	Clinical diagnosis, laboratory research
Dry electrode	Direct contact of metals	Easy to use and reusable	Sensitive to motion artifacts	Short-term wear
Textile electrode	Conductive fabric	Comfortable and suitable for long-term wearing	Signal stability needs to be improved.	Smart clothing, rehabilitation training

2.4.Electrode layout methods

The methods of electrode layout are single-pole leads, double-pole leads, and high-density arrays. The single-pole lead has one electrode positioned on the muscle belly and the reference electrode on the bone, and it is easy but prone to interference. The double-pole lead places two electrodes perpendicular to the direction of the muscle fibers using differential amplification, which is effective in rejecting common-mode interference, and is the most widely used approach today. The high-density array positions several electrodes in a grid formation, and it can be used to gain the spatial distribution information of muscle activities, which would be applied to identify the gestures accurately [2]. **Figure 2** clearly shows the features that characterize the three electrode layout methods.

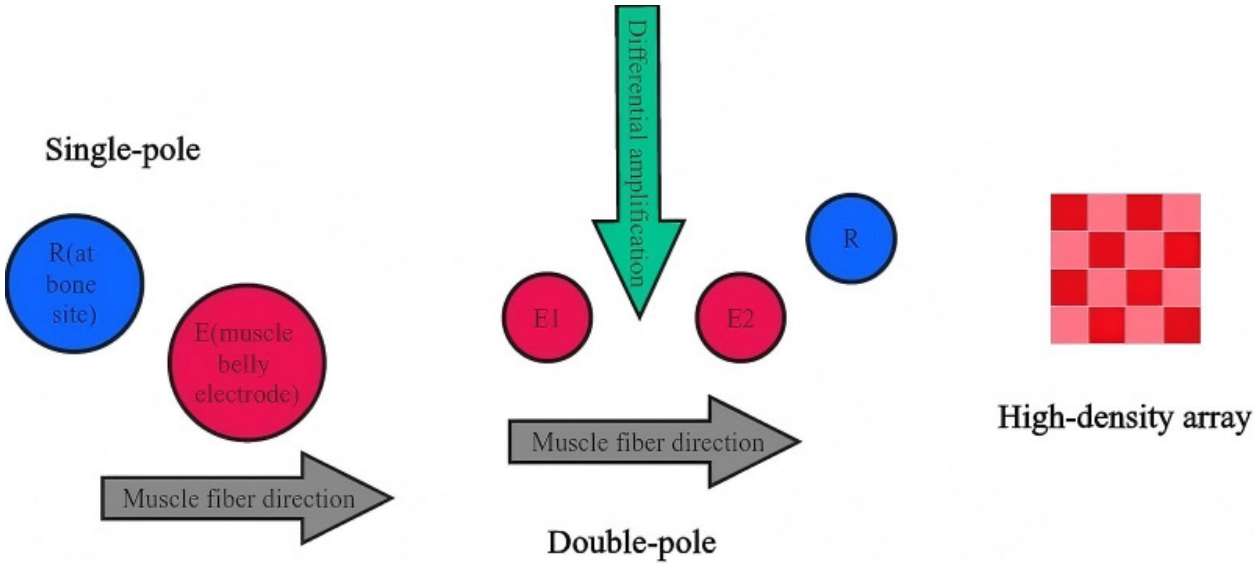


Figure 2. Electrode distribution diagram (Picture credit:Original)

2.5.Sensor module and signal chain

Modern electromyography sensors usually incorporate complete signal processing circuits as shown in **Figure 3**:

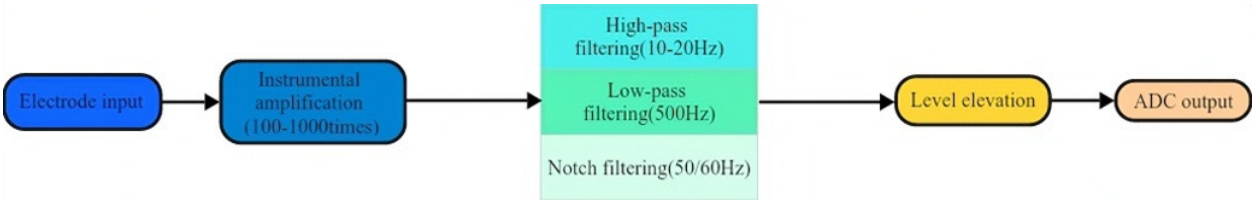


Figure 3. Signal processing procedure (Picture credit: Original)

Take the Gravity electromyography sensor as an example. It outputs an analog voltage ranging from 0 to 3.3 V, which can be directly connected to the ADC of the microcontroller, significantly reducing the development difficulty.

3. Signal processing methods

3.1.Signal preprocessing and noise suppression

The original myoelectric signals contain various noises and need to be preprocessed before being used for feature extraction [3]. **Table 3** presents several common types of noise and the corresponding suppression methods:

Table 3. Types of noise

Types of noise	Source	Method
Power line interference	Power cord (50/60 Hz)	Notch filtering
Motion artifacts	Electrode-skin relative movement (< 20 Hz)	High-pass filtering
Baseline wander	Polarization of electrode (< 1 Hz)	High-pass filtering
Crosstalk	Muscle signal coupling in proximity	Spatial filtering

From **Figure 4(2)**, it can be seen that after being picked up by the electrode, the electromyographic signal contains a large amount of noise, and the amplitude also fluctuates greatly when the muscle relaxes. However, after filtering (**Figure 4(3)**), the signal becomes significantly more stable, and the spectral intensities of the 1 Hz and 50 Hz frequency bands have significantly decreased, as shown in Figure 4(4), indicating that the power line interference and motion artifacts have been effectively suppressed.

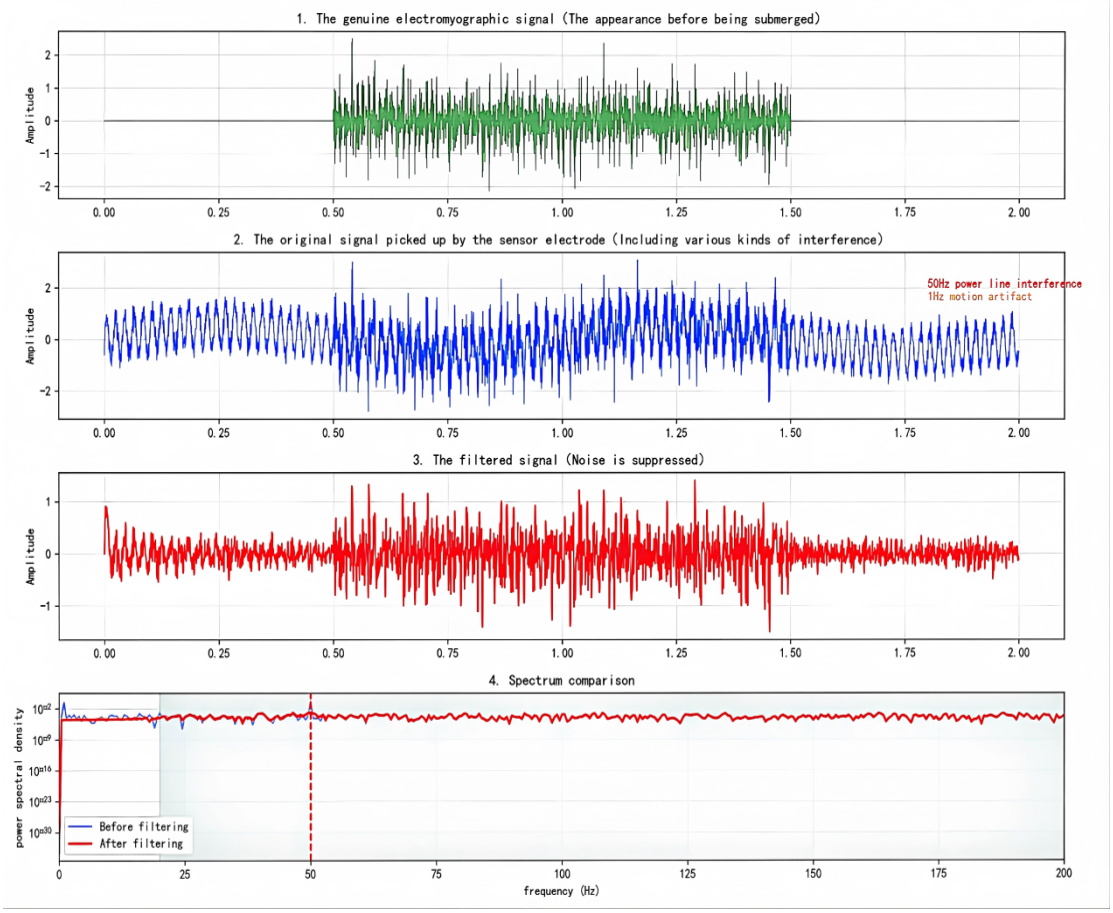


Figure 4. Simulation signal filtering effect diagram (Picture credit: Original).

3.2.Feature extraction

Feature extraction is the process of converting high-dimensional electromyographic data into low-dimensional feature vectors, which is the key to pattern recognition.

3.2.1. Time domain feature

As can be seen in **Table 4**, the commonly used time-domain features for processing electromyographic signals usually include the following types:

Table 4. Time-domain features

Feature	Formula	Meaning	Character
RMS	$\sqrt{\sum_{i=1}^{N}\frac{x_i^2}{N}}$	Signal energy	The most commonly used and smoothest
MAV	$\sum_{i=1}^{N}\frac{\lvert x_i\rvert}{N}$	Mean intensity	The calculation is simple, and it is stable for high-frequency signals
ZC	$\frac{1}{2N}\sum_{i=2}^{N}\lvert sgn(x_i)-sgn(x_{i-1})\rvert$	Frequency information	Sensitive to noise
WL	$\sum_{i=2}^{N}\lvert x_i-x_{i-1}\rvert$	Signal complexity	Reflect the changes in the waveform

Take RMS as an example: using a sliding window for calculation enables real-time feature extraction. The selection of window size should be made with consideration: too small(< 50 ms) leads to more noise, while too large(> 500 ms) results in sluggish response. Usually, a value between 100 and 200 milliseconds is chosen. **Figure 5(a)** shows the original myoelectric signal; green shaded areas indicate muscle contraction periods (0.5–1.5 s, 2.5–3.5 s, 4.5–5.5 s). The raw EMG signal exhibits high-frequency oscillations and significant random noise. **Figure 5(b)** shows RMS with a 50 ms window; the extracted envelope follows the signal trend but contains considerable fluctuations, making it less smooth for threshold-based detection. **Figure 5(c)** shows RMS with a 100 ms window; the curve becomes smoother while maintaining good responsiveness, with only minor ripples during contraction periods. **Figure 5(d)** shows RMS with a 200 ms window; the envelope is well-smoothed with minimal noise, providing a clean threshold decision boundary. This window size offers the best trade-off between smoothness and response time. **Figure 5(e)** shows RMS with a 500 ms window; the curve is overly smoothed, resulting in visible response lag (estimated> 250 ms) that may degrade user experience in real-time control.

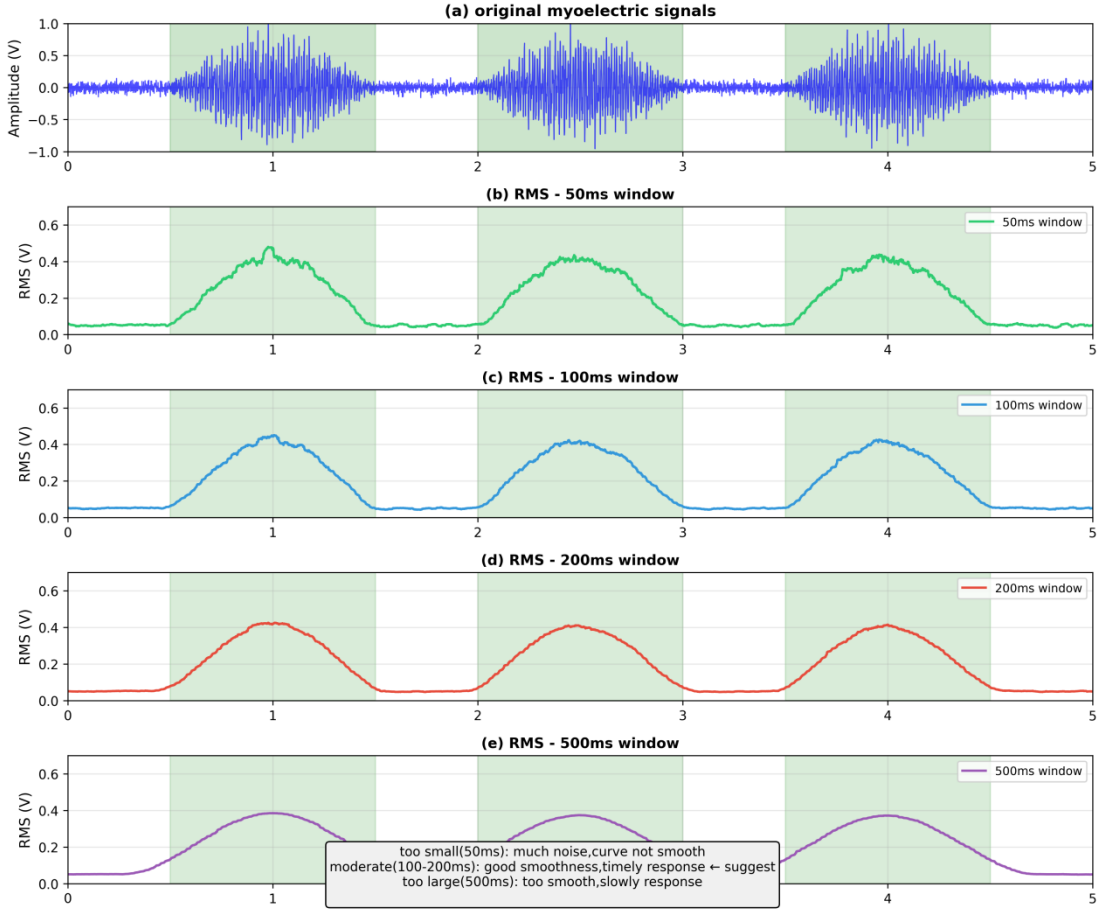


Figure 5. Comparison chart of RMS effects for different window sizes(Picture credit: Original).

3.2.2. Frequency domain feature

The frequency domain features commonly used for extracting the characteristics of electromyographic signals include the two types shown in **Table 5**.

Table 5. Frequency domain feature

Feature	Formula	Physics meaning
MDF	$\int_0^{f_{MDF}} p(f)df = \frac{1}{2}\int p(f)df$	Frequency distribution center
MNF	$\frac{\int fp(f)df}{\int p(f)df}$	Mean frequency

The frequency domain features are particularly effective for monitoring muscle fatigue. During fatigue, the MDF shifts towards lower frequencies [4].

3.3.Pattern recognition and classification

3.3.1. Threshold value method

The threshold value method is the simplest method, which sets a threshold to determine the status. **Table 6** compares several commonly used threshold discrimination methods.

Table 6. Threshold value method comparison

Method	Principle	Advantage	Disadvantage
Fixed threshold	Constant	Simple	Not adapted to individual differences
Percentage threshold	Maximum*percentage	Adaptation to the individual	Require maximum calibration
Statistical threshold	Mean value+k*standard deviation	Strong theoretical foundation	Baseline data needs to be collected
Adaptive threshold	Real-time update	Adapt to the change	Possible update error

The statistical threshold method is based on the principle of normal distribution:

When relaxation, $RMS \sim N(\mu,\sigma^2)$; If $RMS > \mu + 3\sigma (p < 0.13\%)$, judging it contraction.

Figure 6 illustrates the statistical theoretical basis for setting the threshold of the electromyographic signal

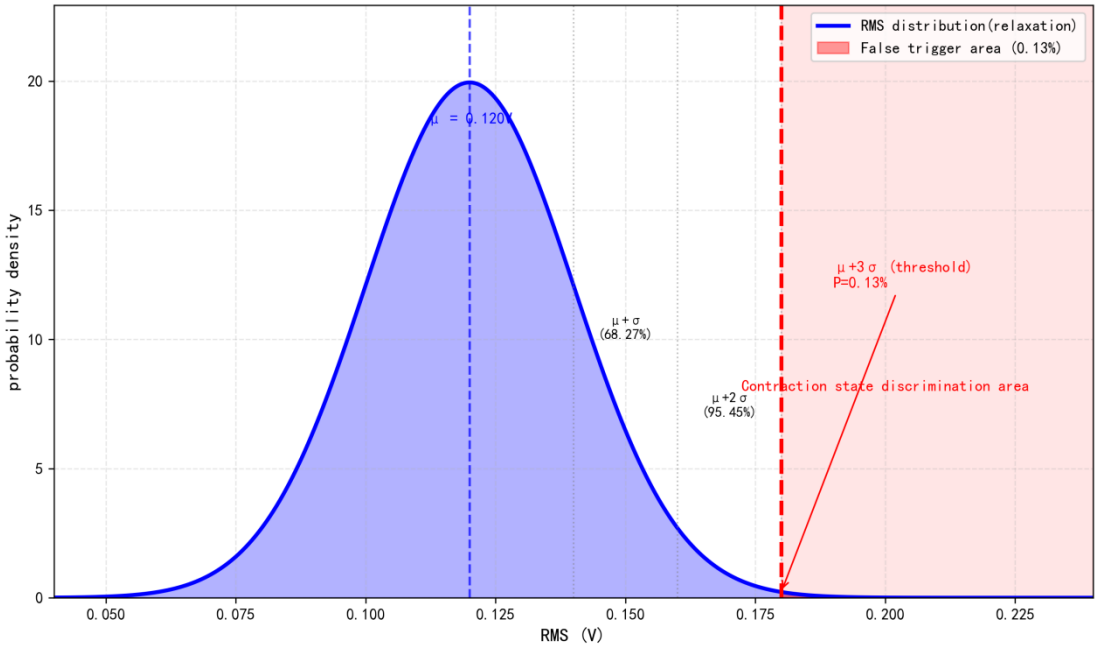


Figure 6. Statistical threshold method normal distribution principle diagram (Picture credit:Original).

3.3.2. Linear classifier

The list of linear classifiers can be represented by LDA and SVM. LDA looks to find a projection direction that maximizes inter-class scatter and minimizes intra-class scatter. It is computationally inexpensive and therefore well suited to be used in real time, and also functions as a reference algorithm for multi-gesture recognition. SVM, however, employs the kernel trick to transform data into a higher-dimensional space and attempts to find the best classification hyperplane. It has a good generalization property, but its parameter optimization procedure is complicated [5].

3.3.3. Neural network

The modern extraction of features from electromyographic signals has undergone an evolution from manual features to deep learning methods [6]. The neural networks mainly used are shown in **Table 7**.

Table 7. Neural network comparison

Network type	Structure character	Advantage	Challenge
MLP	Fully connected layer	Strong nonlinear fitting capability	Prone to overfitting, with poor generalization ability
CNN	Convolution +pooling	Automatic feature extraction, with strong spatial feature recognition capabilities	There is a great demand for data, high requirements for training resources, and poor interpretability.
RNN	Cyclic connection	Handle long sequence data and reduces model complexity	Gradient vanishing makes it difficult to learn long-term dependencies
LSTM	Gate control unit	Good at handling temporal information, capturing long-term dependencies, and solving the problem of vanishing gradients	Slow training process, difficult to deploy in real time

The CNN-LSTM hybrid model, which extracts spatial features through CNN and captures temporal dependencies through LSTM, combines the advantages of both types of models to achieve the highest accuracy rate. However, the model is overly complex and difficult to deploy in real time.

4. Control strategy

4.1. Threshold value control

Threshold control is the simplest of all strategies that translate the intention of the user into the form of a discrete state: The contraction state of the muscle is entered when the RMS is higher than the high threshold. The relaxation state is entered when the RMS is lower than the low threshold.

Hysteresis comparison can avoid frequent switching near the threshold, as shown in **Figure 7**:

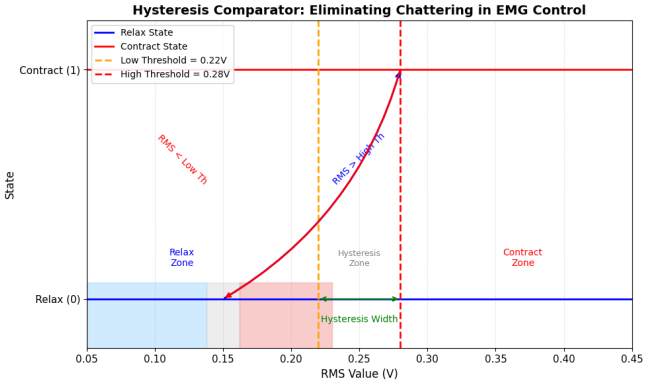


Figure 7. Hysteresis comparison diagram (Picture credit:Original)

The anti-shake processing can prevent single-point noise from triggering incorrectly.

4.2. Proportional control

Proportional control continuously adjusts the output according to the intensity of the electromyographic signal [7]:

$$F_out = k \times RMS$$

Here, k denotes the gain coefficient. This kind of control is more natural, but it must deal with two problems. The first problem is the accuracy of the signal, and it necessitates determining the link between the RMS and the output force or angle. The second problem is fatigue compensation, as, at muscle fatigue, equivalent contraction produces greater RMS, and the gain should be adaptively modified [8].

4.3. Control based on machine learning

4.3.1. Pattern recognition control

Pattern recognition control consists of a sequence in which numerous types of gesture EMG data are gathered, features are extracted, a classifier is trained, and real-time recognition is performed. Typical gesture sets consist of 2–3 gesture types, e.g., fist, open palm, and relaxation, to be used in simple control; 6–8 gesture types that involve, e.g., pinch, hook, and flex fingers to achieve dexterous hand control; or more than 50 fine gestures found in the NinaPro database.

4.3.2. Regression control

Directly regress continuous motion parameters from the electromyographic signals:

$$\theta(t) = f\left(EMG(t-\tau)\right)$$

Common methods include: Ridge Regression, Gaussian Process Regression, and Neural Network Regression [9].

4.3.3. Muscle coordination control

Based on physiological findings, the central nervous system controls multiple muscles in a coordinated manner. By extracting the coordinated structure through matrix decomposition, the control dimension can be reduced:

$$EMG = W \times H$$

Here, W represents the collaborative mode, and H represents the activation coefficient.

5. Challenges and limitations

. Signal-related challenges

Table 8. Challenges of signal aspect

Challenge	Illustration	influence
Electrode position deviation	Changes in position after putting on and taking off the equipment	The model has failed and needs to be recalibrated
Changes in skin condition	Sweating and oil secretion affect the signals	Amplitude and impedance variations

Challenge	Illustration	influence
Muscle fatigue	Long-term use of signal characteristic drift	The control performance has declined
Individual difference	Muscle anatomy and differences in subcutaneous fat	Requires personalized modeling

5.2. System-related challenges

The real-time requirements state that the time between the muscle electrical signal and the exoskeleton response cannot exceed 300ms; if this does not happen, there will be an artificial sensation of the robot lagging, which implies that the algorithms should run well on resource-limited embedded systems [10]. Also, computational complexity is a problem since complex deep learning models can be challenging to execute on low-power MCUs and need model compression methods, including quantization, pruning, and knowledge distillation. Moreover, there are power consumption limits, because the batteries of wearable devices usually have a capacity of 500-2000mAh, and it is necessary to choose between performance and power consumption.

5.3. Clinical translation barriers

Clinical translation barriers have four dimensions. First of all, there are no uniform instructions on how to position the electrodes, which movements to make, or which evaluation factors can be implemented. Second, the validation process is very slow since clinical trials take many years and cost a lot of money. The third aspect is comfort, aesthetics, and usability, which can impact user acceptance. Last but not least, regulatory approval is required to imply that it is a medical device that requires certification such as FDA or CE.

6. Future perspectives

6.1. Multimodal fusion perception

One muscle electrical impulse cannot be used in every situation. The combination of various sensors may improve the robustness. See **Table 9**.

Table 9. Integrating multiple sensors

Sensor	Supplementary information	Integration method
IMU	Body posture, motion artifacts	Kalman filtering
Ultrasound	Deep muscle structure	Feature-level fusion
NIR	Muscle oxygen metabolism	Decision-level fusion
Strain sensor	Muscle deformation	Multimodal neural network

The most recent study uses an intelligent multi-layer perception system based on sEMG, strain sensors, and IMU, and has a joint torque estimation RMSE of less than 0.13 Nm/kg [11].

6.2. Edge computing and on-chip intelligence

The use of smart algorithms on integrated systems is a trend: Model training through big data is done via cloud-based training. Edge inference performs real-time data processing depending on the trained model. Low-power data acquisition is the aim of end-side collection. These three elements combined make a full closed loop of data collection, real-time processing, and model training and optimization [12].

Model quantization (float32 to int8) allows CNN to be executed on ARM Cortex-M cores with a power draw of less than 10 mW [13].

6.3. Personalized adaptive control

The future exoskeleton must be able to adjust to individual variations and time-dependent features. To achieve this, online learning is needed to keep maximizing the model in use, transfer learning is needed to be able to rapidly adapt to new users using the experience gained in source domains, and lifelong learning is needed to collect experience without experiencing catastrophic forgetting [14].

6.4. Integration of soft robotics

Soft exoskeletons have novel demands on myoelectric control that include sensing soft structure deformations, the demand for soft control algorithms, and the need to take into account human-machine coupling dynamics [15].

7. Conclusion

The present article is a systematic review of the electromyography (EMG) control technology applied in robotic exoskeletons, which includes the process of signal acquisition, processing, and methods of control. The major conclusions are as follows.

To acquire a signal, surface EMG has become the norm because it is non-invasive and easy to use, with bipolar leads and high-density arrays used in conventional control and fine gesture recognition, respectively. In signal processing, filtering is necessary before any signal quality can be achieved; time-domain features, particularly RMS, have a small computational cost and are highly effective in real-time; hence, they are well suited to be implemented in an embedded system, whereas frequency-domain and time-frequency features can offer additional information but at a considerable computational expense. Concerning control schemes, threshold control is straightforward and trustworthy in simple rehabilitation; proportional control is more natural, yet needs fatigue correction; pattern recognition can support multi-gesture control, which is very complex; and new control based on muscle synergy control is closely aligned with physiological properties. Major challenges, signal variability, real-time constraints, and clinical translation barriers, are existing bottlenecks. Directions in the future, such as multimodal fusion, edge computing, personalized adaptive control, and incorporating soft robots, will push EMG exoskeletons towards smarter, more natural, and comfortable systems.

Considering that, as newcomers in the sphere of electronic information, we need to learn the whole chain of events in the form of signal to information to control. Myoelectric exoskeleton is an ideal representation of this chain - transforming faint biological signals into purposeful motions, which is exactly what electronic information technology is all about.

Disclosure statement

The author declares no conflict of interest.

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