The Synergistic Assistance Mechanism of Mechanical Exoskeletons and Human Muscles from the Perspective of Biomechanical Characteristics Matching

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Abstract. In the field of perception automation, five mainstream technical solutions have been identified and organized. They are position sensors, pressure sensors, electromyography (EMG) sensors, current sensors, and multi-sensor fusion. At the same time, we've made clear their core features, key performance indicators, and applicable scenarios. Our research shows that multi-sensor fusion has become the core perception solution for high-end exoskeletons. It integrates multidimensional data to reduce the error of a single sensor. When it comes to intention recognition, we compared three algorithms: Online Support Vector Machine (Online SVM), EMG signal recognition, and the empirical formula method. The results show that the Online SVM algorithm, with the zero-moment point (ZMP) as the core feature, can achieve an accuracy rate of 95% after fusing inertial measurement unit data. It has significant advantages in adaptability and real-time performance. The current technology has some problems. There are sensors, and the intention recognition algorithms have a narrow coverage in scenarios. Also, they rely highly on manual intervention. In addition, this paper proposes four optimization paths, which are performance upgrade, scenario expansion, algorithm optimization, and practicality improvement. The research results can provide theoretical references for the structural innovation and control strategy optimization of mechanical exoskeletons. They can also help exoskeleton technology be applied in clinical rehabilitation, daily assistance, and other scenarios.

Keywords: Biomechanical Characteristics Matching, Mechanical Exoskeletons, Human Muscles.

1. Introduction

The mechanical exoskeleton is a wearable human-machine collaborative device. It has become an important technical tool for helping people move and improving their motor function. Its main value lies in the coordinated work of the mechanical structure and the drive system. This can accurately make up for the lack of human muscle strength. This advantage has been proven in some specific situations. For example, there is a mechanical hand exoskeleton designed for pianists. It can be used to help improve playing efficiency. Relevant practices show that after only half an hour of training, professional players can break through the speed limit of their fingertips. Their performance can be significantly improved [1, 2].

However, in the research area of the cooperation mechanism between mechanical exoskeletons and human muscles, there are still limitations in the current results. Most studies focus on improving the assistance performance of a single joint. But there is relatively little systematic research on the biomechanical rules in multi-joint coordination. In fact, human movement is basically a complex process that involves the coordinated interaction of multiple joints. And the cooperation among joints directly affects the overall movement efficiency and biomechanical features. Many scholars have noticed this problem and explored targeted solutions.

Based on the current research situation and practical needs, this paper focuses on ankle torque compensation as the research subject. It systematically analyzes the evaluation standards for biomechanical characteristic matching, key influencing factors, and potential optimization ways. The goal is to provide theoretical references for the structural innovation and control strategy optimization of subsequent mechanical exoskeletons.[9]

2. Key Research Progress and Achievements in Mechanical Exoskeleton Automation Technology

The current perception technology of hand exoskeletons has developed in a way where there are breakthroughs in single functions and multi-dimensional integration. Different sensors have their own uses in different situations. Position sensors have a simple structure and are easy to integrate. They can accurately capture the motion trajectory and joint angles of the exoskeleton. This provides core data for basic motion control. Pressure sensors use a bidirectional force-sensing design. They are very important for rehabilitation, safety protection, and virtual tactile feedback. They can effectively prevent secondary finger injuries and make human-machine interaction more adaptable. Electromyography sensors rely on bioelectrical signal decoding technology. They can make the exoskeleton be controlled according to the user's active intention. They can adapt to individual differences and make rehabilitation training more autonomous. Current sensors are used as auxiliary perception.

The output torque can be indirectly calculated by monitoring the motor current of the elements. This helps ensure the stability of motor operation in complex systems. The multi-sensor fusion technology combines multidimensional data like position, pressure, and electromyography. It can significantly reduce the error of a single sensor. At the same time, it improves motion accuracy, safety, and intention recognition capabilities. This technology has become the mainstream perception solution for high-end exoskeletons. Table 1 will introduce the core technologies, key performances, and application scenarios of some perception technology solutions.

Considering the limitations of the existing technology, we can make improvements in four aspects in the future. First, we can upgrade the performance. We can develop sub-millimeter-level position sensors, 0.1N resolution pressure sensors, and microsecond-level response current sensors. At the same time, we can increase the accuracy of electromyographic signal recognition to over 98% to strengthen the core perception capability. Second, we can expand the functions. We can add a full - hand 27 - degree - of - freedom collaborative monitoring function to the position sensor. We can design a full-hand pressure distribution array for the pressure sensor. Also, we can develop a sensor self-calibration and fault diagnosis module to enhance compatibility and reliability. Third, we can optimize the algorithm. We should focus on breaking through the technical bottlenecks of the combination of multimodal fusion algorithms and artificial intelligence to achieve efficient fusion of multiple data sources, such as electromyography, pressure. [10]

Vision is also considered. At the same time, a scene-adaptive weight adjustment method is developed to cut down computational complexity. Fourth, the practicality has been improved. Through a miniaturized design, the influence of sensors on wearing comfort is reduced, and the dependence on skin condition is lessened. This promotes the application of the technology from the laboratory to scenarios like clinical rehabilitation and daily assistance. Table 2 will introduce the types of algorithms for motion intention recognition, their principles, advantages, and limitations. [5]

Table 1. Automated Perception of Human Movement States

Perception technology solution	Core technical features	Key performance indicators	Usage Scenario [3]
Position sensor (including Angle and displacement sensors)	Joint encoder: joint angle Motor encoder: motor angle IMU: limb segment pose Trajectory feedback for master–slave control Compact, easy to embed in links/gears	Accurately capture the movement trajectories of fingers and exoskeletons. Provide real-time position feedback for motor control to ensure motion accuracy. Some solutions can achieve synchronous monitoring of multiple joint angles. [4]	In the master-slave control mode, the movement trajectories of the exoskeletons are synchronized (such as the exoskeletons of the University of Tokyo and Gifu University). Precise execution of motion paths in preset modes (such as the Harbin Institute of Technology's large hand exoskeleton). Indirect calculation of the motor's rotational torque.
Electromyography sensor (EMG sensor)	Collect electromyographic bioelectrical signals from the hand or related muscles. The intention of finger movement is identified through signal analysis and converted into control instructions for the exoskeleton. It needs to be combined with signal processing algorithms to achieve intent decoding.	The accuracy rate of motion intention recognition is relatively high (for example, the scheme of the Hong Kong Polytechnic University can control stretching/bending through electromyographic signals). Control thresholds can be set according to the strength of electromyographic signals to adapt to individual differences. The signal delay is low, meeting the requirements of real-time control.	Exoskeletons with bioelectric control mode (such as those from the Technical University of Berlin and the Hong Kong Polytechnic University). Active rehabilitation training for the affected hand of stroke patients drives the coordinated movement of the exoskeleton through electromyographic signals.
electric current transducer	Monitor the motor current that drives the exoskeleton. The motor torque and the output force of the exoskeleton are indirectly calculated through the change of current as auxiliary feedback components for motor control, supplementing the force perception data.	Accurately reflect the changes in motor load to indirectly obtain the actual output torque of the exoskeleton and assist in optimizing the control strategy. Ensure the stability of motor operation and avoid overload.	Complex exoskeleton systems driven by DC motors (such as the hand exoskeleton with multiple sensors at the University of Berlin. Rehabilitation training scenarios that require real-time control of motor output force (such as high-precision grasping and stretching training)
pressure sensor	It is installed at the contact points between the exoskeleton and the fingers (such as above and below the knuckles). Detect the pressure exerted by the exoskeleton on the fingers and the output force of the power transmission device. It has the ability of bidirectional force perception and can achieve mechanical feedback.	Monitor the pressure value in real time to prevent fingers from being damaged due to excessive force. Provide a force feedback signal and optimize the exoskeleton and human body interaction fitment; Some schemes can achieve synchronous detection of pressure at multiple points.	Finger safety protection during rehabilitation training (such as hand exoskeletons from Gifu University and the University of Pittsburgh). Force feedback simulation in virtual haptic interaction modes (such as the hand exoskeleton of Nanjing University) and pressure regulation in grasping actions.
Multi-sensor fusion (combinations of the above two or more)	Integrating multiple sensors such as position, pressure, electromyography, and current, the comprehensiveness and reliability of perception are enhanced through data fusion algorithms. Taking into account multi-dimensional feedback such as position, force, and bioelectricity, it achieves precise control.	Multi-dimensional data complementarity reduces the error of a single sensor. The motion accuracy, force control safety, and intention recognition accuracy are simultaneously improved to meet the perception requirements of complex motion scenarios.	High-degree-of-freedom, multi-functional hand exoskeletons (such as the 16-joint 20-degree-of-freedom hand exoskeleton from the University of Berlin) need to balance safety protection and precise rehabilitation training for stroke patients. A rehabilitation scene that combines virtual interaction with actual exercise.

Table 2. Movement intention recognition and decision-making automation

Type of Intention Recognition Algorithm	Algorithm Principle	Advantages	Limitations
Online Support Vector Machine (Online SVM)	Takes ZMP as core feature, fuses IMU attitude/joint encoder data to build input vectors; uses online learning (crutch button labels for real-time training) and polynomial kernel function for "walking/standing" binary classification	Online learning eliminates the need for offline training data transmission, making it suitable for embedded platforms with fast response speed (updating samples every 20ms) [6]. Integrating ZMP features improves stability judgment accuracy; accurate adaptation to different wearers is achievable after 50 steps of training. - The polynomial kernel function delivers better classification performance for gait cycle data than the Gaussian kernel function.	Currently focuses on "walking/standing" intention recognition and does not yet cover complex scenarios such as standing up, sitting down, and going up/down stairs. - Relies on crutch button input for initial labels, making it impossible to build the initial model completely without manual assistance. - The 17-dimensional feature space still imposes certain computing power requirements on embedded platforms, with potential latency risks in complex scenarios [7].
Electromyographic (EMG) Signal Recognition Algorithm (vs. existing technologies)	Collects EMG signals from leg muscles, analyzes signal features (e.g., amplitude, frequency) to recognize motion intentions, and converts them into exoskeleton control commands.	Directly decodes intentions based on human bioelectrical signals, conforming to natural movement habits.	Leg EMG signals of paraplegic patients are weak, leading to high measurement difficulty and poor applicability. Signals are easily interfered with by factors such as skin condition and electrode contact, resulting in insufficient stability.[11]
Empirical Formula Method (vs. existing technologies)	Distinguishes motion intentions using sensor data (e.g., plantar pressure, upper body posture) and preset empirical formulas (e.g., pressure distribution thresholds, posture angle ranges).	Features simple principles, easy implementation, and strong real-time performance.	Empirical formula parameters have poor adaptability; a single set of parameters cannot meet the needs of wearers with different body types and movement habits. Lacks self-learning capability; manual parameter readjustment is required when scenarios change, resulting in low flexibility.

3. Summary of Core Achievements and Improvement Suggestions

At present, there are three main algorithms in the field of intent recognition for lower extremity exoskeleton robots. They are the Online Support Vector Machine (Online SVM), the electromyographic signal recognition algorithm, and the empirical formula method. The online SVM algorithm proposed in the relevant literature uses the zero-moment point (ZMP) as the core feature. It combines IMU and joint data to build a 17 - dimensional feature vector. It realizes intention classification through online learning strategies and polynomial kernel functions. When it fuses IMU and ZMP features, the recognition accuracy can reach 95%. Also, after 50 steps of training, it can adapt to different wearers. It is also compatible with embedded platforms and has a fast response speed. The samples are updated in 20ms [4, 8]. Although the electromyographic signal recognition algorithm can directly decode bioelectrical intentions, it is limited by the weak electromyographic signals of paraplegic patients. Its applicability is insufficient. Although the empirical formula method has a simple principle, its parameter adaptability is poor, and it lacks self-learning ability. It requires frequent manual adjustments [4]. The existing technical limitations can be improved in three aspects. First, expand the application scenarios of the algorithm. Extend the online SVM algorithm from "walking/standing" intention recognition to complex tasks such as standing up, sitting down, and going up and down stairs. Corresponding ZMP feature patterns and sample data for these scenarios need to be supplemented, and the adaptability of the kernel function to multi-classification tasks should be optimized. Second, reduce the reliance on humans. By integrating multimodal data from pressure shoes and IMUs, design a semi-supervised learning strategy to replace the manual input of button labels for the initial model, achieving the autonomous construction of the initial model. Third, optimize the computation. There are power and latency issues. We can use feature dimension reduction algorithms, like principal component analysis, to reduce the input dimension. At the same time, we should optimize the iterative efficiency of online SVM for embedded platforms. This can enhance the real-time response performance in complex scenarios.[10]

4. Conclusion

This paper systematically reviews the research progress of mechanical exoskeletons in the perception and intent recognition stages: multi-sensor fusion, by integrating multi-dimensional data such as position, pressure, and electromyography, significantly reduces the error of a single sensor and simultaneously enhances motion accuracy and safety. Online-SVM takes ZMP as the core feature. After fusing IMU, the recognition rate reaches 95%, and it has the best real-time performance and adaptability. In view of the limitations of the existing sensors, such as insufficient performance, narrow coverage of algorithm scenarios, high reliance on manual labor, and imbalance in computing power delay, four feasible improvement paths are proposed: performance upgrade, functional expansion, algorithm optimization, and practicality enhancement. The above achievements can provide theoretical support for the innovation of exoskeleton structures and the optimization of control strategies, and help them move from the laboratory to clinical rehabilitation, daily assistance, and professional scenarios, achieving the large-scale application of human-machine collaborative assistance technology.[9]

Authors Contribution

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

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