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Research on the Recognition Method of Exoskeleton Rehabilitation Robot Based on Patient Intent Recognition

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Abstract:

With the development of exoskeleton rehabilitation robot technology, the use of such robots can assist patients in achieving basic motor functions such as normal walking, improve the physical condition of patients, and gradually restore the motor functions of the affected limbs. These robot systems are human-centered human-computer collaborative systems, whose primary task is to understand human movement intentions and move in coordination with the human body. The current research methods of human-computer interaction perception systems mainly involve bioelectrical signals and physical signals such as force/torque. This paper reviews the recognition methods of such robots and explores their intention recognition methods in depth. Focusing on the intention recognition technology of exoskeleton rehabilitation robots, this paper analyzes the principles, processes, advantages and disadvantages, and applicable scenarios of the Surface Electromyography (sEMG) and Inertial Measurement Unit (IMU) methods, providing theoretical references for optimized design and clinical applications. By evaluating the rehabilitation effects of each intention recognition method, this paper explains and evaluates their recognition principles, offering certain references for the optimized design and clinical practice of rehabilitation robots.

Keywords: Intention recognition; Exoskeleton rehabilitation robot; Bioelectrical signal; Movement intention

1. Introduction

The exoskeleton robot was first invented by Russian engineer Nicolas Yagen in the 1890s, using compressed air to drive and assist human movement. In the 1960s, the United States began to develop military exoskeletons, such as BLEEX and Hardiman, to enhance soldiers' physical abilities. Today, exoskeleton robots have been widely applied in the fields of medical rehabilitation, industrial assistance, and tourism services. In the medical field, exoskeleton robot can reduce the workload of therapists and help patients with muscle weakness or the elderly to regain the ability to walk, go up and down stairs, etc. Lower limb rehabilitation exoskeletons directly contact the limbs, detect patients' movement intentions in real time, and assist the affected limbs in completing movements. Therefore, accurate intention perception is crucial.

At present, rehabilitation robots mainly use assisted movement therapy to assist paralyzed patients in rehabilitation training. Movement therapy can cause adaptive changes in brain structure and function, and the nervous system can continuously self-adjust and repair itself with changes, thereby restoring patients' limb movement functions. Movement therapy mainly has two training modes: passive training and active training. Junling Fu et al. proposed that using robots to assist patients in active or passive rehabilitation training can reduce the workload by 54.6% compared with traditional manual assisted rehabilitation, while the median error can be controlled within 0.25 N [1]. Passive training is mainly applicable to patients with weak residual muscle strength and poor movement ability, such as those with impaired movement ability caused by symptoms like spinal cord injury. Exoskeleton rehabilitation robots can drive the affected limbs to perform rehabilitation training, but the movement trajectory is set by physicians and can only execute corresponding movements according to the set action patterns, with poor human-computer interaction. In the middle and late stages of rehabilitation, when patients' muscle strength has been restored to a certain extent, rehabilitation robots can provide active rehabilitation training according to patients' movement intentions [2]. Active training helps promote functional recovery, improve limb coordination, and increase patients' enthusiasm for participating in training, with more significant rehabilitation effects than passive training [3]. However, compared with passive training, the implementation of active rehabilitation training is more difficult. Exoskeletons need to accurately and reliably recognize human movement intentions in the human-computer interaction system and decide in time whether the robot should provide movement or assistive force to patients, thereby ensuring the stability of the human-computer interaction control system.

This paper starts from the control mechanism between the human body and exoskeleton robots, reviews the impact of different intention recognition methods on obtaining human movement intentions, and analyzes the existing problems to provide certain references for the optimized design and clinical practice of rehabilitation robots.

2. Control Mechanism of the Human Body and Exoskeleton Robots

The lower limb power exoskeleton control system mainly consists of two parts: the perception system and the control system. The perception system can obtain the movement intentions of the human lower limbs during movement through human-computer interaction, analyze and process them, and then drive the exoskeleton to complete corresponding actions through the control system [4].

Bioelectrical signals can reflect human movement intentions, and force/torque is an intuitive manifestation of human movement intentions. At present, the perception system of lower limb exoskeleton robots mainly obtains and analyzes human joint movement information through sensors and applies the movement patterns of various human joints over time to the corresponding joints of the exoskeleton structure. Since this control method is a passive control, the lower limb exoskeleton robot system can only execute corresponding actions according to the known action patterns established based on human gait data. This poor human-computer interaction makes it difficult to switch between multiple action patterns. Because the main purpose of wearing lower limb exoskeleton robots is to help patients with intelligent rehabilitation, which requires high-frequency switching of action patterns, the perception system must accurately recognize human movement intentions to ensure smooth switching between patterns and high-precision human-computer action coordination, and enhance the interactivity between the human-computer system and the adaptability under different action patterns.

3. Surface Electromyography (sEMG) Technology

sEMG technology is a technique for identifying the intentions of patients' affected limbs by collecting and processing muscle electrical activity signals. The main process can be simply summarized into the following steps: information collection, signal preprocessing, signal analysis and application, and data storage and processing.

Electromyographic signals can be collected by placing electrodes on the patient's skin. These signals are very weak. When the muscles are relaxed, they may produce signals of 1-10μV; during low-intensity muscle contraction, the signals will increase to 10-100μV; as the muscle contraction intensity increases, the signals can reach 100μV-1mV, and in extreme cases, they may be higher, but the maximum will not exceed 5mV [5]. At the same time, the frequency of electromyographic signals is also relatively low, mainly concentrated in the range of 10- 500Hz, with energy concentrated in the range of 30- 150Hz, and the energy distribution is relatively concentrated [6]. The frequency distribution of electromyographic signals can remain relatively stable. In addition, the amplitude of surface electromyographic signals can be

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positive or negative, and the absolute value of the signal is approximately proportional to muscle strength.

To identify weak surface electromyographic signals, surface electromyographic signals can be amplified, filtered, and normalized to eliminate noise and interference. Then, through A/D conversion, the continuous analog signal is converted into a discrete digital signal that can be analyzed. This signal can reflect the activity state of nerves and muscles [7]. It is difficult to prevent the generation of noise during the signal collection process, and noise reduction of electrical signals is required. The degree of noise reduction will greatly affect the subsequent identification and control. At present, the mainstream noise reduction methods can be divided into hardware noise reduction and software noise reduction. Among them, software noise reduction can be further divided into adaptive filtering, wavelet transformation, and other methods for noise reduction. The table below briefly shows the performance and applicable scenarios of each method. The comparison of different noise reduction methods is shown in Table 1

Table 1. Comparison of advantages and disadvantages of various filtering methods

Method	Computation complexity	Real-time	Anti-non-stationary noise	Multiple channels are required	Applicable scene
Traditional filtering	Low	5/5	2/5	deny	Real-time control and power frequency interference suppression
Wavelet transform	Centre	3/5	4/5	Deny	Offline analysis, transient noise removal
Source separation (ICA)	Tall	2/5	3/5	Yes	Multi-channel mixed signal separation
Deep learning	Polar altitude	2/5	5/5	Depending on the situation	Complex noise, big data scenarios
Mixed method	Polar altitude	2/5	5/5	Depending on the situation	High precision requirements (e.g., medical diagnosis)
EMD/VMD	Medium-high	2/5	4/5	Deny	Nonlinear signal and low-frequency noise removal

After the surface skin electrical signals are processed, feature extraction is performed, including the root mean square (RMS) zero-crossing rate and waveform length. Common time-frequency domain features include short-time Fourier transform (STFT), wavelet transform, wavelet packet transform, higher-order spectral analysis, and Wigner-Ville distribution, among others [8].

After completing the data processing, model training is required. Currently, the mainstream methods for model training include deep learning models, transfer learning, and fine-tuning [8]. In addition to traditional machine learning, most widely used model training methods have a common drawback: they are computationally intensive, leading to longer training times. For a detailed comparison, see Table 2:

Table 2. Comparison of various model training methods

Method	Advantage	Disadvantage
Traditional Machine Learning	It is efficient in calculation, friendly to small samples, and highly interpretable	It relies on feature engineering and has limited ability to deal with complex patterns
Deep learning	Automatic feature extraction and processing of high-dimensional complex data	It requires a large amount of data, consumes a lot of computing resources, and is a black box
Transfer learning	Solve data shortage and adapt to personalized needs	It relies on a pre-training model and is sensitive to domain differences
Reinforcement learning	Dynamic strategy optimization and closed-loop interaction	Training instability, low sample efficiency, and safety challenges

Electromyographic (EMG) signals from patients are typically stored locally or in the cloud. For example, they can be stored in the robot's built-in storage devices, such as SD cards or Flash drives, to preserve the original signals or feature data. Cloud storage involves storing the data on servers. Both methods aim to save processed data for subsequent analysis and treatment [9]. However, due to the varying muscle physiological structures and exercise habits of different patients, their sEMG signals can differ significantly. Therefore, it is not advisable to use data from other patients for treatment purposes, and each patient requires personalized adjustments, leading to a large volume of data that needs to be compressed or segmented [9].

sEMG offers significant advantages in the recognition of rehabilitation robot intentions, including non-invasive, safe, and real-time monitoring capabilities. Studies show that sEMG can achieve an accuracy rate of 75%-88% for lower limb gait recognition, while invasive electromyography (iEMG) carries a 1.2%-3.5% risk of infection and causes more pain. Furthermore, sEMG can simultaneously monitor multiple muscles, reducing balance recovery time by 23% in stroke rehabilitation. However, sEMG signals are weak and susceptible to interference, with a signal-to-noise ratio (SNR) 15-20dB lower than iEMG. They require complex filtering processes, and accuracy drops by 30%-40% across users, necessitating personalized calibration. High-precision devices like DelsysTrigno are expensive, but deep learning techniques such as CNN-LSTM promise to enhance performance.

4. Inertial Measurement Unit (IMU) Technology

IMU technology collects three-dimensional motion data of objects by integrating sensors such as accelerometers and gyroscopes, which then calculates the object's motion posture. In rehabilitation training, this technology collects information on patients' movement trajectories and joint changes, and through computation, it enables robots to guide the patient's affected limbs to perform actions like abduction and rotation. The workflow of this technology can be summarized into data acquisition, signal preprocessing and calibration, extraction of motion features and posture calculation, output application and feedback, and data storage and processing.

IMU is a multi-sensor fusion system that primarily consists of an accelerometer, a gyroscope, and a magnetometer. The accelerometer measures the linear acceleration in the X, Y, and Z axes, with a typical sampling frequency ranging from 100 to 1000 Hz. The gyroscope, which provides high sampling rates of 200 to 2000 Hz, measures rotational angular velocity. The magnetometer, which provides heading reference by sensing the Earth's magnetic field, has a sampling rate of 10 to 100 Hz [10]. In practical applications, the IMU system typically uses a microcontroller (such as Arduino) or an embedded computer as the data processing core, collecting and storing sensor data in real-time through standard communication protocols like I2C (for example, the MPU6050). The IMU data collected often contains noise and biases, which require preprocessing. To minimize the impact of noise and biases on subsequent systems, the initial signals are typically filtered and denoised.

After the motion state data of the object is preliminarily processed, it is necessary to extract the motion characteristics of the object, which mainly include acceleration, angular velocity, displacement, attitude Angle, and so on. At present, the main extraction methods are feature extraction based on the time domain

Feature extraction methods, such as frequency domain feature extraction and machine learning-driven feature extraction, such as Cyberdyne's HybridAssistiveLimb rehabilitation exoskeleton robot, which is based on the angular velocity signal of IMU and uses the zero velocity update (ZUPT) algorithm to correct the drift error [11]. Table 3 briefly describes the advantages and disadvantages of the method:

Table 3. Compares the advantages and disadvantages of various feature extraction methods

Method	Advantage	Disadvantage
Time domain + frequency domain features	The calculation is fast and suitable for real-time control	Sensitive to noise and installation location
Jerk/PCA dimension reduction	Suitable for sudden motion recognition	Weak motion recognition ability is weak
ZUPT+HMM	Reduce drift and is suitable for periodic motion	The calculation is complex, and the adaptability to non-periodic motion is poor
Threshold/key point detection	Simple and efficient	Manual parameter adjustment is required, and the generalization ability is weak

Like robots that use sEMG technology for intention recognition, rehabilitation robots that use IMU technology

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for intention recognition also need to be trained in models, and the current methods are roughly the same.

The advantages of IMU technology in rehabilitation medicine have been validated through numerous empirical studies. In data collection, IMU sensors can achieve sub-millimeter-level motion monitoring accuracy. Studies show that the measurement error for hip and knee joint angles is less than 1.5°, and the accuracy of gait cycle recognition reaches 98.7%. The integration of multiple sensors further reduces spatial displacement errors to within 0.3cm. In data processing, the LSTM-based deep learning model significantly improves the accuracy of gait phase classification to 94.2%, a 23% improvement over traditional methods. Combining this with Kalman filtering can increase the signal-to-noise ratio by 18 dB. In rehabilitation training, the real-time IMU feedback system has improved patients' gait symmetry by 37.5%. By optimizing the control strategy with rehabilitation robots, human-machine interaction latency is reduced to less than 50ms, significantly enhancing training efficiency. These quantitative data fully demonstrate the precision, reliability, and clinical value of IMU technology in rehabilitation medicine.

5. Discussion and Analysis

Table 4. Brief comparison between sEMG technology and IMU technology

Characteristic	Surface electromyography (sEMG) technology	Inertial Measurement Unit (IMU) technology
Advantage	Real-time reflection of motion intent Enhance the human-computer interaction experience Non-invasive, suitable for long-term use It can process muscle signals from multiple sites at the same time	High real-time, providing instant motion data feedback The sensor is light and convenient for patients to move freely The cost is low, which is conducive to clinical promotion Strong anti-interference ability, can adapt to a complex environment
Disadvantage	The signal is weak and requires complex filtering and noise reduction Signals are individual-specific and need to be adjusted individually The model has high complexity and certain requirements for hardware equipment	The intention is delayed, and only the limb movements that have occurred can be detected, but the movements cannot be predicted It's hard to discern subtle movements The error increases with time It does not reflect the neuromuscular state and has a limited effect on nerve recovery
Applicable scene	Neurorehabilitation, prosthetic control, static or low-speed control	Dynamic environment, group application, motor function rehabilitation

As can be seen from Table 4, sEMG can predict the patient's movement intention in advance by detecting muscle electrical signals, which is suitable for high-precision scenarios such as fine hand operation and nerve rehabilitation; IMU can adjust the trajectory through motion feedback, but only supports passive training, and has limited effect on nerve rehabilitation.

The adaptive noise cancellation technology based on Wiener filtering can effectively reduce the motion artifacts in sEMG signals during autonomous movements, with an attenuation range of 62%±8% [12]. Additionally, by integrating gyroscope angular velocity and accelerometer data using a gradient descent algorithm, the system achieves accurate attitude estimation. Under static test conditions, the average Euler angle error is less than 1° (RMSE=0.82°±0.15°), significantly reducing the phenomenon of integral drift [13].

6. Conclusion

This paper explores the technology of exoskeleton rehabilitation robots based on patient intent recognition, focusing on the technical characteristics of two primary methods: sEMG and IMU. The study reveals that sEMG technology can predict early motor intentions through muscle electrical signals, offering advantages in neuromodulation rehabilitation, but is susceptible to interference and exhibits significant individual differences. In contrast, IMU technology, which integrates multiple sensors, directly captures the movement status of limbs, providing strong real-time performance but with limited ability to predict motor intentions. The paper concludes that sEMG is better suited for fine-grained rehabilitation scenarios, while IMU is more suitable for mass application needs.

In the future, it is essential to advance multi-modal information fusion technology, integrating the predictive capabilities of sEMG with the feedback advantages of

IMU. It is also crucial to address key issues such as signal synchronization and algorithm optimization. Research findings indicate that, with advancements in artificial intelligence and sensor technology, this technology has the potential to enable more natural human-computer interaction and precise rehabilitation treatments. This paper recommends enhancing clinical validation and optimizing personalized treatment plans to promote the widespread application of this technology in medical rehabilitation.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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