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Review

Measurement, Evaluation, and Control of Active Intelligent Gait Training Systems—Analysis of the Current State of the Art

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Abstract: Gait recognition and rehabilitation has been a research hotspot in recent years due to its importance to medical care and elderly care. Active intelligent rehabilitation and assistance systems for lower limbs integrates mechanical design, sensing technology, intelligent control, and robotics technology, and is one of the effective ways to resolve the above problems. In this review, crucial technologies and typical prototypes of active intelligent rehabilitation and assistance systems for gait training are introduced. The limitations, challenges, and future directions in terms of gait measurement and intention recognition, gait rehabilitation evaluation, and gait training control strategies are discussed. To address the core problems of the sensing, evaluation and control technology of the active intelligent gait training systems, the possible future research directions are proposed. Firstly, different sensing methods need to be proposed for the decoding of human movement intention. Secondly, the human walking ability evaluation models will be developed by integrating the clinical knowledge and lower limb movement data. Lastly, the personalized gait training strategy for collaborative control of human–machine systems needs to be implemented in the clinical applications.

Keywords: rehabilitation and assistance system; lower limbs; intention recognition; gait training; gait evaluation; human–machine interaction control strategy

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1. Introduction

Walking is one of the most common behaviors in human daily life, and the ability to walk is an important factor for human beings to live independently. However, neurological diseases such as stroke sequelae and Parkinson's disease can lead to impairment of human motor function and decline in walking ability [1], which can seriously affect the quality of life and health of patients. The World Health Organization survey shows that the incidence of stroke in China ranks first in the world, and stroke is characterized by high incidence rate, high disability rate, high mortality rate, and high recurrence rate [2]. According to the report of the National Bureau of Statistics of China, the elderly population in China will reach 267 million, accounting for 18.9% of the national population in 2022. The accelerated process of aging has increased the number of people suffering from neurological diseases, and the conflict with the lack of medical resources has become a serious problem in the health care system [3]. At present, human beings cannot break the laws of nature to prevent the decline in their own motor functions, and many injuries to the body's motor function are irreversible. It has become one of the urgent problems in society to help the elderly or patients overcome movement disorders, restore their walking function, and improve their daily living ability.

Active intelligent gait training systems are robotic devices that actively interact with human lower limbs to provide support and assistance for the body's motor function. State-of-the-art rehabilitation training walkers or robotic systems mainly have problems such as poor gait adaptability, inability to quantify and feedback rehabilitation effect, single training strategy, and limited sensor usage environment [4–12]. Facing major national needs and the main economic battlefield, it is of great significance to develop intelligent rehabilitation equipment to realize gait perception, evaluation, and feedback in the home environment, and to help rehabilitation physiotherapists to assist patients in restoring motor function. The gait training system is a large area of research which integrates mechanical design, sensing technology, intelligent control, and robotics technology. At the forefront of the research of intelligent gait training systems and evaluation methods, there are three important basic scientific problems to be solved, which include: (1) the measurement of lower limb movement and the prediction of movement intention, (2) the construction of a walking ability evaluation model based on clinical knowledge and lower limb movement data, and (3) the formulation of personalized gait training strategy of collaborative control of human–machine system. Therefore, the key words "gait measurement and intention recognition", "gait evaluation", and "gait training control strategy" were used in the literature review. Additionally, this review not only selected publications that directly describe or introduce any gait training system, but also retains those publications that focus on any of the three basic scientific problems mentioned above.

In this review, the current active intelligent gait training systems are investigated and discussed from three perspectives, in accordance with three critical scientific problems put forward above, which are measurement and prediction of lower limb movement, evaluation of the effect of gait rehabilitation, and the control strategy of gait training. The main limitations and challenges are then discussed, and potential future directions of intelligent gait training systems are put forward.

2. Human Gait Measurement and Intention Recognition

2.1. Gait Movement Measurement

The active intelligent gait training systems have the ability to monitor patient's movement in real time [13]. At present, human's body movements are mainly measured through the fixed force platform and optical motion capture system [14–16] in the gait laboratory, or multiple movement and force sensors worn on the limb [17–19]. The former is highly accurate but limited by the measurement environment, and the latter may interfere with the normal human movement.

The current main human movement measurement methods used in gait training systems are shown in Figure 1. Gait motion measurement techniques used in each of the included studies [14–36] and their characteristics are shown in Table 1. Vision-based methods are one of the important methods for monitoring the posture and movement of the human body and have a wide range of applications [20–23]. Based on the image global joint summation problem or the hierarchical detection fusion problem, deep learning methods have been widely studied for the estimation of human pose [24,25]. However, visual methods have problems such as clothing occlusion, dark environment, high system complexity, difficult installation, and privacy issues, and there are limitations in actual human–machine coordinated movement. The wearable sensing system of human body dynamics analysis consists of multiple sensors, including gyroscopes, pressure sensors, angle sensors, inertial sensors, etc., but it has difficulties in obtaining displacement and relative poses from human to machine. The radio frequency (RF) signal-based method can use the data characteristics of the human body and its motion in the radar image to measure the three-dimensional relative pose and radial velocity [35]. The latest research [36] shows that it has obvious advantages in solving problems such as occlusion and three-dimensional reconstruction, but at present it still needs in-depth research on issues such as decoupling RF signals of human and machine movement, fusion understanding based on physical models and data, and generalized measurement of abnormal gait. Therefore, it is necessary to study a new type of non-contact sensing technology solution, combining the kinematics information of the lower limbs and plantar pressure detection to form a composite information perception system to accurately predict the movement trend of the patient's lower limbs and use it to evaluate the patient's health and athletic ability.

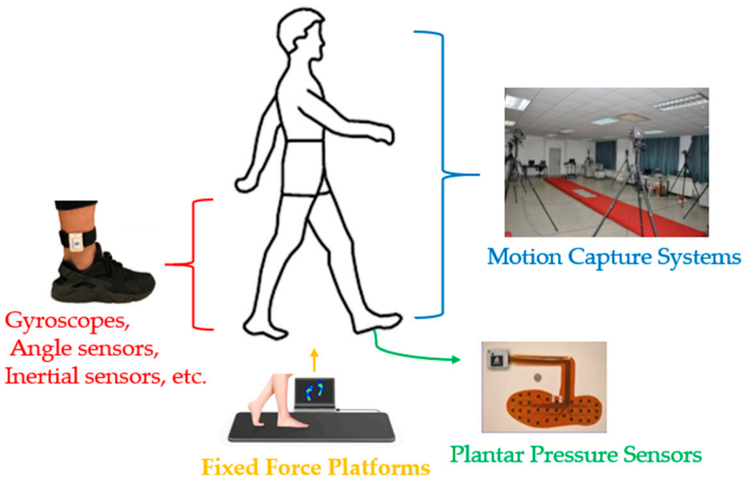

Figure 1. State-of-the-art motion measurement techniques used in gait training systems.

Table 1. Gait motion measurement techniques used in each of the included studies and their characteristics.

Study	Sensing Techniques	Advantages	Challenges
Jensen et al. [14] Xie et al. [20] Bao et al. [21] Steinert et al. [22] Tran et al. [23] Toshev et al. [24]	One camera Three noncontact cameras Pupil Labs eye tracking system 2D smartphone camera Seven Kinect sensors(cameras) Images taken by a camera	Motion capture systems represented by Vicon are currently regarded as the "gold standard" for motion capture by their high accuracy	Greatly affected by the environment, high system complexity, difficult to install, and privacy issues
Yang et al. [35] Zhao et al. [36]	Radio-frequency identification (RFID) tags Radio frequency (RF) signals from RF-Avatar	Measure in the presence of occlusions, baggy clothes, and bad lighting conditions	Decoupling of RF signals of human–machine coordinated movement
Veilleux et al. [15]	Six large force platforms	No image information will be left, and user privacy will not be violated	Only in the laboratory
Zeng et al. [16] Mazhar et al. [17] Trkov et al. [18] Li et al. [19] Schicketmueller et al. [26,29]	Smart sensor shoes A flex sensor on a leather shoe inertial sensors on lower limbs Designed strain gauge on leg Inertial measurement units	Unrestricted use environment, simple to use, user privacy will not be violated	May intervene with the normal motion, difficulties in obtaining displacement and relative pose of human–machine
Martini et al. [27] Wang et al. [30] Bae et al. [31] Livolsi et al. [32] Bae et al. [33] Chen et al. [34]	Embedded joint angle sensors Foot pressure sensor and IMU Force sensors in the foot plates Hip encoders, pressure-insoles Inertial measurement units A single IMU	Unrestricted use environment, simple to use, user privacy will not be violated	May intervene with the normal motion, difficulties in obtaining displacement and relative pose of human–machine

2.2. Movement Intention Recognition

For patients with impaired motor function but can still move and do some daily activity, the willingness to actively participate in gait training is especially important in the rehabilitation process [37]. Clinical studies have shown that active involvement of patients in the rehabilitation training is more effective in the neurological reconstruction and motor function recovery. Therefore, as an important input information of active intelligent rehabilitation and assistant robotics device, human lower limb movement intention needs to be captured in real time.

The current typical intention recognition methods used in gait training systems and the statistics of recent research studies using each method are shown in Table 2. The neuro-rehabilitation training robotics devices should show "transparency" in the patient's walking assistance process, that is, reduce the intervention of the patient's active gait as much as possible [38], and the key lies in the understanding and prediction of the patient's movement intention. Current intention recognition methods are mainly based on bioelectric signals and motion signals. The electroencephalogram (EEG) signals are the overall reflection of the movement intentions in brain [39], and have the shortest latency, but it has a low signal-to-noise ratio, easily interfered by noise [40,41]. The Electromyographic (EMG) signals reflect the state of muscle activation and the feedback control based on EMG signal can effectively improve the human–machine coordination in rehabilitation training [42–45], but it has strong ambiguity and is affected by factors such as surface contact status, muscle displacement, and muscle fatigue [46]. The intention recognition method based on motion signal mainly uses kinematic signals such as position, angle, and speed, and kinetic signals such as interaction force/torque, which has high reliability, robustness, and accuracy [47–50]. Xu et al. [51] proposed a compliance control algorithm for walking-aid robots based on multi-sensor fusion, which allows the robot to obey human movement by recognizing user intentions. Esteban et al. [52] also carried out related research, using EMG signals and Artificial Neural Network (ANN) algorithms to recognize human walking intention and proposed a robotic knee exoskeleton for assistance and rehabilitation. Wu et al. [53] put forward a coordinated control strategy based on human–machine interaction and the principle of minimum interference. However, the information of human motion and force is the result of the movement, with a certain time lag between the motion intent. Therefore, in response to the active adjustment needs of human-in-the-loop control, it is necessary to study new motion perception systems and intention prediction models with self-learning capabilities, and to improve the stability, synergy and adaptability of human–machine collaboration based on active intention feedback.

Table 2. Intent recognition method used in each of the included studies and their characteristics.

Intent Recognition Methods	Study	Characteristic
Electroencephalogram (EEG) signal method	Liu et al. [39]	High accuracy: 80.16 ± 5.44%
	Engemann et al. [40]	The best model depends on noise
	Bi et al. [41]	To recognize intention under the attended and distracted states
Electromyographic (EMG) signal method	Zhuang et al. [42]	Proved to be better than interaction-torque based method
	Zhang et al. [43]	Back Propagation (BP) neural network was used
	Xie et al. [44]	General regression neural network optimized by golden section algorithm was used
	Rabe et al. [45]	Anterior sonomyography sensor fusion with surface EMG
	Fougner et al. [46]	3.8~18% average classification error due to muscle fatigue
	Mora-Tola et al. [52]	Artificial Neural Network (ANN) algorithms were used

Table 2. *Cont.*

Intent Recognition Methods	Study	Characteristic
Kinetic signals method	Guo et al. [47]	A robot dynamics model including the active force of human was established, and contact force was used to analyze intention
	Pinheiro et al. [50]	The interaction torque's direction and magnitude were both used
	Xu et al. [51]	A compliance control algorithm based on intent was proposed
	Wu et al. [53]	A minimal-intervention-based admittance control strategy was developed
Kinematic signals method	Gong et al. [48]	Two IMUs and an imbedded BPNN-based algorithm were used
	Zhu et al. [49]	Recognition accuracy rate can reach 97.64%

3. Evaluation of Gait Rehabilitation

Clinical gait analysis and evaluation is of great significance in active intelligent gait training systems. Quantitative analysis methods based on sensor data are important methods for gait rehabilitation evaluation. An increasing number of researchers in physical therapy, bioengineering, neurology and rehabilitation have been participating in this field of study. In the early research studies, gait analysis and evaluation usually took the form of scales, such as the Fugl-Meyer exercise scale [54]. According to the scale, medical staff perform the diagnosis and evaluation of motor function, the monitoring of disease progression, and the evaluation of curative effect. The result of evaluation is often affected by a large number of subjective and inaccurately measurable parameters in the clinical scale [55].

Table 3 shows number of gait evaluation studies, which sensors and features were used in each research [56–77], and the real-time of gait evaluation. Gait parameters are usually used to assist medical staff in diagnosis, rating and scoring of motor function, monitoring the progress of the patient's condition, and evaluating curative effect. Gait measurement equipment such as motion capture systems and wearable inertial sensors have been widely used in clinical practice. Some researchers used the gait parameters measured by these large systems to predict Parkinson's diagnosis and Hoehn-Yahr (H-Y) classification [67,68]. There are also researchers who used the changes in gait parameters before and after the patient receives treatment and training to evaluate the treatment effect [69]. Caramia et al. [70] used eight inertial measurement units placed on the lower extremities and trunk to estimate several gait parameters such as step length, stride speed, etc. and extract features from them to distinguish between healthy people and patients with H-Y grades 1 to 3 in order to achieve diagnosis and grade prediction. However, there are problems such as inconvenient use of sensing equipment, lack of clinical significance of data features, difficulty in matching the scale, and an incomplete assessing system. Wang et al. [71] carried out preliminary research based on clinical needs, using as few human sensor measurement data as possible, and using nonlinear data classification methods to achieve quantitative evaluation of dyskinesias in patients with abnormal gait. Skvortsov et al. [72] also investigated the feasibility of gait analysis and walking function evaluation based on the stance phase of stroke patients using biofeedback technology.

Muscle synergy theory describes a potential neuromuscular control mechanism of vertebrate limb movement [73]. According to the muscle synergy theory, nerves do not control a certain muscle alone, but recruit muscles on the spinal cord to form muscle groups, that is, muscle synergy. The muscles in the same muscle synergy are activated at the same time. Compared with controlling each muscle individually, using one control signal to activate multiple muscles theoretically provides a simplified system. Numerous experimental research results support this theory [74,75]. Studies have shown that muscle activation during motor tasks can be described in terms of low-dimensional control that reflects muscle synergy. The downward commands of the nervous system to the musculoskeletal system are manifested in muscle synergy, which is reflected in muscle activation through spinal cord circuits or reflexes, thereby forming a force in the musculoskeletal system, driving the musculoskeletal system to move and producing specific actions.

Table 3. Sensors and features used in gait evaluation method in each of the included studies.

Study	Sensors Used	Features Used in Gait Evaluation	Real-Time
Anaya-Reyes et al. [56]	Vicon MX T20	Step phase durations and cadence	−
Alberto et al. [57]	3-D motion capture system	Stride width and gait velocity	−
Ma et al. [58]	Three Force Sense Resistors	Knee and hip joints and FSRs data	−
Chomiak et al. [59]	Ambulosono system	Step length, distance traveled, velocity, and cadence	+
Tran et al. [60]	A motion capture system and four force sensors	Center of mass, the center of pressure, and step parameters	−
Park et al. [61]	Force sensors	Angles, active force, and resistive force	−
Sconza et al. [62]	Dynamometer	Knee extensor strength, double-time support, and step length ratio	−
Wang et al. [65]	3-D motion capture system	Cadence and single stance time	−
Tamburella et al. [66]	Angle sensors	Gait speed	−
Wahid et al. [67]	8-camera video motion analysis system	Stride length, step length, and double support time	−
Rehman et al. [68]	GAITRite instrument	Step velocity and step length	−
Carlotta et al. [70]	Inertial measurement units (IMU)	Step length, step time, and stride speed	−
Wang et al. [71]	Inertial measurement units (IMU)	Right spatial-temporal and kinematic gait parameters	+
Skvortsov et al. [72]	Neurosens inertial sensors	Knee and hip joint range of motion	−
Cheung et al. [74]	EMG sensors	EMG signals (muscle activity)	−
Safavynia et al. [75]			−
Longatelli et al. [77]			−
Rinaldi et al. [76]	EMG sensors, Vicon, and force platform	Both gait parameters and muscle activity	−
Seo et al. [78]	EMG sensors and IMU		−

Abbreviations: + real-time evaluation; − off-line evaluation.

Based on the muscle synergy theory, many research studies have been carried out to diagnose gait disorders and neurological diseases by measuring the activation state of lower limb muscles during walking [76–80]. However, the existing methods for measuring muscles exercise have drawbacks. On the one hand, Surface Electromyography (sEMG) signal measurement has limitations which include the lack of ability to test the deep muscles, the easily interfered EMG sensors, and the difficulty for the extraction process of the EMG signal envelope to accurately demodulate the neural excitation when the motor neuron action potential is generated. On the other hand, Indwelling Electromyography (iEMG) causes a certain degree of damage to human muscles, which is not suitable for long-term exercise detection with multiple measurements. At the same time, the existing simulation software is generally based on a variety of rule constraints such as muscle force-length relationship constraints, muscle force and joint motion coupling constraints, etc., and optimization theories such as minimizing physiological consumption. However, according to the results of human motion modeling and analysis by related researchers [79,80], in patients with gait disorders, it is often difficult to meet the above constraints due to nerve-muscle-skeletal damage, and the dynamic representations such as joint torque are affected by motion compensation under the condition of external load changes.

4. Control Strategy of Gait Training Systems

Traditional walking devices, such as crutches, walkers, wheelchairs, etc., are mostly passive devices, which cannot solve the problem of coordinated dynamic training of body and lower limb muscle when the elderly and patients walk [81]. On the contrary, active intelligent mobility assistance devices interact physically with the human body, as well as coordinated movement, to provide support and assistance for the body's motor function and help the body maintain and restore its motor function to the greatest extent [82,83]. The typical control diagram of active intelligent gait training systems is shown in Figure 2.

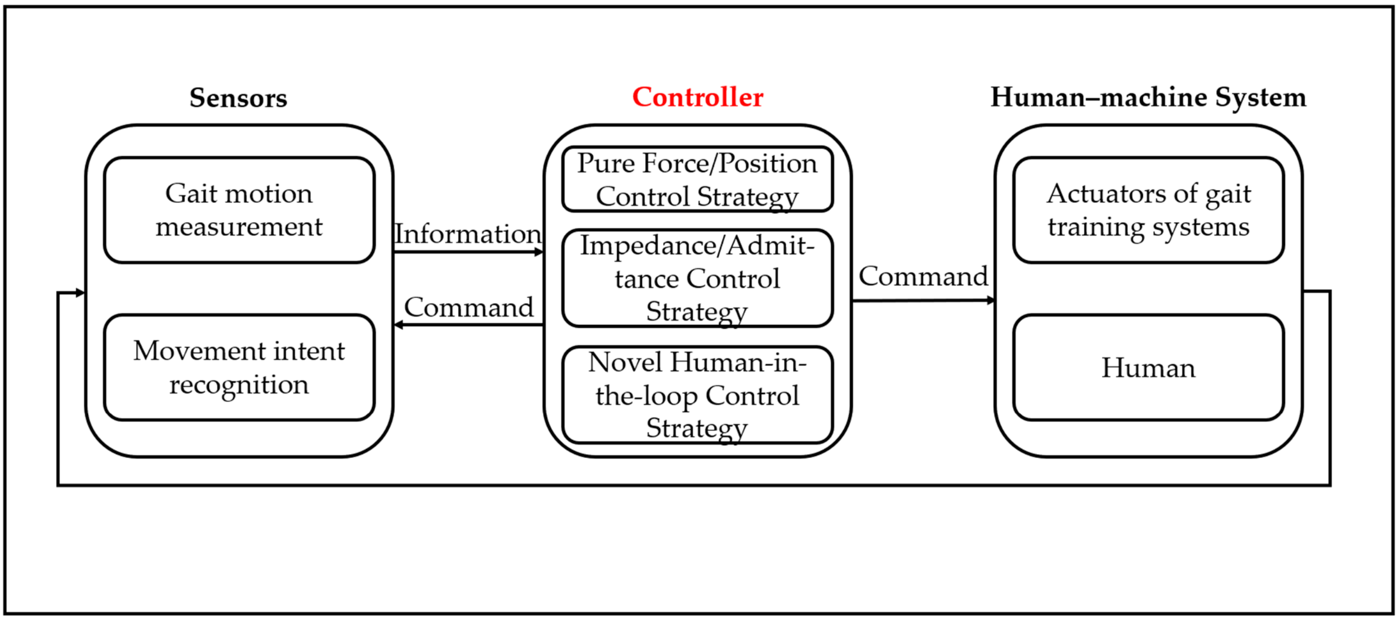

Figure 2. Typical control diagram of gait training systems.

A walker is a walking rehabilitation assistive device used to assist users in standing and walking activities which can effectively help users improve their walking ability and is of great significance to a large number of disabled or elderly people. Based on this, intelligent walking rehabilitation assistive robotics devices effectively use the current rapid development of technology to help users break through the original limitations of walking ability to a certain extent and improve their mobility to meet their daily needs. These technologies include mechanical design technology, embedded system technology, sensing and detection technology, automatic control technology, motor control technology, microelectronics technology, interface technology, and software programming. Table 4 shows several gait training systems and their control strategies from recent studies [84–102]. Pure force/position control means the gait training systems make corresponding operations by detecting human gait events, but do not care about the information of human–machine interaction, while systems with impedance/admittance control strategy use the human–machine interaction information such as interaction force/torque and relative position. Novel human-in-the-loop control represents a large number of control strategies that both recognize the motion intention of humans and detect the human–machine interaction information, described as 'human-in-the-loop' because the information of the human body takes part in both the input and feedback of the closed-loop control. Yu et al. [84] developed an intelligent three-wheeled mobility aid, which is equipped with infrared sensors and laser rangefinders to ensure human–machine–environmental intelligent interaction in motion. Tao et al. [85] studied the intelligent mobility assistance rehabilitation training device for the needs of standing and gait rehabilitation. A standing support and gait training system that maximizes the patient's own rehabilitation exercise ability was developed by using the pressure sensor on the sole of the foot to detect the user's balance or falling state and feeding back the human lower limb joint and muscle force to a load-reducing suspension system. Zhao et al. [88] developed a gait rehabilitation robot to improve the safety and availability of rehabilitation training for patients. A built-in-robot camera was used to obtain leg movement data, and the knee angle was estimated by a New-type ESMF algorithm to deal with the problem of the brief disappearance of the marker point in the field of view.

Table 4. Gait training systems and control strategies of each included.

Device Name	Control Strategy	References
Gait rehabilitation device	Open-loop position control based on GRFs	Tao et al. [85]
Novel Robotic Walker	Position control based on gait event	Ye et al. [86]
Gait Training Robot	Force control method based on gait event	Miyake et al. [87]
Walking Assist Robot	Position control based on fall detection	Zhao et al. [88]
Hybrid Rehabilitation Robot	Manually changed training modes and speed control	Kim et al. [91]
C-ALEX	Open-loop force control base on gait event	Hidayah et al. [96]
Gait Assist Robot	Training mode switch based on task and gait feature	Scheidig et al. [99]
Lower-Limb Exoskeleton	Speed control based on gait parameters	Ma et al. [100]
Intelligent Mobility Aid	Admittance-based mobility controller	Yu et al. [84]
Rotational Orthosis	Admittance control of the ankle mechanism	Mu et al. [89]
Gait rehabilitation robot	Adaptive admittance control based on interactive force	Guo et al. [90]
Improved rotational orthosis	Admittance control based on ankle force	Mu et al. [92]
Clinic gait training robot	Admittance control based on relative position	Shunki et al. [93]
2-DOF Exoskeleton	Admittance control based on interactive force	Chen et al. [101]
Robot Assisted Gait Training	Assist-as-needed Control based on prediction	Zhang et al. [94]
GAREX	Logic compliance adaptation and assist-as-needed	Zhong et al. [95]
Ankle Robotic Orthosis	Assist-as-needed Impedance Control Strategy	Lopes et al. [97]
Biofeedback Exoskeleton	Speed control based on predicted user response	Zhang et al. [98]
AGoRA	Closed-loop control based on intention and gait feature	Mayag et al. [102]

Functional Electrical Stimulation (FES) is a method of applying low-frequency pulsed current or amplifying it through signal-current conversion and then sending it into the human body to produce immediate effects, artificially causing movement in humans who are paralyzed by damage to the central nervous system. Recently, a large number of research studies proposed robotic systems for gait rehabilitation based on FES method [103–105]. Studies have proven that, combined with FES, the assistive torque required of the gait training systems can be reduced and the muscle strength and joint range of motion of the human body can be improved. However, due to the use of electrode pads, this rehabilitation strategy still has problems such as the inability to stimulate deeper muscles or the trauma of electrode implantation in sEMG and iEMG in Section 3.

Locomat is a robotic gait training system. It is used for gait training for patients with abnormal gait caused by brain injury, spinal injury, neurological injury, muscle injury, and orthopedic diseases, and to improve the motor ability of patients with neurological diseases. In the first few generations of prototypes, Locomat also used the common impedance control based on torque feedback [106], but in the latest generations of Locomat Pro, novel control strategy such as automatic gait-pattern adaptation and path control strategy are applied. Locomat Pro can also perform diagnostic evaluation of patients' gait and there are many cases of clinical application [107–109]. However, it is difficult for such a bulky and expensive product to enter millions of households, and the compliance of the control can still be improved. For patients who have lost their mobility due to nerve damage, how to fully mobilize the patient's own movement intention instead of "passive walking" so as to achieve the treatment of nerve injury diseases is a difficult point in the study of the intelligent gait rehabilitation training systems.

5. Limitations and Challenges

Rehabilitation and training of gait is a current research hot spot. From the systematic analysis of the current research status of the active intelligent gait training systems, it is not difficult to see that there are still key issues in terms of sensing, evaluation, and control. Key technologies such as the decoupling of radio frequency signals of human–machine coordinated movement, the understanding based on fusing physical models and gait data, and the generalized measurement of abnormal gait are in urgent need of breakthroughs. To be specific, when capturing patients' motion using RF signals, both the wearable gait training device and the human body reflect RF signals. That makes the decoupling of the return signals from the two very important, and it is also the limitation of current research studies. The methods of lower limb movement analysis and movement intention prediction based on radio frequency principles need to be further studied. As the current intention recognition based on EEG signals is easily interfered by noise, the EMG signals-based method has strong ambiguity. Moreover, the intention recognition based on kinematic or kinetic signals has a long latency.

As a mobility aid for gait rehabilitation and training, if the evaluation criteria for the rehabilitation effect are difficult to define and the efficacy cannot be guaranteed, it will be difficult to meet the diverse and personalized needs of users. The current clinical scale for gait analysis and evaluation relies on the subjective assessment of the doctor and the self-perception of the patient. In addition, the existing sensing data features lack clinical significance and are difficult to correspond to the scale, and the evaluation system is inadequate. How to quantitatively evaluate the effect of gait training with multi-dimensional information still needs in-depth research.

A crucial problem of control of the active intelligent rehabilitation assistance devices for lower limbs is that it needs to allow the users to spontaneously participate in motion, which is of great importance for patients with nerve injury. However, the current gait rehabilitation training systems have difficulty accurately recognizing the user's movement intentions to make corresponding assistance strategies. As users' requirements for comfort and safety continue to increase, the human-in-the-loop control, with information of human body taking part in both the input and feedback of the controller, is receiving increasing attention. However, due to the difficulty of quickly and accurately identifying the user's intent, the research studies on human–machine cooperative intelligent control for personalized gait rehabilitation training is still too preliminary.

6. Future Directions

To address the core problems in the sensing, evaluation, and control technology of the active intelligent gait training systems, the following possible future research directions are proposed. We believe that the key is to focus on scientific issues such as the decoding of lower limb movement intention based on the principle of radio frequency, the construction of a walking ability evaluation model combined with clinical knowledge base and lower limb movement data, and the personalized gait training strategy for collaborative control of human–machine systems.

Among the many methods of detecting and sensing human lower limb movement, the method based on the radio frequency signal is relatively preliminary, but it has obvious advantages and broad prospects. A new type of non-contact motion sensing method based on the principle of millimeter wave echo reflection needs to be studied. For instance, a non-contact small radio frequency sensor such as a millimeter wave radar first needs to be developed. Using the signal features generated by human motion on the radar image and Doppler signal spectrogram as target features, similar to Daniel et al. [110], and using the space occupancy status and motion frequency shift information contained in the frequency characteristic data of the range view as input, the features in the input data are encoded by the convolutional neural network (CNN) method, and an estimator is generated to output the joint position and motion information of the object [111]. By combining the real-time data with the models of the kinematics and dynamics of human lower limbs, the human lower limb movement may be predicted. In conclusion, it is of important scientific significance to study a new non-contact sensing principle and the method of model-driven and data-driven fusion, to integrate the characteristics of different information dimensions, to build a more concise, fast, and accurate online decoding model of composite information for patient's gait training, and to predict patient's movement intentions.

Based on the knowledge of rehabilitation medicine, combined with the results of motion recognition and prediction, the evaluation model of gait rehabilitation training effects needs to be established, and the method of generating personalized rehabilitation training prescriptions needs to be studied. Based on the extracted non-steady-state motion signals of the lower limbs, the time–frequency characteristics of the vital signs signals such as EMG signals can be analyzed. In order to evaluate the movement synergy of the healthy and abnormal limbs of the human body, the mechanism of human muscle synergy needs to be further studied. Combining the lower extremity musculoskeletal model with the static optimization algorithm to calculate the muscle activation degree during human walking, the evaluation method of the muscle coordination degree on the lower extremity muscle movement coordination ability of the patient's exercise training can be studied. Finally, the evaluation of gait training effects for different ages and different training stages will be realized.

The workflow of an ideal gait training system should be as follows: based on the evaluation of walking ability and the needs of gait rehabilitation training, the movement mode of gait training can be determined. The corresponding human motion intention and motion reference trajectory are obtained through the non-contact motion sensing system. After this, the desired motion trajectory of the gait training system is generated. Combined with the motion intention of the lower limbs of the human body and some simple control methods, the gait training system will flexibly assist the patient to complete the desired action. All in all, the key to the formulation of control strategies is gait evaluation and intention recognition, while obscure and sophisticated control theory is secondary. By studying the collaborative control method of the gait rehabilitation training system and the patient, based on principal component analysis, multiple regression, and neural network, the association model between gait data and clinical evaluation can be constructed, and a personalized gait training strategy with multi-layer, and cooperative closed-loop control of "human in the loop" can be designed. Based on this, carrying out research on the collaborative control of human–machine systems based on personalized rehabilitation strategies, evaluating the perception and control performance of the gait training system, and generating clinical evaluation reports on the effects of rehabilitation training have important academic significance and extensive clinical application value.

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