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The Research Progress on Sensing Technologies in Lower Limb Exoskeleton Robot Motion Intent Perception Systems

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Abstract:

Lower limb exoskeleton robots have demonstrated great potential in the field of medical rehabilitation, especially in assisting patients with limited mobility to recover lower limb motor functions. The accuracy of the movement intention recognition system is a critical factor influencing the control effectiveness of exoskeletons. Sensor technology plays a crucial role in this system, as it accurately collects information such as gait phase, joint angles, and muscle activity, ensuring that the exoskeleton can adjust its movement strategy in real-time. This study analyzes the application and development of inertial measurement units (IMUs), plantar pressure sensors, and surface electromyography (sEMG) sensors in movement intention recognition systems. However, issues such as data synchronization, signal noise, and individual differences remain, requiring further optimization of sensor configuration and data processing strategies. Future research will focus on the introduction of intelligent compensation algorithms, multi-sensor fusion, and collaborative sensing, and the optimization of sensor performance, thereby enhancing the system's accuracy, stability, real-time capability, and adaptability, promoting the widespread application of exoskeleton robots in rehabilitation training.

Keywords: Sensing technologies; lower limb exoskeleton robot; motion intent perception systems.

1. Introduction

Lower Limb Rehabilitation Exoskeleton (LLE), for many years, has received considerable attention within the sphere of medical recovery, and has been largely focused on assisting people with limited mobility to rehabilitate their lower limb motor skills. Technology development makes exoskeleton robots not only be used for recovery training but also can help elderly people walk and help spinal cord injured people to recover function. Giving outside power support, exoskeletons copy normal walking, which permits sick people to conquer walking problems and begin getting themselves up step by step. Exoskeleton robots, compared with traditional rehabilitation devices, can be adjusted at any time based on a person's gait to provide personalized and accurate rehabilitation training.

The motion sensing system in the lower limb exoskeleton robot is one of the key parts; it intends to precisely understand the patient's movement idea, discover gait phases, and change the action scheme as on the obtained information. The accuracy of gait recognition will have a great impact on the control effect of the exoskeleton, which will directly affect the efficiency and safety of the whole rehabilitation training. Accurate motion perception can help improve trainees' training effect and can also avoid accidents leading to pain and injury due to wrong control.

Sensor tech is important for this system. The sensors collect the patients' motions, such as the gait phase, joint angles, muscle activities, and so on. Then the information is processed in the feedback to the exoskeleton. The sensor performs, which impacts the precision and speed of response of the sensing system. Using high precision, low latency sensors, it makes it possible for the exoskeleton to respond really fast to what the patient is moving, which allows them to start walking normally again.

The Inertial Measurement Unit (IMU) sensor is the main sensor people use; it measures how the body moves via its acceleration and gyroscope and helps it identify the stages of the step, such as when we're standing up and swinging. Plantar pressure sensor monitors the change of pressure when the feet hit the ground and provides key information about the change of gait phase. EMG sensors can sense the electrical activities coming from the muscles of the body and give such information – the direct muscle movement intentions to the exoskeleton: These sensors working together allow the lower limb exoskeleton to truly follow the patient's changes in gait and have the exoskeleton respond as well in the same way in the moment.

However, there are some difficulties encountered regarding the sensor configuration, like how to choose the right sensor, make sure that all the data collected is real-time and accurate, and deal with noise and interference of the signal. In the future, with the development of technology, the performance improvement of sensors and the combination of systems will also provide theoretical grounds for the improvement and utilization of lower limb exoskeletons.

2. Motion Intention Recognition System

2.1 Importance of Motion Intention Recognition in Exoskeleton Systems

Motion intention recognition is identifying the user's motion intentions based on gait features of the user by capturing with different sensor systems in real time. In the lower limb exoskeleton robots, the motion intention recognition is done such that the exoskeleton system will act on the movements and be coordinated, and help out for correct assistance or support to be provided to the users in an effort to improve the experience and help with gait recovery or improvement.

Motion intention recognition tech app in exoskeletons is very necessary. Firstly, accurate motion intention recognition contributes to the exoskeleton dynamically conforming to the user's gait pattern and movement necessities. This will include determining exactly which part of the walk, and then determining whether to increase the help that is provided or whether to stop, to avoid wasting energy, but also to avoid too much support. Secondly, motion intention recognition can also be personalized for customization, that is to say, it can give personal assistance based on the personal physical condition and movement habits of the person, to achieve maximum comfort and effects.

2.2 Core Tasks of Motion Intention Recognition

Gait pattern recognition mainly deals with recognizing the different gait types like walking, running, climbing stairs, and down stairs. The key process is to distinguish various movement modes and gaits, then choose the corresponding exoskeleton assisting mode for each form of movement. In exoskeleton control systems, gait pattern recognition usually needs to combine various sensor data, such as inertial sensors, pressure sensors, etc., to carry out a comprehensive analysis.

To recognize the phase of gait refers to the process of identifying the different stages of the gait cycle, such as the Stance phase and the Swing phase. If it wants to control the exoskeleton properly, task recognition is very important. Since each step requires a different way of control. Similarly to the stance phase, the exoskeleton needs to support a lot when it comes to the user's bodyweight and movement changes, while for the swing phase, the control system could give less effort in order to simulate how the normal gait is.

The subdivision of the gait phase commonly comprises several sub-divisional sub-phases like loading response LR, mid-stance MST, terminal stance TST, pre-swing PSW, initial swing ISW, mid-swing MSW, and terminal swing TSW. Correct phase recognition is important for switching any stage of the exoskeleton system's control strategy to avoid wrong joint torque and to make the gait look smooth and natural.

State switching, a term for the transitions from one phase of gait to another. Through constant observation of the changes in the step, it can then continuously alter its current Step. The user transitions from walking to running, and the exoskeleton control system should change its gait

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phase recognition algorithm according to the new gait mode. It needs to switch to a set of control strategies compatible with the new mode. State switching accuracy and timely performance greatly influence the exoskeleton's response velocity and effectiveness.

Sensors are the basic form of data acquisition, recording the user's dynamic information in real time, and giving real-time, accurate information about gait patterns, phases, and states. Different kinds of sensors, like IMUs, plantar sensors, and EMG sensors, are all very important for the recognition of motion intention.

2. Sensor Technologies in Lower Limb Exoskeletons

Choosing a sensor is important to recognize the exact motion intentions. The sensing configuration within a lower limb exoskeleton system has to be able to precisely gauge the user's motion state and deliver pertinent data to the controlling system so as to guarantee the accuracy of gait recognition. Common types of sensors would be IMU, plantar pressure, sEMG sensor, and so on.

2.1 Inertial Measurement Unit (IMU)

The Inertial Measurement Unit (IMU) mainly includes accelerometers and gyroscopes, and is commonly used in gait recognition by acquiring acceleration and angular velocity information during movement. The accelerometer can be used to measure acceleration and therefore capture the movement of the foot throughout movement. The gyroscope measures angular velocity so that it can capture the body's rotation through its gait cycle. When those sensors are used at the same time, it's possible to figure out all the various stages in the gait cycle and tell about things like how far someone steps with each step they take, how fast they walk, and what parts of the gait cycle they're in.

Bartlett et al. configured the IMU as a 6-axis sensor fixed on the leg of the participant, mainly measuring the angle change of the thigh relative to the gravitational direction [1]. They processed the thigh angle data and used the phase variable method to represent gait as a phase space trajectory, extracting features for walking, going up stairs, and going down stairs. Gait recognition achieved 99.4% for walking and 100% for ascending stairs.

Liu et al. put forward a scheme that could tell what stage people were at when they walked and used IMU and something called HMM. In order to collect participants' angular velocity signals, researchers applied an IMU sensor made by InvenSense on their toes [2]. For gait phases division, they used the HMM model to divide the gait cycle into 4 phases: heel strike, foot flat, heel off, and toe off. This IMU configuration demonstrated high accuracy and stability in gait phase recognition in dynamic environments, with an accuracy rate of 91.88%.

Choi et al. focused on using the Xsens Technologies MTi-3 AHRS IMU sensor, installed on the front of each participant's thigh [3]. The sensor recorded the thigh's angle and angular velocity at a sampling frequency of 1 kHz, collecting both gait and running data. The study optimized feature selection using a genetic algorithm (BGA) and determined the optimal time window length (LTW) using Bayesian optimization (BO). After optimization, the error in gait estimation decreased from 1.284% to 0.910%, while the running error reduced from 1.997% to 1.484%.

Fullerton et al. researched how to use multiple body-worn accelerometers to recognize human activity types in a free-living environment [4]. Ten participants wore nine IMU sensors, which were placed on the left and right ankles, hips, wrists, upper arms, and spine, with a sampling frequency of 10 Hz. The system achieved a 97.6% accuracy in recognizing major activities, and over 95% accuracy for 29 sub-activities, including 100% accuracy for cycling, running, and self-care activities.

In Su et al.'s study, 12 healthy subjects wore seven IMUs (Myon/Cometa aktos-T) placed on the thigh, tibia, foot, and pelvis, with a sampling frequency of 2000 Hz, post-processed to 50 Hz [5]. The data were used to predict angular velocities of the lower limb segments (thigh, tibia, foot) and five gait phases (loading response, single-leg stance, terminal stance, pre-swing, and swing phase). Multi-step predictions for 100 ms and 200 ms were achieved with accuracy rates of 94% and 92%, respectively, with a prediction accuracy of 97% for the swing phase, making it the most accurate.

Sarshar et al. used two XSENS MTw Awinda three-axis IMU sensors, installed on both ankles, with a sampling frequency of 100 Hz [6]. The sensors collected three-dimensional angular velocity, rotation matrix size (RotMat), and free acceleration, which were used as input features for the model. The LSTM regression model was employed to predict foot off-ground, mid-swing, and foot contact phases, achieving an average accuracy of 99.45% on the test dataset.

Karakish et al. used six IMU sensors, installed on the front of the thigh, tibia, and foot, to collect accelerometer and gyroscope data for real-time motion pattern prediction, including walking, running, and ascending stairs, among other activities [7]. A total of 2,111,962 samples were generated and trained using MLP and CNN models. After combining gait phase information, the Root Mean Square Error (RMSE) decreased to 0.226 deg/s and 0.217 deg/s, demonstrating the advantages of combining IMU configurations with deep learning models.

2.2 Plantar Pressure Sensors

Plantar pressure sensors, installed in insoles or on the soles of shoes, can monitor the contact pressure between the foot and the ground in real-time, helping to identify the different phases of the gait cycle. And these sensors will catch important moments when they do the walk, like stepping on the heel, flat feet, and toes going up. Check the pressure on different areas like the back of the feet, the area between the feet, and the tips of the toes. It can tell if it is the first walking, the second walking, or the third one, and see what may follow too.

Heng et al. used Multi-walled Carbon Nanotubes (MWCNTs) and Polydimethylsiloxane (PDMS) to make a Force Sensing Resistor (FSR) sensor [8]. After laser surface treatment, the sensor's resistance has dropped a lot, and the stability is also quite good. Put sensors at 6 important places on the insole - heel, arch, and toe - to catch and send out changes in how squishy it feels right when it happens. From the experiments, it was found that the FSR sensor had good sensitivity for a 0-25N pressure range, which was also shown to be a sensitivity of 0.29 N^-1(3.63 MPa^-1). After 5000 cycles of load/unload, it had good consistency and stability.

Xia et al. combined IMU and FSR data to monitor gait phases in real-time [9]. The FSR data had a sampling frequency of 100 Hz, and convolutional neural networks (CNNs) were used for feature extraction, followed by bidirectional long short-term memory (BiLSTM) to capture temporal gait information, and finally a Softmax layer for classification. The experimental results showed that the composite model achieved 92.99% accuracy in gait phase classification, with classification accuracy for the left foot stance phase reaching 96% and for the right foot stance phase reaching 97%.

Cheng et al. researched a lower-limb motion intention recognition method based on multi-source information fusion, focusing on the use of plantar pressure sensors to collect six common movement modes: standing, horizontal walking, uphill walking, downhill walking, stair climbing, and stair descending [10]. Data analysis showed that when using FSR data for motion mode classification, support vector machines (SVM) and Bagging methods could achieve high-accuracy gait pattern recognition. Particularly, feature extraction from plantar pressure signals provided important clues for recognition.

2.3 Surface Electromyography (sEMG)

Surface Electromyography (sEMG) directly captures the electrical activity of muscles, providing more accurate motion intention data for gait recognition. sEMG signals offer millisecond-level control precision, making them particularly valuable in exoskeleton control systems for real-time motion adjustments. Due to its non-invasive nature and ease of installation, sEMG has found wide application in practical settings.

Guo et al. used six sEMG signal acquisition systems and collected signals from the gastrocnemius, tibialis anterior, biceps femoris, rectus femoris, vastus medialis, and vastus lateralis muscles using Biometrics wireless multi-channel signal acquisition equipment [11]. The gait phases in the experiment included heel strike (HS), foot flat (FF), toe off (HO), and swing (SW). By combining the Long Short-Term Memory (LSTM) model, they achieved a classification accuracy of 91.44%.

Yuan et al. used a 16-channel wireless sEMG signal acquisition system, with four channels collecting sEMG signals from the quadriceps, biceps femoris, gastrocnemius, and tibialis anterior muscles of the left leg [12]. Healthy male volunteers walked at different speeds (1.5 km/h, 2.0 km/h, and 2.5 km/h), while gait data were collected using the SIAT lower limb exoskeleton robot in a zero-torque mode. The LSTM model took these four sEMG signals as input, with the output being two gait phases: stance (ST) and swing (SW). The model's classification accuracy was 97.61% at 1.5 km/h, 97.89% at 2.0 km/h, and 97.75% at 2.5 km/h.

Cai et al. conducted experiments with 10 healthy subjects wearing eight sEMG sensors, placed on the thigh, semitendinosus, lateral gastrocnemius, and medial gastrocnemius muscles. They used the LDA-PSO-LSTM algorithm for multi-phase gait recognition. The results show that the LDA-PSO-LSTM model achieves 94.89% at 2.5km/h and 93.80% at 3.0km/h. The lower-limb exoskeleton robot can successfully recognize the motion intention with the effective processing of the EMG signal and the optimization of the model.

3. Challenges

3.1 Sensor Data Fusion and Synchronization Issues

For the enhancement of gait recognition's precision, lots of studies utilized multi-sensor fusion; sEMG signal was combined with IMU sensor (accelerometer and gyroscope), or in combination with plantar pressure sensors. This kind of configuration can provide more thorough data support, but it brings about certain difficulties too, especially the problems with synchronizing data. For example, the sampling frequency of IMUs is usually 100Hz, but the sampling frequency of sEMG is often higher, such as 1000 Hz. Therefore, the synchronization when fusing data must be precise, otherwise it will affect the accuracy of gait classification.

For example, in Yuan et al, the data synchronization of the sEMG signals with optical motion capturing systems like Vicon was an issue. Since the sEMG signal had a sampling frequency of 1000Hz and the Vicon system a sampling frequency of 100Hz, it was necessary to create 16 sEMG data points for each Vicon data point [11]. Then this temporal alignment error was carried forward into a wrong division of gait phases.

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3.2 Signal Noise and Interference

IMU signals have always been affected by several factors like where the sensor was put, how it moved on the body, problems when the sensor touched the skin, and stuff like electromagnetic interference. Disturbances and noise can lead to fluctuations in the acquired signals, which would affect the next step of gait recognition and phase prediction. Sarshar et al utilized IMU signals for their gait phase estimation [7]. Though it used an IMU sensor with high precision, with a sampling rate of 100 Hz, still a lot of noise was present in those signals because of the placement of the IMU device on the body and connecting it to the circuit. This kind of noise will impact the correct segmentation of the gait phase. Second is high-frequency noise, usually caused by vibration of sensors and electromagnetic interference from the outside.

In reality, there are lots of issues that would interfere with sEMG signals, like sensor noise, motion artifact, electrode/skin interface issues, and crosstalk. This could cause the emergence of unstable sEMG signals, thereby affecting the accuracy of the gait recognition.

Speaking particularly of Cai et al.'s work, the sEMG signal possessed a 1000Hz sampling frequency and utilized a Butterworth filter to eliminate 50Hz power frequency noise [13]. db4wavelet was used for thresholding noise reduction, where high-frequency noise is reduced in the signal. Although it implemented the denoising process, there is still some interference with the signal, which impacts the gait recognition results, as there is a reduction in the gait recognition in class accuracy during the gait transition is reduced [10].

3.3 Individual Differences and Adaptability Issues

Because people might have slightly different builds, different ways of walking, and different body movement patterns, even if people use the same type of sensor, they might see different results. In Su et al's paper, it was demonstrated that for 10 healthy individuals, gait data resulted in LSTM model accuracies that significantly differed between each individual, with a maximum of 97.6% and a minimum of 92.0% [10]. This means an individual's difference can have an influence on how accurately a system like gait recognition can work, and getting around this might need customising models for different people or gathering more data.

Each user's gait signals have quite different signal patterns and amplitudes. Personalized training of the system and adjustments are necessary. In Guo et al. EMG Gait Classification, due to different body weights and heights, there were differences in the amplitude and feature extraction of the gait signals; the result show that when the height difference exceeds 5cm or the weight difference is more than 5kg, the gait recognition accuracy of the participant is reduced [10].

3.4 System Stability and Long-term Reliability

Regarding multi-sensor systems, among which the IMU is one of the most used sensors, it faces issues of signal drift and sensor calibration over long periods of use. Marcos Mazon et al mentioned that when using two IMUs (placed on the upper and lower legs) for gait recognition, although the system's F1 score was as high as 0.92 ± 0.01, the accuracy of gait classification decreased over time due to errors and drift in the IMUs [14]. In another study by Marcos Mazon et al., which involved long-term gait recognition, the classification accuracy of IMUs and pressure sensors was initially high, but over time, sensor data drift and changes in sensor placement led to performance fluctuations [14].

3.5 Real-time Performance and Computational Complexity

In lower limb exoskeleton robot systems, real-time performance is a critical requirement. The model must process data and provide feedback in an extremely short amount of time. However, LSTM and CNN models often require longer computation times, especially when dealing with large data volumes. In Su et al.'s study, they pointed out that when using an LSTM model, the processing time for gait recognition was 2.4 ms, but as the data volume increased or more complex neural networks were used, the processing time could significantly increase, leading to delays [10]. For CNN models, the execution time for real-time gait classification could be as high as 142 ms, which, for real-time feedback systems, could negatively impact the system's response speed and user experience.

4. Future Development Directions

4.1 Sensor Self-calibration and Intelligent Compensation

Su et al. introduced a weighted loss function in the LSTM network that reduces the weight of long-term predictions to enhance the accuracy of short-term predictions [10]. This allows the system to maintain high accuracy even in long-duration prediction tasks. Research has shown that after introducing intelligent compensation, the error (RMSE) of prediction results significantly decreases, especially during the transition between the swing and stance phases of gait. Compensation techniques can effectively reduce errors caused by noise.

Plantar pressure sensors (FSR) are prone to signal drift and poor contact issues over long-term use. Heng et al. mentioned that using laser-treated conductive rubber sensors can effectively reduce surface resistance fluctuations, thus improving sensor stability and minimizing the impact of drift on data [4]. Experimental data showed that after laser treatment, the sensor's maximum resistance decreased from 215 kΩ to 1.78 kΩ, and the resistance fluctuation decreased from 13.49% to 0.51%, indicating that the sensor's stability during long-term use was significantly improved.

Xia et al. also proposed using machine learning algorithms for data fusion and compensation [6]. Gait classifying in gait classification tasks, the CNN-BiLSTM network model is capable enough to classifying gait phases by extracting local features and making use of their temporal information. According to the experimental results, this model can reach a maximum accuracy of 95%, which is about Gait phase Classification. Besides, the average accuracy of CNN-BiLSTM is 0.417% higher than LSTM, and 0.596% higher than GRU. This shows that an intelligent compensation algorithm is able to compensate for errors that exist in individual sensor signals and improve the accuracy of the system's classifier.

Cai et al. propose an intelligent reward method based on LSTM + PSO [9]. Gait phase recognition, LSTM learns the long-term relationships based on the current and historical signals, and PSO can also optimize the LSTM network structure and make more accurate gait phase classification. From experimental results, the gait phase classification accuracy can maintain a stable accuracy rate greater than 94.89% after applying this strategy.

4.2 Multi-sensor Fusion and Collaborative Sensing

Cheng et al. The Beckhoff module was used to develop a multi-channel sensor information acquisition system in one study that could collect information from many sensors at once [14]. sEMG signals were used to reflect muscle electrical activity, IMU signals provided acceleration and angular velocity data, and plantar pressure sensors captured changes in pressure during foot contact in the gait cycle. This resulted in a 280-dimensional feature vector (sEMG: 120 dimensions, IMU: 144 dimensions, plantar pressure: 16 dimensions), which was normalized to reduce the impact of different feature contributions on the results. By using different fusion strategies, such as single fusion, multi-modal switching, and multi-modal hybrid strategies, the system fused data from different sensors to enhance the recognition of lower limb movement patterns. This approach achieved higher recognition rates, particularly in identifying complex gait phases, such as the transition between the stance and swing phases.

Cai et al. used eight sEMG sensors to record lower limb muscle activity and combined this data with eight NOKOV motion capture cameras and four reflective markers to record key events in the gait cycle [15]. They employed an LDA-PSO-LSTM model for feature dimensionality reduction, transforming the original high-dimensional data into a 6-dimensional feature space. Experimental results showed that at a walking speed of 2.5 km/h, the average recognition accuracy of the model was 94.89%, and at 3.0 km/h, the accuracy was 93.80%.

4.3 Miniaturization and Low Power Design of Sensors

The convenience and comfort of lower limb exoskeleton robot systems are closely related to the size and power consumption of sensors. Future sensors need to be more compact, allowing for flexible placement on the exoskeleton device. At the same time, low-power sensor designs will help extend battery life, which remains a significant challenge, especially in wearable devices. To improve the real-time performance and long-term stability of motion intention recognition, researchers need to develop low-power, high-precision sensor technologies that can operate for extended periods without sacrificing performance.

4.4 Development of Environmentally Adaptive Sensors

In the future, low limb exoskeleton robots need to work in many different environments, such as indoor, outdoor, and uneven roads. To do this, sensors need to be able to work in complex environments. They must have good environmental adaptability. Take a plantar pressure sensor as an example, it needs not just to detect gait phase but also needs to be correct on different surfaces (dirt, grass, stairs, etc.). Sensors should make themselves fit in with the different environments and change their working parameters according to the change of environment.

5. Conclusion

Lower limb exoskeleton robots' development in motion intention recognition systems has progressed quickly, and sensor technology holds a central place in it, being broadly adopted by gait recognition and motion intention perception. This paper discusses the applications and problems of various sensing technologies such as IMUSensors, Plantar Pressure Sensors, and sEMG sensors, looking at them from many different points of view.

IMUs are a familiar type of sensor that can accurately obtain acceleration and angular velocity data; they are also easily influenced by vibrations and drift, and the like, thus affecting the accuracy of gait recognition. Plantar pressure sensors can sense changes in foot pressure to tell which parts of the step a person is taking, but these changes can be changed by how things around them feel and where on the foot the plantar pressure sensors are placed. EMG signals and EEG signals, these things can be quite more precise in giving off data about someone's intentions for moving around based on muscle electrical activity and

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brain electrical activity. However, these signals will be affected by noise and disturbance, which leads to unstable.

The technology gets better, and it must use multi-sensor fusing for increasing gait recognition correctness and system stability. Incorporating data from the IMUs, PLPs, sEMGgs, other sensors, etc., allows the weakness of one sensor to be compensated and provides a better result for a motion intent. But, as for synchronizing the sensors and improving on the fusion algorithms and making the system even more complex, there still needs to be dealt with.

As for future research, it will focus on how to make better use of the sensors, improve data fusion technology, overcome individual differences and environmental influences, and break through real-time performance, low power consumption, and self-calibration technology. These advancements will drive the widespread application of lower limb exoskeleton technology in medical rehabilitation, walking assistance for the elderly, and other fields.

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