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Review of gait prediction of lower extremity exoskeleton robot

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Highlights

- Gait prediction relies on multimodal sensor data, and the acquisition of multimodal information, such as physical sensors and bioelectrical signal sensors, is introduced in order to monitor and analyze the lower limb movement in real time, and provide a data basis for prediction.
- The application of machine learning algorithms in gait prediction technology, such as Support Vector Machine, Random Forest, and Back Propagation Neural Network, is reviewed to construct an optimized gait prediction model, which provides effective support for the intelligent control of exoskeleton.
- Compared with machine learning algorithms, the article summarizes the researchers' efforts to extract and un derstand the hidden patterns in gait data by constructing neural network models related to different deep learn ing algorithms, which are used to improve the accuracy and robustness of gait prediction.

Abstract

In recent years, gait prediction has gradually become a cutting-edge research direction in the fields of biomechanics and artificial intelligence. Gait prediction technology, which analyzes an individual's walking patterns to predict future changes, is crucial for the precision of rehabilitation and exoskeleton robot control. This paper reviews the recent research progress in the field of gait prediction, focusing on the multimodal information acquisition methods based on physical sensors and bioelectric signals, as well as the application of machine learning and deep learning algorithms in gait prediction. By analyzing different sensor data fusion strategies, the importance of multimodal information fusion for improving the accuracy of gait prediction is emphasized. Furthermore, this paper introduces the performance of traditional machine learning algorithms such as Support Vector Machine, Random Forest, and Back Propagation Neural Network, as well as deep learning models such as Long Short-Term Memory, Convolutional Neural Network, and Transformer in gait prediction, highlighting the advantages of deep learning in feature extraction and adaptability to complex scenarios. Finally, this paper explores future directions for the development of gait prediction technology, emphasizing improvements in timeliness, accuracy, and personalization to advance exoskeleton robotics and related fields.

Keywords: Gait prediction, multimodal information acquisition, machine learning, deep learning

Introduction

Amidst the intensifying trend of global population aging, the incidence of neurological disorders precipitated by factors such as traumatic brain injury, spinal cord injury, stroke, and Freezing of Gait has been on the rise [1-4]. Exoskeleton robot is a kind of intelligent mechanical structure worn on the outside of the user 's body. By combining sensing, control, information, fusion, mobile computing and other technologies, the human body's feeling, thinking, movement and other organs are combined with the machine's perception system, intelligent processing center and control execution system, so as to improve and strengthen the human body 's physical function or for medical rehabilitation [5]. It is a new type of electromechanical integration device, which has the functions of support, movement and protection.

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Combined with key technologies such as mechanical structure, control, driving mode and human-computer interaction, it enables the wearer to perform tasks that would otherwise be impossible [6].

Gait prediction is a frontier research direction in the fields of biomechanics and artificial intelligence, involving the analysis and prediction of human walking patterns [7]. It has numerous applications in lower limb exoskeleton robots, with real-time gait monitoring and adjustment being the primary application. This technology integrates various sensors (accelerometers, gyroscopes, pressure sensors, etc.) and computer vision to capture the lower limb movement data of users, and analyzes and identifies the trends of gait changes. Based on these data, predictive models trained by machine learning and deep learning algorithms can monitor the gait patterns of users in real-time and predict changes in gait. Exoskeleton robots can adjust the amount of assistance, motion synchronization, and movement patterns according to the predicted results, helping users walk more naturally. This is particularly important for patients with neuromuscular diseases, those with sports injuries, or those who have been bedridden for a long time, as it provides personalized gait assistance to help them regain the ability to walk.

Furthermore, gait prediction technology can significantly enhance the motion stability and fall prevention capabilities of exoskeleton robots. By analyzing the gait characteristics and load distribution of users, predictive models can identify unstable states in advance, allowing the exoskeleton system to react preemptively, such as increasing support force when the user is about to lose balance. This is especially suitable for the elderly, patients with balance disorders, or users in the rehabilitation phase, effectively reducing the secondary injuries caused by falls.

In the field of rehabilitation, gait prediction offers the possibility of personalized rehabilitation training programs for exoskeleton robots. By collecting and analyzing the gait data of patients over the long term, predictive models can assess the progress of rehabilitation, identify problems in gait, and adjust the rehabilitation plan. For example, assistance can be adjusted according to the patient's recovery, and help the patient to gradually regain the ability to walk independently [8]. This not only accelerates the rehabilitation process but also improves the effectiveness of rehabilitation.

Gait prediction technology can also help healthy individuals enhance their athletic performance. For professions that require long periods of walking or walking with loads, such as soldiers and firefighters, exoskeleton robots can optimize movement through gait prediction models, adjust energy output, and allow users to complete longer walking tasks with less physical exertion. This feature can also be applied to outdoor activities such as hiking and mountaineering, helping users maintain stable walking on complex terrains and reducing the risk of injury [9].

Currently, gait prediction, as a key technology in lower limb exoskeleton robots, integrates sensors, computer vision, machine learning, and deep learning to achieve high-precision capture and analysis of gait [10]. By learning from a vast amount of gait data, predictive models can identify specific patterns in individual gait and forecast potential trends of change, providing a scientific basis and decision support for related fields, thereby further advancing the development of lower limb exoskeleton robots.

Acquisition of multi-modal information for gait prediction

In the process of gait prediction, the acquisition of multimodal information is necessary, and methods based on sensor data play a crucial role in gait prediction research. Different types of sensors, such as Inertial Measurement Units (IMUs), surface electromyography (sEMG), and plantar pressure sensors, are widely used for the collection, analysis, and prediction of gait data [11-14]. These sensor data allow for real-time monitoring and analysis of the state of human lower limb movement, providing a solid foundation for the prediction of gait patterns. The commonly used multi-modal information acquisition methods for gait prediction are shown in **Figure 1**.

Signal acquisition based on physical sensors

During the acquisition of sensor data, IMUs are widely used for capturing gait information due to their high precision and portability. An IMU is a device that integrates accelerometers, gyroscopes, and magnetometers, capable of measuring and reporting the specific forces, angular velocities, and magnetic fields surrounding an object's attitude. In gait analysis, IMUs are typically attached to the lower limbs or feet to capture data such as angular velocities and accelerations of various human joints during walking. By combining these data with deep learning models, such as long short-term memory (LSTM) networks, high-accuracy gait

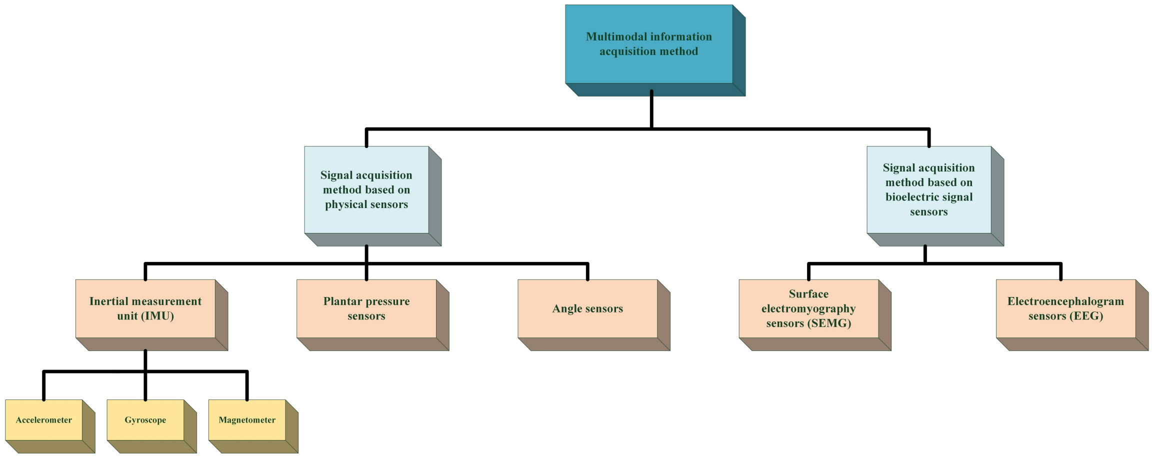

Figure 1. Multi-modal information acquisition methods for gait prediction.

classification and prediction can be achieved [15]. Zhang and colleagues have mentioned that fusing IMU sensor data with data from other sensors can significantly enhance the effectiveness of gait feature extraction, thereby improving the accuracy of gait recognition [16]. Additionally, there is literature introducing the embedding of IMU sensors within waist control components to obtain real-time joint angle information, combined with an LSTM model augmented with an attention mechanism for gait prediction [17].

Plantar pressure sensors provide detailed gait information by measuring the force and distribution of pressure as the foot contacts the ground during walking [8]. These sensors are usually embedded in the insole or dedicated pressure measurement board, which can capture the pressure distribution of the foot in the support phase, the movement path of the pressure center, and the pressure peak. By analyzing the pressure distribution across different regions of the foot, subtle changes in gait can be inferred. A study has introduced a method for analyzing human motion by collecting pressure data from four specific locations on the plantar surface, based on the pressure variation patterns observed at different foot positions during movement [18]. Four sets of sensors were placed at different locations on the left and right feet to detect signal variations in the corresponding regions. This setup assists the exoskeleton robot's perception system in detecting changes in foot gait signals during walking at a constant speed of 1.5 m/s. Through these signals, the sample data of the human body during exercise can be obtained to facilitate subsequent research. In addition, the plantar pressure sensor can also be used to detect gait events such as standing phase and swing phase, providing important input data for gait prediction algorithms [19].

Signal acquisition based on bioelectric signal sensors

Bioelectrical signals from surface sEMG and electroencephalogram (EEG) can reflect the state of muscle activity and brain neuron activity in a very short time. sEMG and EEG commonly utilize sensors that are affixed to the muscular and cerebral surfaces, thereby providing significant portability. The integration of sEMG signals with data from additional sensors enables the effective identification of gait patterns and the prediction of lower limb movement intentions [20]. Liu used a special double-sided tape to attach the sEMG sensor to three muscles closely related to joint movement, namely rectus femoris, vastus lateralis and biceps femoris, combined with an angle sensor to record the coordinated motion data of the subjects. Their study established an attention-based Convolutional Neural Network (CNN)-LSTM model for generating personalized gait trajectories of affected limbs [21]. Some researchers combined electromyography (EMG) signals with EEG signals [22]. The feature-level fusion method was used to fuse EEG and EMG for lower limb motion intention recognition, with accuracy rate reached 90.23%. Compared with the single EEG feature, the feature fusion method improved the recognition accuracy by 2.73%.

Multi-sensor data fusion

Multiple studies have shown that relying on a

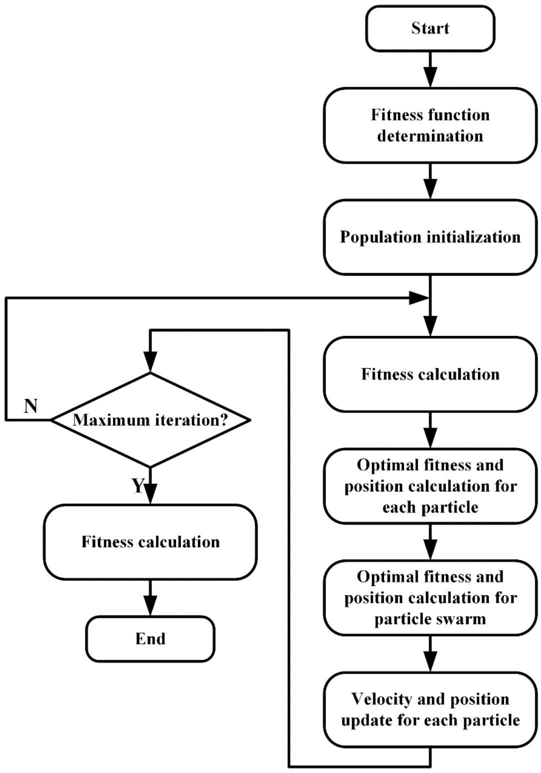

Figure 2. Flowchart of PSO-SVM algorithm. This figure was cited from [30]. PSO, Particle Swarm Optimization; SVM, Support Vector Machines.

single sensor often fails to achieve sufficient accuracy [23-25]. The fusion of data from multiple sensors is a key strategy for improving the accuracy of gait prediction. By integrating data from various sensors, such as accelerometers, gyroscopes, and pressure sensors, more comprehensive and precise gait characteristic information can be obtained. A multimodal neural network model, which combines sEMG signals with inertial sensor data, can effectively predict gait patterns. These methods leverage the temporal continuity and spatial complementarity of multi-sensor data, significantly enhancing the stability and accuracy of gait prediction [26].

In a study, researchers combined plantar pressure sensors and attitude angle sensors to identify and predict gait [23]. The plantar pressure sensors were primarily distributed across three key load-bearing areas: the heel, the forefoot, and the toes, allowing simultaneous collection of pressure values from these regions during movement. Attitude angle sensors were affixed to the thigh, calf, and foot to obtain real-time posture angles. The study further combined least mean squares and recursive least squares algorithms, resulting in minimal error between the original and predicted data, demonstrating effective prediction performance. Multi-sensor data fusionprovides more accurate, more comprehensive, and more robust recognition capabilities in gait prediction, which helps to improve performance and user experience in various application scenarios [27].

Classification of gait prediction algorithms

Machine learning algorithms

In gait prediction for intelligent lower limb exoskeleton robots, machine learning methods have shown significant potential, particularly in processing sensor data to recognize and predict gait phases and trajectories [28]. By integrating and analyzing data collected from various sensors, optimized gait prediction models can be developed, providing effective support for the intelligent control of exoskeletons.

Traditional machine learning algorithms, such as Support Vector Machines (SVM), Random Forest (RF), Backpropagation (BP) Neural Networks, and Linear Regression models, play a crucial role in the field of gait prediction.

SVM

SVM is a supervised learning method that offers significant advantages, particularly in handling high-dimensional data. It possesses strong generalization capabilities and robust pattern recognition abilities, making it well-suited for nonlinear problems. Due to these unique optimization objectives and classification abilities, SVM holds potential for important applications in the field of gait analysis and prediction [29]. The research team led by Wu employed a Particle Swarm Optimization (PSO)-SVM approach, which uses PSO to optimize the SVM parameters C and G, to develop a predictor for gait phase prediction based on spatial features. The specific algorithm flow is shown in **Figure 2**.

In terms of input, the exoskeleton robot is equipped with four angular sensors that capture the hip and knee joint angles during walking, forming a sensor network. Finally, according to the plantar pressure distribution, four gait phases of heel-contact, foot-flat, heel-off and toe-high are determined. The experimental results show that the PSO-SVM method can predict the gait phase well [30]. In another study, Luo and colleagues proposed using SVM to train the mapping relationship between EMG signals and motion, aiming to classify lower limb gait patterns and predict the continuous movements of the hip, knee, and ankle joints in the sagittal plane [31]. When performing regression predictions on joint angles, the

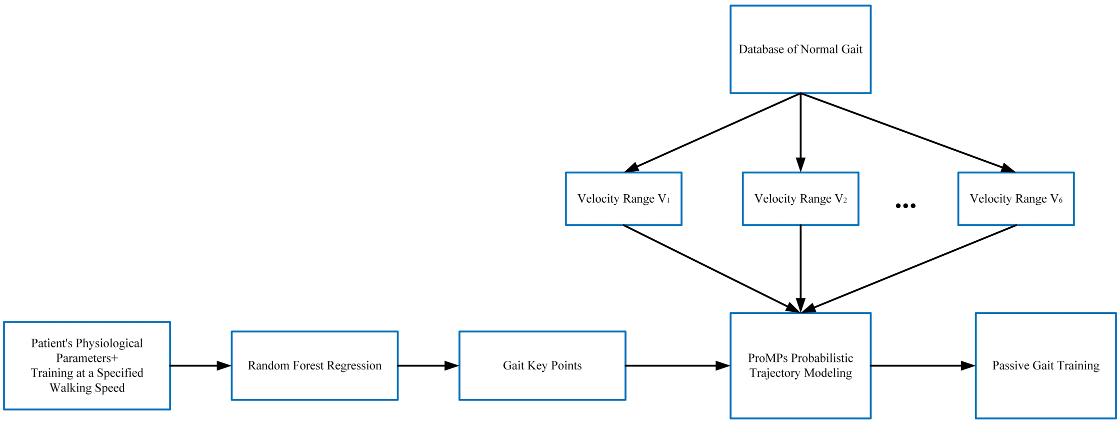

Figure 3. Structure of the passive training gait prediction algorithm combined with ProMPs. This figure was cited from [35]. ProMPs, Probabilistic Movement Primitives.

best-performing subject exhibited a minimum prediction error of 7.02° for the knee joint, 7.97° for the hip joint, and 5.11° for the ankle joint. For all subjects, during walking at a comfortable speed, the root mean square errors (RMSE) for the predicted hip, knee, and ankle joint angles were 9.35°, 10.82°, and 6.87°, respectively, with percentage errors of 20.63%, 15.95%, and 17.11%.

To predict continuous lower limb movements, Duan et al. also employed SVMs to develop a model for each gait phase [32]. In their study, an SVM classifier was first used to identify the corresponding phase model, and then SVM was employed to predict the joint angles. They also compared SVM with the traditional joint angle prediction method using the whole segment motion data for modeling, and found that the effect of joint angle prediction was significantly improved, especially the correlation coefficient of the ankle joint with smaller amplitude and more complex motion increased from about 0.9 to more than 0.99, and the average RMSE decreased from 1.5°- 3.0° to 0.2°- 1.0°. In addition, Qin et al. proposed a prediction algorithm based on least squares support vector regression (LS-SVR) using human lower limb gait sample data to predict the next human lower limb movement, with an accuracy rate of 99.6% [19].

RF

RF can be applied for gait prediction to enhance both accuracy and generalization capabilities [33]. As a powerful ensemble learning method, RF constructs multiple decision trees and combines their predictions to effectively handle nonlinear problems and reduce the risk of model overfitting. It is well-suited for directly processing high-dimensional datasets and can significantly shorten training time through parallel processing. Ren et al. proposed a gait pattern prediction method based on anthropometric features, using the RF algorithm to design personalized gait trajectories for different patients [34]. Finally, the prediction accuracy of the RF model was evaluated by 5-fold cross-validation, and the RMSE and Pearson correlation coefficient were used as evaluation criteria. The study also compared the prediction results with those of the Multilayer Perceptron Neural Network (MLPNN) model, finding that the RMSE of MLPNN exhibited greater volatility. Due to the need to apply gait prediction to some hemiplegic rehabilitation patients in daily life, Lu and others proposed a gait prediction algorithm based on RF and Probabilistic Movement Primitives (ProMPs) to solve the problem of single gait and poor adjustability in passive training of hemiplegia rehabilitation, and the specific process is shown in **Figure 3** [35]. The algorithm takes normal human gait data and the specified gait speed V as inputs, trains the RF-ProMPs, and outputs the predicted angles y_1^*... y_m^* for m knee gait keypoints, and then updates the trajectory model according to the predicted angle values y_1^* of the gait key points to predict the trajectory. Using the mean absolute error (MAE) as well as the correlation coefficient ρ, the errors were found to be at a low level. For active training of hemiplegic patients, the study suggests that it was feasible to use only hip and knee angles for gait phase prediction. After testing, the Pearson-RF model was used, combining the variable importance of RF and the Pearson's correlation coefficients for the input feature filtering. Compared with the SVM using all the features, the average precision rate of the RF with feature filtering increased by 10.04%, and the average recall rate increased by 10.24%.

BP neural network

In addition, BP neural networks have been widely used in gait prediction, and have shown great potential in gait prediction and analysis with their powerful nonlinear mapping ability. By correctly selecting the network structure, activation function, loss function, and reasonable optimization algorithm, the accuracy and efficiency of gait prediction can be effectively improved. Niu's research team used plantar pressure data to predict lower limb gait cycle characteristics (hip and knee angle curves), and obtained gait trajectories by querying the database. The database is constructed by BP neural network used to predict the gait data of the subjects [36]. The experimental results showed that the average error of the hip angle curve was 0.247° and the average error of the knee angle curve was 0.435°, which illustrates the effectiveness of the gait prediction method. In order to predict the gait to be able to offset the problems such as sluggishness of the exoskeleton robot that may be caused by the delay of the system, so that the exoskeleton robot can follow the human behavior in real time and control, Ma et al. designed two algorithms, interpolation and BP neural network, to predict the gait data, and found that the BP neural network exhibited better prediction [37].

Other machine learning algorithms

In addition to the common machine models mentioned above, there are other machine modeling algorithms that have fetched good results. Tanghe et al. proposed a real-time method for predicting future joint angles, velocities, accelerations, and acuteness during walking with a wearable exoskeleton device, as well as the timing of gait events such as the initial contact, foot flat, heel off and toe off [38]. The core of the approach is to utilize gait patterns learned from normal walking using probabilistic principal component analysis, which are then used in the online phase for state estimation and prediction.

Then, cross validation was used to prove the effectiveness of this method for trajectory and event prediction. Another team of researchers proposed a gait prediction method based on Deep Gaussian Processes (DGP) to estimate the operator's gait intention in real time and to compensate for the measurement delay of the IMU. In order to deal with the problem of gait prediction accuracy under small-scale training data, the study again used the Dual Stochastic Variational Inference (DSVI)-DGP model [39]. DSVI-DGP improves the prediction performance of the model by simplifying the intra-layer correlation while maintaining the inter-layer correlation. The method is effective in predicting the operator's gait and has a high prediction accuracy that keeps the error within acceptable limits.

In order to develop a personalized gait pattern prediction model for gait planning of lower limb exoskeleton robots, Shen et al. proposed a gait parameter extraction based on Fourier transform and a gait parameter prediction model based on Multilayer Perceptron Neural Network (LASSO) regression [40]. Fourier transform is used to convert the sagittal angle curves of ankle, knee and hip joints at different speeds into discrete gait parameters, which are used as input and trained in the regression algorithm [40]. LASSO regression can select variables during model training by adding L1 norm penalty term, so as to simplify the model and reduce the risk of over-fitting. Comparing this model with the SVR model and Gaussian Process Regression model constructed by scikit-learn packaged in python, the LASSO regression model showed better prediction performance with higher correlation coefficients and lower mean absolute errors. **Table 1** presents gait prediction studies related to machine learning algorithms.

Deep learning algorithms

Deep learning is a type of machine learning that uses data for learning and prediction, but puts more emphasis on modeling and predicting complex data through deep feature extraction and representation learning [41]. Deep learning plays a central role in gait prediction, which significantly improves the accuracy and robustness of gait prediction by constructing complex neural network models to extract and understand hidden patterns in gait data. Specifically, deep learning can automatically learn complex features from large amounts of data, reducing the need for manual feature engineering and improving the model's ability to generalize to complex scenes.

The classical deep learning algorithms commonly applied to gait prediction are LSTM Network, CNN, Transformer and so on [8]. The application of these deep learning algorithms in gait prediction not only improves the accuracy of recognition, but also enhances the model's ability to adapt to complex scenes.

LSTM

LSTM networks excel in processing time-series data and capturing long-term dependencies. The hierarchical features obtained from training on large-scale datasets have the ability to inte-

Table 1. Related studies based on machine learning algorithms

Researcher	Prediction Method	Predictive Accuracy
Wu et al.[30]	PSO-SVM	Average simulated gait pattern pattern success rate: 87.19%
Luo et al.[31]	SVM	Hip angle prediction: 20.63%； Ankle angle prediction: 17.11%; Knee angle prediction: 15.95%;
Duan et al.[32]	SVM	Correlation coefficient between predicted and measured values: > 0.99 Average Root Mean Squared Error (RMSE): 0.2°–1.0°
Qin et al.[19]	LS-SVR	Accuracy: 99.6%
Ren et al.[34]	RF	Compared with MLPNN, the RMSE volatility of MLPNN is relatively larger.
Lu et al.[35]	Hemiplegic passive rehabilitation training：RF-ProMPs Hemiplegia active rehabilitation training：Pearson-RF	Hemiplegic passive rehabilitation training: The adjustment error of gait trajectory is less than 0.3 °. Hemiplegia active rehabilitation training: Compared with the SVM using all features, the average precision rate of the random forest after feature selection is increased by 10.04 %, and the average recall rate is increased by 10.24 %.
Niu et al.[36]	BP Neural Network	Average error for hip joint angle curve: 0.247° Average error for knee joint angle curve: 0.435°
Ma et al.[37]	BP Neural Network	Compared with the interpolation algorithm, the prediction effect is better.
Tanghe et al.[38]	Probabilistic principal component analysis	Using cross-validation, it is proved that this method is effective for trajectory and event prediction.
Chen et al.[39]	DSVI-DGP	Comparison with K-Nearest neighbors, support vector, back-propagation neural network, gaussian process, bayesian neural network, and DGP: The DSVI-DGP model has the smallest RMSE, indicating the best prediction performance.
Shen et al.[40]	LASSO	Comparison with SVR and Gaussian Process Regression: The LASSO regression model has a higher correlation coefficient and lower MAE.

Note: PSO, Particle Swarm Optimization; SVM, Support Vector Machines; LS-SVR: least squares support vector regression; RF, Random Forest; BP, Backpropagation; SVM, Support Vector Machines; ProMPs, Probabilistic Movement Primitives; MLPNN: Multilayer Perceptron Neural Network; RMSE, root mean square errors; DSVI, Dual Stochastic Variational Inference; DGP, Deep Gaussian Processes; LASSO, Multilayer Perceptron Neural Network; MAE, mean absolute error.

grate data from different sensors, strong generalization ability, and the robustness to factors such as occlusion, change of view angle, and change of clothing in real application scenarios. Su et al. used the LSTM network to predict the future trajectory (angular velocity) and five gait stages (loading response, mid-stance, terminal stance, preswing and swing) of the thighs, shanks, and feet through the collected IMU data [42]. All predicted trajectories exhibit a strong correlation with the measured trajectories, with correlation coefficients exceeding 0.98. Additionally, the prediction accuracy for gait phases reaches 95%. Sun et al. used inertial assessment platform sensors to collect gait information, which was then preprocessed to form input features [43]. These features, along with the corresponding assistive force cycles, were fed into an LSTM model to predict gait patterns, including uniform walking, variable walking, upstairs, and uphill. The final mean squared error (MSE) values were all below 0.1, and the proposed method achieved an average prediction accuracy of 97.23%. This demonstrates the high accuracy and reliability of the method in predicting assistive force cycles. Moosavian et al. proposed using LSTM networks to predict future trajectories and classify walking phases for RoboWalk (a weight support assist device) [44]. The accuracy of the prediction is about 98.5%, and the overall error of all gait patterns is less than 5 degrees. In addition, Lu et al. used the deep neural network of LSTM architecture to accurately predict gait phase through thigh and calf inertia data. During the test, the gait data of two healthy participants were calibrated. Through the classification and prediction of the LSTM model, a stable gait phase prediction was achieved using the time history data of 40 sample points. During walking experiences in structural and over-ground environments, the algorithm achieved an average accuracy of 85.6% and 73.3%, respectively. The lowest RMSE was 0.143, achieved during the identification of 40 consecutive gait phase estimates for the current gait phase [45].

CNN

The majority of researchers tend not to use one model alone, but build gait prediction models combing models such as CNN, Deep Neural Network (DNN), Conformer and others. CNN are outstanding in feature extraction and image processing. Ren et al. constructed a gait trajectory prediction model based on CNN, LSTM and attention mechanism gait trajectory prediction [46]. The model achieved low MSE and MAE values for the tasks of predicting right knee, left knee, right hip, and left hip angles, indicating that the model was able to accurately predict gait trajectories. In addition, Zhu et al. also used a CNN-LSTM model for the prediction of joint angles [47]. In order to obtain the eigenvalues reflecting the gait characteristics, they introduced an improved principal component analysis (PCA) method during data preprocessing for dimensionality reduction, effectively removing redundant information. Finally, by comparing with traditional machine learning methods such as BP neural network, RF, SVR, etc., it is found that the improved PCA algorithm outperforms the traditional BP neural network and SVM in terms of convergence time and prediction accuracy, with better final prediction performance. Liu et al. also used the collaborative gait prediction model of CNN-LSTM network based on attention mechanism to predict the gait trajectory of the affected limb according to the sEMG signal of the healthy lower limb and the knee joint angle [21]. Coordinated gait trajectories with low MAE and high Pearson correlation coefficient were generated.

Transformer

Using traditional Recurrent Neural Networks or LSTM networks, it is difficult to capture long-term dependencies in time-series data through the mechanism of self-attention, whereas this can be effectively realized in the Transformer model. Through its parallel processing capabilities and positional coding, Transformer not only improves processing efficiency, but also ensures chronological accuracy. Its flexible modeling structure allows for adaptation to data of varying complexity, while the encoder-decoder architecture is particularly well suited for predicting future points in time. Therefore, some researchers have constructed a transformer-based network to predict the angle of the hip and knee joints. They adjusted the Transformer architecture while retaining the ‘sequence-to-sequence’ structure, and proposed a gait prediction model (Transformer-Based Neural Network: TFSformer) to integrate information in plantar pressure data and predict joint angles [48]. The experiments compared TFSformer with CNN, Transformer and CNN Transformer. In the single-step prediction task, the average MSE of TFSformer was reduced by 10.83%, 15.04% and 4.74% compared to CNN, Transformer and CNN Transformer, respectively. The average MAE was reduced by 20.40%, 29.09% and 10.43%, respectively. In the multi-step prediction task, TFSformer achieved the lowest MAE. TFSfomer showed strong robustness and stability in this study. Regardless of the individual gait diversity, it can predict the gait trajectory of different people with a small error. Zhao et al. proposed a novel gait prediction method that combines LSTM networks with Conformer models [49]. Among them, the Conformer model is a Seq2Seq (sequence-to-sequence) model that combines the CNN and Transformer models, utilizing the CNN to enhance the ability of extracting local features and retaining the Transformer model’s adeptness at capturing content-based global interaction capabilities. The temporal characteristics of the gait data are initially extracted using LSTM, and the depth temporal and spatial characteristics in the lower limb gait data are further mined using Conformer. The results also show that the accuracy of the model proposed in this paper is greatly improved, with an average accuracy of 0.9489, which is 3.17% higher than the average accuracy of LSTM, and 4.56% higher than the average accuracy of Recurrent Neural Networks.

Multi-model fusion strategy

In the field of gait prediction, multi-model fusion strategy can significantly improve the accuracy and robustness of prediction. Since gait data usually contain complex biomechanical characteristics and variable walking patterns, a single model may be difficult to capture the full picture. Multi-model fusion can understand and predict gait patterns more comprehensively by combining the advantages of different algorithms. In addition, the fusion strategy can reduce the risk of overfitting a specific data subset and improve the generalization ability of the model in different populations and under different conditions. Guo et al. proposed a new method of fusing multimodal signals-transferable multi-modal fusion (TMMF), which achieves continuous prediction of knee joint angle and corresponding gait phase by fusing multimodal signals [50]. The architecture is shown in **Figure 4**. In the process of collecting data, virtual reality tracker, EMG signal acquisition equipment, and gyroscope are fixed on the left leg of the subject to obtain virtual reality data, EMG data, and gyroscope data. The data

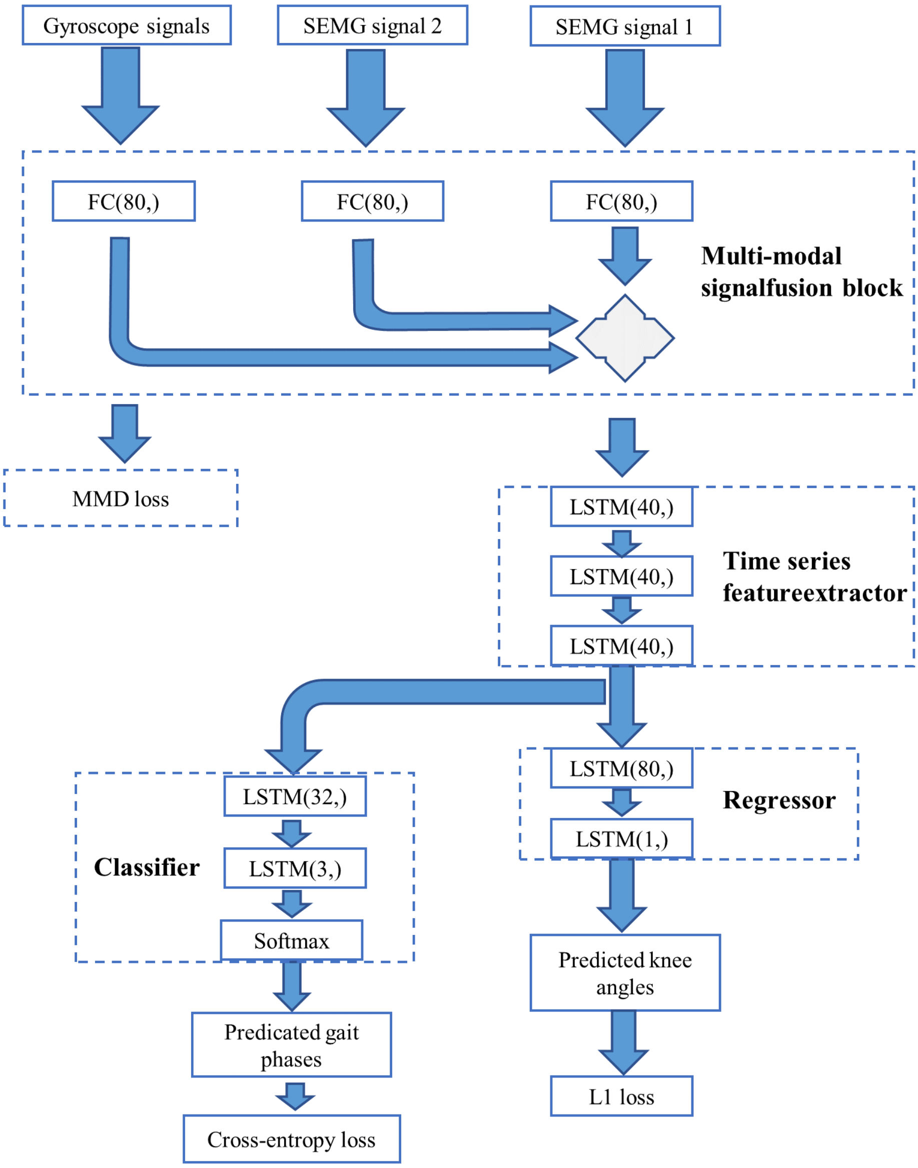

Figure 4. The visualization of the proposed TMMF architecture configured with LSTMs and FC layers. This figure was cited from [50]. LSTM, long short-term memory; FC, fully connected; TMMF, transferable multi-modal fusion.

were preprocessed to generate three-channel data inputs into the TMMF to predict knee angles and gait phase profiles. In particular, the TMMF consists of a multimodal signal fusion module (three FC layers (fully connected layers) and a cascade operation to extract distributional features), a time-series feature extractor (consisting of three LSTM layers, each containing 40 hidden units), a regressor (consisting of two FC layers), and a classifier (consisting of two FC layers and a softmax layer). The TMMF achieved a RMSE of 0.090 ± 0.022 for knee angle prediction, indicating that the predictions were very close to the actual values. In terms of gait phase prediction, TMMF achieved an accuracy of 83.7% ± 7.7%, showing high classification accuracy. Finally, the classifier was used to predict the corresponding gait phase.

some researchers have applied generative adversarial networks (GANs) to the field of gait prediction. Wang et al. enhanced human gait data through GANs and attention mechanisms, and input the collected real gait data and synthetic gait data into the two-stage attention model (LSTM based baseline prediction model and attention model) that was constructed for gait trajectory prediction [51]. The two-stage attention model performed better, with the attention mechanism showing a higher ability to learn the dependencies between historical gait data, which help to accurately predict the current values of hip angle and knee angle in the gait trajectory. The predicted gait trajectories based on historical gait data can be further used in gait trajectory tracking strategies. A study has described a method called GaIn to

Table 2. Related research based on deep learning algorithms

Researcher	Prediction Method	Predictive Accuracy
Su et al.[42]	LSTM	Correlation coefficient between predicted and measured trajectories: >0.98 Prediction accuracy for gait phases: 95%
Sun et al.[43]	LSTM	MSE for gait pattern prediction: <0.1 Average prediction accuracy: 97.23%
Moosavian et al.[44]	LSTM	Prediction accuracy for trajectories: ~98.5%
Lu et al.[45]	LSTM	Average accuracy in structured and over-ground environments: 85.6% and 73.3%
Ren et al.[46]	CNN-LSTM	Prediction of right knee, left knee, right hip, and left hip joint angles: Achieved low MSE and MAE (Mean Absolute Error) values
Zhu et al.[47]	CNN-LSTM	Prediction error: 1.34 ± 0.25 degrees Comparison with traditional machine learning methods (BP Neural Network, RF, SVR): The improved PCA algorithm outperformed traditional BP Neural Networks and Support Vector Machines in both convergence time and prediction accuracy.
Liu et al.[21]	CNN-LSTM Based on Attention Mechanism	Convergence time and prediction accuracy: Outperformed traditional BP Neural Networks and Support Vector Machines Generated gait trajectories: Exhibited lower MAE and higher Pearson Correlation Coefficient
Chereshnev et al.[52]	GaIn	Average prediction error: 4.55
Wang et al.[51]	GANs+LSTM+ Attention Mechanism	Hip joint angle prediction: RMSE: 0.0031–0.0129 MAE: 0.0027–0.0112 Knee joint angle prediction: RMSE: 0.0069–0.0280 MAE: 0.0051–0.0236
Guo et al.[50]	TMMF	Knee joint angle prediction: RMSE: 0.090 ± 0.022 Gait phase prediction: Accuracy: 83.7% ± 7.7%
Ren et al.[48]	TFSformer	Single-step prediction task: Average MSE: TFSformer reduced MSE by 10.83%, 15.04%, and 4.74% compared to CNN, Transformer, and CNN Transformer, respectively. Average MAE: TFSformer reduced MAE by 20.40%, 29.09%, and 10.43% compared to CNN, Transformer, and CNN Transformer, respectively. Multi-step prediction task: MAE: TFSformer achieved the lowest MAE.
Zhao et al.[49]	LSTM-Conformer	Average Accuracy: 94.89%

Note: LSTM, long short-term memory; CNN, Convolutional Neural Network; MSE, mean squared error; MAE, mean absolute error; RF, Random Forest; BP, Backpropagation; SVR: least squares support vector regression; PCA, principal component analysis; RMSE, root mean square errors; GANs, generative adversarial networks; TMMF, transferable multi-modal fusion; TFSformer, Transformer-Based Neural Network.

control non-invasive robotic prostheses and to predict leisure walking-related activities (such as walking, taking stairs, and running) through GaIn's thigh-based exercise [52]. The user's activity intention can be recognized by sEMG sensors, while in the gait inference component recurrent neural networks Recurrent Neural Networks and LSTMs are used. Based on the angular and angular velocity data of the thighs, the patterns learned by the network are used to infer the motion of the calves and feet. The system has high prediction accuracy, with an average prediction error for calf motion of 4.55. **Table 2** presents gait prediction studies related to deep learning algorithms.

Conclusion and future prospects

Summary

The wearable lower extremity exoskeleton robot shows great potential in the field of rehabilitation treatment and assisted walking. This article introduces some of the current cutting-edge robots (BLEEX, BaiHong, ReWalk, HAL, etc.), focusing on their assistance and rehabilitation functions in lower extremity exoskeleton robotics. Additionally, the acquisition methods of multi-modal data are introduced, including acquisition based on physical sensors and physiological electrical signal sensors. The fusion of multi-modal data provides a more comprehensive and accurate understanding of gait characteristics. Gait prediction has attracted much attention as a key technology for improving the control accuracy and adaptability of exoskeleton robots. Researchers have constructed biomechanical models by combining multimodal sensor data such as IMUs, plantar pressure sensors, and accelerometers, and have applied methods such as SVMs, RFs, BP neural networks, LSTMs, and CNNs, to achieve gait phase recognition and prediction. Future research directions include combining multimodal sensor data and advanced algorithms to improve the timeliness, accuracy, and robustness of prediction, while also developing personalized gait prediction methods. Gait prediction technology holds great potential in the fields of rehabilitation therapy, assisted walking, and sports training, driving the evolution of exoskeleton robots towards intelligence and personalization.

Challenges of gait prediction technology

The challenges of gait prediction techniques include the following:

1. Complexity of data acquisition and processing: Gait prediction needs to utilize multimodal sensor data, such as IMU, force sensitive resistor, and acceleration sensors, but the acquisition and processing of these data are more complex. The fusion, synchronization, and calibration of different sensor data are technical challenges, and the collected raw data often have noise and uncertainty, and requires effective signal processing and filtering to accurately reflect the user's gait information.

2. Selection and optimization of machine learning algorithms: Gait prediction involves various machine learning algorithms, such as SVM, RF, BP, probabilistic principal component analysis, and DGP. In practical applications, it is essential to select the appropriate algorithm based on the characteristics of the specific task and the nature of the data, followed by optimizing the algorithm's parameters to enhance both prediction accuracy and efficiency.

3. Handling of long-term dependency relationships: Gait, as a complex motor process, involves time series data with long-term dependency relationships. Traditional machine learning algorithms have limitations when dealing with such extended temporal sequences. Therefore, more specialized deep learning methods, such as LSTM networks and DNN, are required to better capture time-series information and improve prediction accuracy and robustness.

4. Implementation of personalized gait prediction: There are significant individual differences among users, including variations in body structure and gait habits. Accurately predicting personalized gait and adjusting prediction models based on individual differences are critical challenges that need to be addressed in future gait prediction technologies.

Future gait prediction technologies should focus on timeliness, accuracy, and personalization. By integrating multimodal sensor data with advanced machine learning algorithms, these technologies can further enhance the control precision and adaptability of lower limb exoskeleton robotics, providing greater support in fields such as rehabilitation, assisted walking, and movement training. The continuous development and refinement of gait prediction technology will open up broader prospects and opportunities for research and applications in the field of biomedical engineering.

Future research directions

Several key development directions are anticipated for future research in gait prediction for lower limb exoskeleton robots. First, integrating multimodal sensor data with advanced machine learning algorithms will significantly enhance the timeliness, accuracy, and robustness of gait prediction, thereby improving the control and adaptability of exoskeleton robots. Second, the study of personalized gait prediction methods is expected to become a focal point. By analyzing individual differences such as physiological characteristics and movement habits, more precise and adaptive models can be developed, leading to customized rehabilitation outcomes and optimized athletic performance. Finally, the application of gait prediction holds great promise in fields such as rehabilitation therapy, assistive walking, and athletic training, offering more effective treatment and support solutions for both rehabilitative and healthy populations, ultimately improving human health and quality of life.

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