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Control technologies of lower limb rehabilitation exoskeleton robots based on surface electromyography: A review

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Highlights

In this review, the latest progress of threshold control, proportional control and pattern recognition control based on surface electromyography in lower limb rehabilitation exoskeleton robots are presented.

Abstract

The aging population is accompanied by a decline in human body function, leading to an increasing number of people with lower limb dysfunction, which has become a global public health challenge today. The lower limb rehabilitation exoskeleton robot based on surface electromyography is a current research hotspot. It can help people with lower extremity dysfunction perform better rehabilitation training. This review presents the analysis and processing of surface electromyography, feature extraction and recognition, as well as the control methods for lower limb rehabilitation exoskeleton robots.

Keywords: Surface electromyography, lower limb exoskeleton robot, feature identification, rehabilitation treatment, man-machine interaction

Introduction

The aging of the population is leading to a decline in human body function. The knee joint is particularly susceptible to injury because it is the largest and most intricate part of the human body [1]. Lower limb rehabilitation exoskeleton robots (LLRERs) can replace rehabilitation physicians to give accurate, efficient, intelligent, and scientific lower limb rehabilitation training, reduce the burden of clinical treatment, and help people with disabilities restore their physiological functions.

At present, there are many ways to control intelligent LLRERs based on bioelectrical signals, such as electroencephalogram, electromyogram (EMG), electro-oculogram, surface electromyography (sEMG), and electroneurographic signals. Compared with other bioelectrical signals, sEMG is less affected by the external environmental factors and has the characteristics of non-invasiveness, ease of acquisition and good robustness in measurement. The sEMG itself contains the body motion state and intention information of human muscles [2]. The generation of sEMG is about 30-150 ms ahead of muscle contraction [3]. Therefore, sEMG can be collected to predict the continuous motion intention of the lower limb and applied to the human-computer interaction control of the LLRER.

The lower extremity exoskeleton rehabilitation robot based on sEMG can increase the patient-computer interface and has deep control characteristics such as real-time controllability and sensitivity. The real-time controllability

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of this rehabilitation robot can help patients achieve real-time control and improve the safety of equipment. The perceptibility of this robot can perceive the treatment condition and alter the control strategy in time to optimize the real-time control effect, so that the rehabilitation training can be adjusted autonomously.

sEMG Analysis and Data Processing

sEMG is a comprehensive reaction of action potential generated by shallow muscle contraction on the skin surface, which can be obtained from the surface of human muscle by the surface electrode [4]. Feature extraction is the basis for the analysis of sEMG, because sEMG cannot be directly used to control a LLRER without preprocessing. To ensure the accuracy of sEMG control, additional analysis and feature extraction are required to extract feature information relating to muscle or joint motion intention and filter out duplicate information [5]. Currently, ongoing research on sEMG is expanding the utilization of feature extraction methods for sEMG analysis. The theoretical methods can be classified into time domain analysis, frequency domain analysis, time-frequency domain analysis, high-order spectral analysis, and chaotic and fractal analysis.

Time domain analysis

The time domain analysis method reflects sEMG changes with time and is one of the most widely used sEMG feature extraction methods due to its simplicity and high computational efficiency. The root mean square (RMS) value, zero crossing points, integrated electromyography value, variance, waveform length, Willision amplitude, autocorrelation function, slope change number, EMG histogram, etc. can be calculated by the sEMG amplitude-time graph as the time domain features of sEMG [6-14]. Raj et al. extracted the integrated electromyography value and zero crossing time domain features of biceps sEMG and used these two time domain features as input parameters of the radial basis function neural network model. The results showed that they had a good effect in identifying human forearm movement [15]. Duan et al. proposed the top and slope time-domain feature extraction algorithm, which can better extract the temporal properties of sEMG and has better recognition accuracy in human lower limb motion patterns [16].

Frequency domain analysis

The time domain feature, as a characteristic value of sEMG, is easy to calculate and easy to extract, therefore, widely used. However, the time domain feature is greatly affected by muscle contraction force, whereas this problem can be addressed by frequency domain analysis, which reflects the changes in sEMG in the frequency dimension. Frequency domain analysis primarily involves converting the sEMG signals from the time domain to the corresponding frequency domain signal using Fourier transform. This transformation allows the extraction of power spectrum, spectrum, and other relevant information from the frequency domain signal of sEMG [17]. In order to quantitatively describe the relative changes and power spectrum curves of different frequency components of sEMG, the mean power frequency and the median frequency are often chosen as the frequency domain eigenvalue indexes of sEMG [18]. Hameed et al. used the mean instantaneous frequency value of sEMG as an adaptive decision threshold to detect flexor activity with higher robustness [19].

Time-frequency domain analysis

Both time domain analysis and frequency domain analysis can only conduct a single analysis of either time-domain or frequency-domain characteristics of sEMG, whereas time-frequency domain analysis is based on the functions of both time and frequency domains. It can comprehensively analyze the both characteristics and combine their advantages to make full use of the energy changes presented by sEMG in different frequency and time domains [20]. At present, the time-frequency analysis methods of sEMG mainly include the short-time Fourier transform (STFT), the Wigner-Ville transformation, Choi-Williams distribution, and the wavelet transform (WT) [21-23].

The STFT can segment non-stationary signals, which can then be analyzed and processed as stationary signals. However, the STFT has limitations in sensitively reflecting the direction of the time-frequency domain and signal mutation. It can only deal with slowly changing signals. Therefore, the STFT can be used to analyze and extract the sEMG when it changes slowly. The Wigner transform is the Fourier transform of instantaneous correlation function of signals. It provides information about the time-frequency distribution characteristics of signal energy. Choi-Williams distribution can use its exponential core function to filter out the influence of cross terms on the sEMG, which can lead to information redundancy. Furthermore, the control parameter can be used

Table 1. Comparison of sEMG feature extraction methods

Feature extraction methods	Advantages	Disadvantages
Time domain analysis	Simple calculation with features that are easy to extract	Unstable, and incapable of fully utilizing the information of the sEMG
Frequency domain analysis	Characteristically stable	Only suitable for handling stable sEMG
Time-frequency domain analysis	Having time-frequency domain characteristics	Not sensitive to the capture of mutational signals
High-order spectral analysis	Capable of reconstructing the amplitude and phase of the sEMG, recognizing the nonlinear structure of its time series and automatically suppressing various additive Gaussian noises	Immature technology, and complex calculation
Chaotic and fractal analysis	Capable of extracing the cluster distribution characteristics of sEMG in different action postures	Complex parameters and calculation

Note: sEMG, surface electromyography.

to adjust the resolution of automatic terms and the influence of cross terms based on the characteristics of the collected sEMG. The WT inherits and builds upon the concept of localization in the STFT and overcomes the disadvantage of a fixed window size in the STFT that does not adapt to frequency changes. Stretching and shifting can be used for multi-scale refinement for the local mutation of sEMG in order to capture arbitrary detail feature changes. Karheily et al. used the STFT, the continuous WT, and Stockwell time-frequency domain characterization to classify hand motion, and reported an accuracy of 90.05%, 89.92%, and 90.96%, respectively [24]. Chen et al. employed the STFT method to establish a STFT embedded system that detects muscle contraction, and reported an accuracy of up to 91.55% [25].

High-order spectral analysis

sEMG is a kind of non-stationary, non-deterministic, nonlinear, and non-Gaussian micro signal. However, because traditional random signal processing technology is based on second-order statistics, the power spectrum and linearity of sEMG cannot meet the actual requirements. High-order spectral analysis can effectively suppress all kinds of additive Gaussian noise, and detect the phase and amplitude of nonlinear structure reconstruction at the same time [26]. Using high-order spectral analysis of sEMG can make full use of the various information features of sEMG. Zhang et al. processed sEMG with the complex Morlet WT and constructed multi-order tensor data information containing time, space, frequency, and task information, which can effectively analyze the multi-dimensional feature information of sEMG under fatigue [27].

Chaotic and fractal analysis

Traditional sEMG analyses are based on linear analysis theory, but linear analysis theory is only a tool for solving nonlinear problems. Chaos theory is a kind of stochastic process that appears in a deterministic system and has the characteristics of nonlinearity, uncertainty, non-balance, and sensitivity. Chaos theory can be used for the analysis and processing of sEMG and is helpful to extract more information from sEMG [28, 29]. The clustering characteristics of chaotic features can be expressed through Lyapunov index, phase planar graph, power spectrum and other parameters. Fractal theory is the product of chaotic dynamic processes. It has the characteristics of self-similarity and irregularity under different scales. You et al. showed that the fractal dimension and the maximum Lyapunov exponent reflected the clustering characteristics of different action postures, and the chaotic feature could be used as the input of the classifier, which improved the robustness of action recognition [29]. Khodadadi et al. calculated the collected sEMG by using the Petrosian method and the Grassberger & Procaccia method and obtained fractal dimension and correlation dimension chaotic features, respectively, where fractal dimension and correlation dimension well described the chaotic behavior of biceps sEMG [30].

The characteristics of sEMG signals are shown in **Table 1**.

Control technologies based upon sEMG

sEMG can represent muscle activity intention 30-150 ms in advance and is associated with muscle function and activity status to various

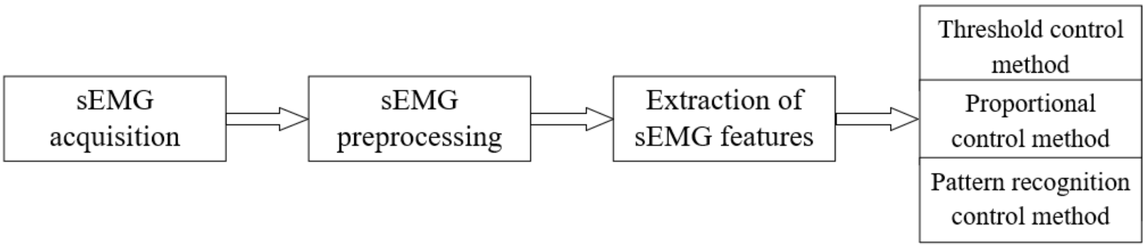

Figure 1. Flow diagram of lower limb exoskeleton control based on sEMG.
sEMG, surface electromyography.

degrees. Therefore, sEMG is often used in assistive devices, functional electrical stimulation, and other rehabilitation control fields. The motion intention of the lower limb is obtained after the sEMG collected from the skin is handled by amplification, filtering, differentiation, integration, machine learning, and deep learning. Then, the motion intention information is applied as the driving control source of the LLRER [31, 32]. Thus, the LLRER can be controlled for rehabilitation training and other functions. At present, with the development of sEMG research, there are increasing control methods for LLRERs based on sEMG. The methods can be classified into three categories according to the theoretical methods used: threshold control method, proportional control method, and pattern recognition control method. **Figure 1** shows the control flow of the LLRER based on sEMG.

Threshold control method

The threshold control method is also called digital switch control. It takes the amplitude or characteristic value of the sEMG as the input parameter. Setting a fixed threshold and employing adaptive decision threshold algorithms are typical threshold determination strategies. Fixed thresholds are often defined based on feature values extracted by sEMG and determined through many experiments following completion of the specified task. The adaptive decision threshold method may autonomously adjust the threshold changes based on the amplitude characteristics of sEMG and is intact by sEMG nonautonomous amplitude variations. This reduces the number of false alarms that may occur with a fixed preset threshold and improves biomimetic robot control performance.

When the threshold control system detects that the input parameter of the control object exceeds the threshold value, it outputs the control command signal to regulate the rehabilitation training of the LLRER. Krebs et al. of the Massachusetts Institute of Technology extracted the amplitude of the sEMG as the input parameter of the threshold control system. When the amplitude of the sEMG exceeded the threshold, they started controlling the rehabilitation robot in real time to provide stroke patients with supplemental rehabilitation treatment [33]. Zhang et al. collected sEMG of medial gastrocnemius and tibialis anterior, and used RMS value as input parameter of the threshold control system, and then generated control instructions to control exoskeleton for dorsiflexion and plantar flexion movements [34]. Wang et al. collected sEMG of the left calf, right calf, left shoulder, and right shoulder, respectively, and calculated the instantaneous power of sEMG by using the STFT, and then used the instantaneous power as the input parameter of the threshold control system to automatically generate real-time control signals [35].

Xu et al. tried to solve the problem of real-time control of multifunctional prostheses among high-level amputee individuals with two different methods. The first method used the pattern recognition algorithm to classify sEMG and then used pattern recognition to control multifunctional prostheses. The second method used threshold control based on the mean absolute value of sEMG. The experimental results showed that the threshold switch control based on mean absolute value of sEMG could accomplish all motor tasks in less time and was more accurate and smoother in both experimental and practical applications [36]. Hameed et al. adopted the frequency feature of sEMG as an adaptive decision threshold to reduce errors caused by ineffective fixed decision thresholds, and the sEMG detection performance was significantly improved [19]. Si et al. used the double threshold method to assess and detect the RMS of sEMG to recognize various lower limb motion modes (walking, straight leg lifting, tiptoeing, and squatting). The results of the experiments demonstrated that the double threshold algorithm exhibited remarkably decent detection accuracy for lower limb motions not only under normal conditions, but also under fatigue conditions [37].

Table 2. Comparison of control effects based on sEMG threshold control method

Research institution	Site for sEMG acquisition	The chosen eigenvalues for the sEMG	Control effect
MIT	Biceps, Triceps, Chest muscle	Amplitude	Better rehabilitation training for stroke patients
Shanghai University	MG and TA	RMS	Achieve real-time dorsiflexion and plantar flexion mode movement
East China University of Science and Technology	Left calf, Right calf, Left shoulder, Right shoulder	Instantaneous Power	Achieve real-time extraction of control instruction signal
Shanghai Jiao Tong University	Triceps brachii, Biceps brachii	MAV	Achieve real-time control of multifunctional prosthesis for high amputee patients
Universiti Putra Malaysia	Flexor Digitorum Superficialis muscle	Average Instantaneous Frequency Value	Improve the performance of sEMG motion detection
University of Electronic Science and Technology of China	Rectus femoris, Biceps femoris and Gastrocnemius muscles	RMS	Achieve high accuracy of lower limb motion detection

Note: sEMG, surface electromyography; MIT, Massachusetts Institute of Technology; MG, medial gastrocnemius; TA, tibialis anterior; RMS, root mean square; MAV, mean absolute value.

Figure 2. HAL-3 on the left and HAL-5 on the right. This figure is cited from [41, 48]. HAL, Hybrid assistive limb. HAL, Hybrid assistive limb.

Threshold control, also known as digital switch control, is relatively easy to implement, but it cannot proportionally reflect the amplitude characteristic change of sEMG. It is only suitable for mode switch control of exoskeleton robots, with promising detection performance and control effect. The control that needs the linkage of output torque and speed of control system with the amplitude and variation of the eigenvalue of sEMG may not be a suitable threshold control method, but it is undoubtedly the optimal choice for the control to only use sEMG as the real-time digital switch. **Table 2** shows the control effects of the threshold control mode in controlling the robot in different research institutes.

Proportional control method

The threshold control method does not fully utilize the rich motion intention information of sEMG, and only dual-mode or limited multi-mode control can be used to control the lower limb exoskeleton robot. To compensate for the lack of threshold control, the proportional control can output control signal instructions in proportion to the sEMG signal, thus adjusting the system's open-loop gain and improving the control system's steady-state accuracy. In this manner, the output force, speed, torque, and other parameters of lower limb exoskeleton robot can be regulated proportionally based on the strength of the sEMG signal. Sawicki et al. collected sEMG of the soleus muscle as the input control parameter of a lower limb orthotic control system and found that subjects' muscles could be adjusted to respond to the change in musculoskeletal biomechanics, resulting in a better control effect [38]. As shown in **Figure 2**, hybrid assistive limb (HAL) was created in conjunction with Cyberdyne Systems by the University of Tsukuba in Japan. The HAL-3 has four disk motor drives on the buttocks and knees as joint driving forces. The HAL-5 also includes drives at shoulder and elbow [39-41].

Figure 3 shows the lower limb exoskeleton robot developed by Fleischer et al. based on sEMG control. Fleischer collected sEMG from the leg muscle to establish a linear relationship between sEMG amplitude and joint torque during knee movement [42]. The lower extremity exoskeleton robot could be controlled systematically to carry out auxiliary motion [43]. Hofmann et al. improved the amplitude estimation based on Bayesian filtering and applied it

Table 3. Comparison of control effects using the sEMG proportional control method

Research institution	Site for sEMG acquisition	The chosen eigenvalues for the sEMG	Control effect
University of Michigan	Soleus	Amplitude	Achieve adaptive adjustment of lower limb orthotics by sEMG
Technical University of Berlin	Rectus femoris, Vastus medialis, Vastus lateralis, Semimembranosus	Amplitude	Simplify the control of lower limb exoskeleton robot
Tsukuba University and Cyberdyne Systems	Rectus femoris	Amplitude	Achieve HAL movement in accordance with the subject's motor intent
Emory University	Arm	Amplitude based on Bayesian filtering	Achieve precise control of multifunctional prosthesis

Note: sEMG, surface electromyography; HAL, hybrid assistive limb.

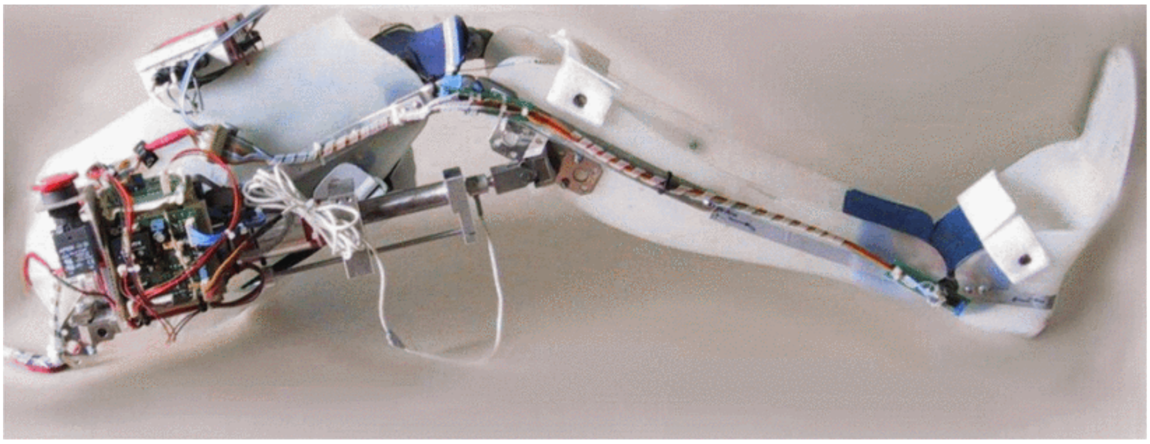

Figure 3. Lower limb exoskeleton robot based on leg sEMG control. This figure is cited from [43]. sEMG, surface electromyography.

to the Statistical Process Control framework. The efficiency of this method for Statistical Process Control electromyographic control was thoroughly investigated using goal-oriented online experiments on healthy and limb-disabled subjects, respectively. Experiments showed that compared with traditional amplitude estimators, the proposed Bayesian filtering amplitude estimation framework could estimate the potential "neural drive" carried by sEMG from the nervous system more smoothly, and was more sensitive to the mutation of neural signals [44].

Proportional control compensates for the limitations of threshold control by responding to changes in the amplitude and eigenvalue of the sEMG through feedback. Proportional control can adjust the speed and torque of the lower limb exoskeleton machine force according to changes in the contraction strength of sEMG, making it conform to the natural control of human factors engineering. **Table 3** shows the comparison of control effects of rehabilitation equipment developed by different research institutes using proportional control.

Pattern recognition control method

To enrich the information obtained from sEMG, various sEMG feature sets are proposed, and pattern recognition methods are used to distinguish the types of movements activated by different limbs and parts. To establish the mapping relationship between sEMG and gesture intention, pattern recognition uses machine learning and deep learning. When pattern recognition control is applied to the lower limb exoskeleton robot and other rehabilitation medical equipment, the trained pattern recognition system first judges the sEMG, and then the pattern recognition system output control instructions to drive the motor, air pressure, hydraulic, and other driving systems, resulting in perceptual control of the lower limb exoskeleton robot.

Li et al. combined the general regression neural network with the Adaboost algorithm to create a powerful classifier, with the accuracy for motion pattern classification reaching 96.7% [45]. Zou et al. used the multi-scale fuzzy entropy feature vector as the input vector of the support vector machine, and the average

Table 4. Comparison of control effects using the sEMG pattern recognition method

Research institution	Site for sEMG acquisition	Pattern recognition algorithm	Control effect
Jilin University	Finger	GRNN- Adaboost	The accuracy of motion pattern classification was up to 96.7%
Shanghai Jiao Tong University	Palmaris longus, flexor superficialis, brachioradialis, extensor digitorum	SVM	The average recognition accuracy reached 97%
Nankai University	Radial long wrist extensor, radial wrist flexor, extensor digitorum	WNN	Maximum recognition accuracy can reach 100%, and average classification accuracy is up to 94.67%
Ain Shams university	Arm	RNN	The prediction accuracy reached 99.6%

Note: sEMG, surface electromyography; GRNN, general regression neural network; SVM, support vector machine; WNN, wavelet neural network; RNN, recurrent neural network.

recognition rate reached 97%, which was 3% higher than the original fuzzy entropy used as the feature input parameter [46]. Duan et al. classified sEMG using discrete WT and wavelet neural network algorithms, and trained wavelet neural network using back propagation and gradient descent algorithms. For sEMG, wavelet neural network has a maximum recognition accuracy of 100% and a classification accuracy of 94.67% on average [16]. Bittibssi et al. classified and recognized sEMG using the recurrent neural network model based on long short-term memory, convolution peephole long short-term memory, and gated recurrent unit, with a prediction accuracy of 99.6% [47].

The lower limb exoskeleton robot can be controlled in multiple functional modes using pattern recognition control, which enhances user-friendliness and enables a more sophisticated and intelligent human-machine interaction. On the other hand, proportional control allows adjustment of the robot's output parameters, such as speed and torque, according to the strength of surface EMG signal. **Table 4** compares the control results of different research teams who used pattern recognition to control robots.

Conclusion

In conclusion, the analysis and feature extraction of sEMG have provided us with a variety of approaches to effectively handle different types of sEMG signals. With the continuous development of signal processing technology and the combination of various processing technologies, we will have a deeper understanding of sEMG. Therefore, the extracted feature values will possess enhanced capabilities for motion intention recognition. This will enable extensive utilization of sEMG for real-time synchronous control of LLRERs.

The control methods based on sEMG involve threshold control, proportional control, and pattern recognition control. Different control strategies can be adopted based on the properties of different mechanical structures. Due to various injury sites and phases of rehabilitation treatment, patients with lower limb dysfunction have different rehabilitation needs for intelligent LLRERs. sEMG is frequently employed in rehabilitation medical devices, human-computer interface, and other fields, because it can reflect limb motion intention. Although the LLRER based on sEMG has achieved good research results, it still faces challenges such as intelligent rehabilitation treatment process, continuous improvement of comprehensive performance, and establishment of the LLRER evaluation system.

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