Dean&Francis

ISSN 2959-6157

Control Method for Lower Limb Exoskeleton Robot Based on Surface Electromyography Signals

Chengxi Xie

College of Mechanical and Electrical Engineering, Guangdong University of Technology, Guangzhou, Guangdong, China
nongxin@asu.edu.pl

Abstract:

Against the backdrop of the continuous growth in global demand for medical rehabilitation, the research on control methods for lower limb exoskeleton robots is particularly important as key equipment to improve the quality of life of individuals with lower limb dysfunction. This article systematically reviews the research progress of control methods for lower limb exoskeleton robots based on surface electromyography (sEMG) signals. Firstly, the bioelectric properties of sEMG signals and their core advantage in motion intention recognition - the ability to capture muscle activation status 100-200ms in advance - were discussed. Subsequently, the key steps of sEMG signal processing and intent recognition algorithm were elaborated. This article focuses on control methods and provides a detailed review of traditional PID control, adaptive sliding mode control for high-precision trajectory tracking, variable impedance control for dynamically adjusting joint impedance based on the Hill muscle three-element model, multimodal fusion control combined with multi-source information such as sEMG and Inertial measurement unit (IMU) to enhance environmental adaptability, and Non-Convex Function Activated Anti-Disturbance Zeroing Neurodynamic(NC-ADZND) human-machine interaction control. By comparing experimental data and analyzing the advantages and limitations of various methods, the development direction of this field was finally discussed.

Keywords: Surface electromyography signal, lower limb exoskeleton robot, motion intention recognition, control method

ISSN 2959-6157

1. Introduction

Over 300 million patients worldwide require rehabilitation for lower limb dysfunction, notably stroke-induced hemiplegics with Central Nervous System (CNS) injury-related motor loss needing prolonged therapy. Exoskeleton robots provide precise assistance, standardized gait training, and reduced therapist workload, enhancing rehabilitation efficiency, walking ability, and secondary injury prevention. Traditional pre-programmed gait exoskeleton robots are difficult to meet personalized rehabilitation needs, while control methods based on surface electromyography (sEMG) signals demonstrate their advantages: they can capture muscle activation signals 100- 200ms in advance and decode motion intentions [1, 2]. Research has shown that the sEMG signal can accurately calculate joint driving torque, dynamically adapting rehabilitation training intensity to the patient's condition. This technology can not only assist in the reconstruction of motor function for patients with spinal cord injuries, strokes, etc., but also improve the daily living abilities of the elderly and disabled [3].

This article focuses on sEMG-based control for lower limb exoskeletons, analyzing signal characteristics and intent recognition foundations. It critically compares mainstream strategies—including PID, adaptive sliding mode, variable impedance, multimodal fusion, and intelligent control—evaluating their performance and limitations. The analysis aims to advance intelligent, adaptive exoskeleton technology by identifying future research directions.

2. Analysis of Electromyographic Signal Characteristics

Electromyography (EMG) signals exhibit bioelectric characteristics, with amplitudes ranging from 50 μV to 5 mV, and are positively correlated with the intensity of muscle contraction. Experimental data shows that when the human body squats deeply, the amplitude of the quadriceps muscle electromyographic signal can be increased by 3-5 times. In terms of frequency domain characteristics, the energy of electromyographic signals is mainly distributed in the range of 0-500Hz, where the low-frequency components of 0-50Hz are related to muscle fatigue status, while the high-frequency range of 150-500Hz reflects the rapid contraction ability of muscles. In addition, continuous exercise can cause signal amplitude attenuation, which poses challenges to signal processing [4].

In addition, compared to electroencephalography (EEG), although EEG is more real-time, it is affected by brain activity and useless information can reduce the accuracy of action recognition, making it more complex and difficult. With the continuous maturity of sEMG acquisition technology, its non-invasiveness and flexibility are gradually showing their advantages. EMG, as a non-invasive physiological signal acquisition technology, can capture electrical signals generated by muscle activity through electrodes attached to the surface of muscles, which is simple and accurate [5].

3. Movement Intention Recognition Based on Surface Electromyography Signals

3.1 SEMG-Based Human Motion Intent Recognition Operates Through Three Approaches

First, identifying human motions by collecting and noise-filtering sEMG signals; Second, predicting physical parameter dynamics (torque, joint angles, angular velocity) via sEMG; Third, determining lower-limb compliance metrics (limb stiffness, joint damping) through sEMG analysis [1]. The first step in motion intention recognition is to collect electromyographic signals from multiple muscle groups. Zhai used a flexible electrode array from Biometrics Ltd to synchronously collect sEMG signals from six muscle groups in the lower limbs, including the rectus femoris, biceps femoris, and gastrocnemius muscles, with a sampling frequency set at 5000Hz. In this experiment, the Euclidean distance of each movement was systematically sorted out based on the determination of each muscle and its corresponding functional action [6]. Secondly, methods such as bandpass filtering are used for noise preprocessing. Simulink is a powerful dynamic system simulation module in MATLAB, and its module library's Filter Designer module can assist users in designing filters according to their needs. The Filter Designer in MATLAB/Simulink can be used to build the filtering module in the sEMG signal processing system [1]. Then, methods such as root mean square (intensity), zero crossing rate (fast/slow), and sliding window technique (dynamic change) are used to extract feature values. Multiple time-domain feature values can also be extracted, such as mean absolute value (MAV), root mean square value (RMS), waveform length (WL), zero crossing frequency (ZC), and slope sign change frequency (SSC). Qin Peng combines the three feature values for feature extraction, and finally selects the root mean square value, zero crossing point, and slope sign with the highest recognition rate, with a recognition rate of 91.39% [7].

Finally, there are many methods for model dataset prediction, including traditional methods such as BP neural network [4] and PCA principal component analysis. Support Vector Machine (SVM) is a supervised learning method that has shown advantages in solving small sample, nonlinear, high-dimensional pattern recognition problems [7]. For temporal signal processing, Long Short-Term Memory (LSTM) networks effectively solve the gradient vanishing problem of Recurrent Neural Networks (RNNs) by introducing gating mechanisms. The memory unit of LSTM can selectively retain or forget historical information, and performs well in processing temporal data such as electromyographic signals [8]. The beetle optimization algorithm is a swarm intelligence optimization algorithm proposed by Jiankai Xue et al. in 2022 to simulate the rolling, dancing, foraging, stealing, and breeding behaviors of beetles. GRU simplifies the network structure by merging the input and forget gates of LSTM into update gates. Experiments have shown that the DBO-GRU model maintains recognition accuracy of over 90% while reducing training time by 35% compared to traditional LSTM [9].

In summary, high-precision motion intent recognition is achieved through multistage sEMG signal processing (acquisition → denoising → feature extraction → model prediction). Traditional feature extraction methods reach 91.39% recognition rates, while emerging deep learning models further enhance performance via temporal processing advantages. Notably, intelligent optimization algorithms maintain >90% accuracy while reducing training time by 35%, advancing lower-limb rehabilitation robots toward intelligent and personalized development.

4. Control Method of the Lower Limb Robot Based on the sEMG Signal

4.1 PID Control

The characteristics of torque and force in human-computer interaction can effectively distinguish different motion modes. Huang junfen's research showed that when walking up stairs, the average hip extension torque was 12.5 n · m, which was about 45% higher than that of walking on the ground at 8.6 n · M. the peak knee flexion torque appeared in the middle of the support phase (about 9.8 N · m). When going downstairs, the knee joint buffering torque increased significantly (32% higher than that when going up stairs), and the fluctuation range of vertical ground reaction force reached 120% of body weight [8]. When moving uphill, the horizontal forward thrust is maintained at 15-20% of body weight. When walking on the ground, the torque of the hip and knee joints showed regular alternating changes, and bimodal characteristics appeared in the gait cycle. These dynamic characteristics provide a reliable basis for motion pattern recognition. Then the gait data were sorted out through three steps of proportion, integration, and differentiation, and the angle changes of the hip and knee joints in various situations were recorded. According to the inverse dynamics, the inverse dynamics equation of the exoskeleton and joint angle repair value is generated [8].

4.2 Adaptive Sliding Mode Control

Sliding mode control is a simple control algorithm suitable for nonlinear systems. It is an algorithm that keeps approaching the model. This algorithm can effectively make up for the imprecision of the model. The adaptive sliding mode control algorithm has superior tracking performance for the trajectory of the simplified model of the lower limb.

In the study of the comparison between the expected angle and simulation angle of adaptive sliding mode control and PID control, Zhang Yixing inputs the trigonometric function as the expected angle trajectory of the hip and knee joint into the PID control algorithm and adaptive sliding mode control algorithm for comparison. The trigonometric function corresponding to the hip joint is input into the PID controller for a simulation test. The error between the expected trajectory and the simulation trajectory is more than 0.5 ° at the peak and trough positions, where the difference is most obvious. In comparison, the adaptive sliding mode control has only 0.12 ° error, which is significantly better than PID [9, 10].

4.3 Variable Impedance Control

The theoretical basis of variable impedance control is mainly based on the Hill muscle three-element model (including contraction element, parallel elastic element and series elastic element). Dengfuling's research shows that through the real-time analysis of surface electromyography (sEMG) signals, the muscle activation level and its corresponding stiffness changes can be estimated indirectly (mainly related to the characteristics of parallel elastic elements) [7]. Using this estimated value, the controller dynamically adjusts the impedance parameters of the exoskeleton joint (such as stiffness coefficient K and damping coefficient b), rather than only outputting fixed position or torque commands. For example, when the sEMG signal is enhanced (indicating the increase of muscle force and stiffness), the controller will correspondingly increase the impedance value of the joint to provide stronger support; On the contrary, when the muscle relaxes and the stiffness decreases, the joint impedance also decreases, allowing more free passive movement. This impedance adaptive adjustment mechanism based on sEMG significantly improves the flexibility and compliance of the exoskeleton during assisted walking and coping with disturbances, and reduces the human-computer interaction conflict. However, the challenge is that there are significant individual differences and time variability in the mapping relationship

ISSN 2959-6157

between muscle sEMG signal and joint stiffness/damping, which needs to be combined with online learning or an adaptive algorithm for dynamic modeling and updating.

4.4 Multimodal Fusion Control

Multimodal fusion control aims to comprehensively use a variety of sensor information to improve the perception and adaptability of the system to the complex environment and user intention. Hu Shuai's research shows that a more comprehensive human machine environment state perception model is constructed by fusing surface electromyography (sEMG) signal (directly reflecting neuromuscular activation intention) and inertial measurement unit (IMU) data (real-time acquisition of joint angle, angular velocity, acceleration and other kinematic parameters), combined with plantar pressure information and other state feedback [11]. This fusion not only enhances the robustness and accuracy of motion intention recognition (especially in unstructured scenes such as gait phase transition, going up and down stairs), but more importantly, these multimodal state feedback are directly used in closed-loop control, so that the exoskeleton can dynamically adjust the auxiliary strategy according to the real-time user intention, its own motion state and ground interaction (such as slope and obstacles). Kalman filter and other technologies are used to solve the problem of time-space synchronization of multi-source signals. However, the challenge of this method lies in the complexity of feature selection and parameter collaborative optimization among multimodal information sources, which requires fine algorithm design and individualized calibration.

4.5 Human-Computer Interaction Control

The core goal of human-computer interaction control is to realize the natural, safe and coordinated cooperative movement between the exoskeleton and the user. The key is to accurately understand the user's intention and make a compliant and adaptive response. The NC-ADZND controller proposed by Liu Yongbai for the upper limb exoskeleton is a frontier exploration in this direction [12]. The controller innovatively integrates the parallel control framework (constructing a virtual artificial system and a real system running in parallel, interactive optimization) and a data-driven method. Its core lies in the use of a nonconvex activation function to deal with complex nonlinear human-computer interaction dynamics, which significantly improves the performance of the system in anti-interference robustness and task adaptability (such as coping with muscle strength changes in different patients and unexpected body movements). Through data-driven dynamic modeling, nc-adznd can achieve high-precision tracking of exoskeleton target trajectory (usually from the user's intention), effectively detect and resolve human-computer interaction conflicts, and ensure the comfort and safety of collaborative movement. Although the research is aimed at the upper limb, its core ideas (parallel interaction optimization, nonconvex activation enhanced robustness, data-driven dynamic modeling) have important enlightenment and transplantation potential for solving the human-computer interaction control challenges faced by the lower limb exoskeleton, which are highly nonlinear, large individual differences, and require real-time compliant response. The difficulty of its application lies in the computational complexity and the demand for high-quality training data.

5. Discussion and Analysis

The advantage of the traditional control method, PID control, is that its algorithm structure is simple, the proportion, integral, and differential steps are independently adjustable, and it can realize the stable tracking of joint angle in periodic gait (such as walking on the ground). However, due to its poor adaptability to nonlinear dynamics (joint torque mutation when going up and down stairs), it is difficult to cope with sEMG signal attenuation caused by muscle fatigue. The simulation results show that the peak or trough tracking error is more than 0.5 °, which is much larger than the adaptive sliding mode control [13].

The adaptive sliding mode control significantly improves the adaptability to the perturbation of model parameters (such as joint friction mutation) through the robustness of the sliding mode surface and the dynamic adjustment of the adaptive law. The trajectory tracking accuracy is better than that of traditional PID control, and the maximum error at the crest or trough is 0.12 °, which is basically consistent with the expected line in other places. The existing problem is the need to balance the switching parameters of the sliding mode surface and the chattering problem of the joint driver, which may affect the comfort of patients [9].

The innovation of variable impedance control is to estimate joint stiffness based on the Hill muscle model, and dynamically adjust exoskeleton impedance parameters (such as the damping coefficient) to achieve human-computer interaction flexibility [7]. However, there are individual differences in the mapping relationship between muscle stiffness and sEMG signal, which need to be combined with an online learning algorithm to update the model in real time. The future improvement is to develop a subject-adaptive Hill model using transfer learning to reduce calibration burden.

The advantage of multimodal fusion control is that it integrates sEMG and IMU data, takes into account motion intention prediction and environmental perception, and improves the adaptability of complex scenes (such as going down stairs). The time-space alignment of multi-source signals is realized through a Kalman filter to enhance the control robustness [11]. The existing problem is that the multi-channel signal feature weight allocation needs to be calibrated individually, which increases the system initialization complexity.

6. Conclusion

The lower limb exoskeleton control technology based on sEMG is promoting the development of rehabilitation robots to be more intelligent and humanized. This technology enables the machine to "understand" the user's movement intention by interpreting the electrical signals sent by the human muscle, so as to achieve real human-computer cooperation.

In terms of technical implementation, researchers first need to solve the problem of sEMG signal acquisition and processing. Because muscle electrical signals are susceptible to interference and individual differences are large, we use flexible electrodes and an intelligent filtering algorithm to ensure the signal quality. In the process of motion intention recognition, artificial intelligence technologies such as deep learning are combined to enable the system to accurately judge the actions that users want to make, whether walking, going up and down stairs, or other complex actions.

At present, there are several typical control methods in practical applications. The traditional PID control is simple and reliable, which is suitable for basic training; Adaptive control can deal with the individual differences of different users; The latest intelligent control algorithm shows stronger adaptability and anti-interference. It is particularly worth mentioning that the movement of the exoskeleton is more natural and smooth through the impedance control method that imitates the characteristics of human muscle.

Of course, there are still some bottlenecks to break through in this technology. For example, how to shorten the system response time and make the action more immediate. How to improve the adaptability to different users; And how to ensure the comfort of long-term use. In the future, with the development of artificial intelligence and flexible electronic technology, we have reason to expect the emergence of a more intelligent and considerate exoskeleton rehabilitation robot, which will bring a better rehabilitation experience to people with mobility difficulties.

References

[1] Xiaodong Zhang, Jiangcheng Chen, Yin Gui. Electromyography perception and human-computer interaction control method of lower limb rehabilitation robot. vibration Testing and Diagnostics, 2018.

[2] Jian Zeng Research on lower limb exoskeleton rehabilitation robot based on EMG signal control. North China University of Technology, 2021.

[3] Xunju Ma Research on gait switching control method of Lower Limb Rehabilitation Exoskeleton Robot Based on sEMG signal. North China University of water resources and hydropower, 2019.

[4] Bingzhu Wang, Changwei Ou, Nenggang Xie, Lu Wang, Tiantang Yu, Guanghui Fan, Jifa Chu. Lower limb motion recognition based on surface electromyography signals and its experimental verification on a novel multi-posture lower limb rehabilitation robot. Computers and Electrical Engineering, 101, 2022.

[5] Lei Shi. Research on hand motion recognition method based on multi-channel sEMG signals. Henan University of Technology, 2024.

[6] Fuling Deng. Research on cooperative control method of flexible lower limb exoskeleton based on sEMG. Chongqing Jiaotong University, 2024.

[7] Zhongli Gus. Research on muscle fatigue identification and compliant control for rehabilitation exoskeleton robots. Chongqing Jiaotong University, 2023.

[8] Maqiang Zhai. Research on human lower limb movement intention recognition method based on sEMG signal. Chongqing: Chongqing University, 2021.

[9] Peng Qin Research on the rehabilitation strategy of lower limb exoskeleton rehabilitation robot based on sEMG. Shenyang University of Technology, 2021.

[10] Junfen Huang, Leyi Guo, Yingyu Cao. Design of upper and lower limb coordinated active rehabilitation motion control system for rehabilitation robot. medical and health equipment, 2023.

[11] Yixing Zhang. Gait tracking of lower extremity exoskeleton robot based on adaptive sliding mode control. Sensor World, 2024.

[12] Long Chen, Hui Liang, Hui Wang. Structure and control strategy of multi degree of freedom lower limb exoskeleton rehabilitation robot based on sEMG. Journal of Qingdao University of Science and Technology (NATURAL SCIENCE EDITION), 2024.

[13] Shuai Hu. Design of lower limb rehabilitation robot based on motion intention recognition and multimodal state feedback. Hangzhou University of Electronic Science and Technology, 2024.