Advances in Wearable Technology for Intelligent Rehabilitation and Motion Analysis

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Abstract. The integration of artificial intelligence (AI) with wearable technology is creating a transformative paradigm in healthcare, particularly within rehabilitation and motion monitoring. This review systematically explores this convergence, highlighting how AI-enhanced wearables address critical limitations of conventional methods, such as discontinuous observation and delayed response in hospital or home-care settings. By leveraging continuous, real-time data collection from diverse sensors, these devices offer an unparalleled platform for remote patient management. This capability is increasingly vital against a backdrop of global demographic shifts, including aging populations and a rising prevalence of chronic conditions, which amplify the demand for advanced, accessible rehabilitation solutions. The article delves into specific technological foundations, including sensor-based and vision-aided monitoring systems, and their data processing pipelines powered by AI algorithms. Subsequently, it examines cutting-edge applications across key domains: gait and upper-limb rehabilitation, the use of intelligent exoskeletons, and the emerging field of vision-language-action (VLA) models for holistic intervention. The discussion extends to motion monitoring for athletic recovery and managing musculoskeletal disorders. By synthesizing these developments, this review aims to provide a foundational framework and offer directive insights for future technical innovation, product design, and scholarly research, thereby accelerating the advancement of personalized and proactive healthcare.

Keywords: Ai-assisted wearables, rehabilitation, motion monitoring.

1. Introduction

Wearable devices generally refer to specialized equipment affixed onto the human body, which can serve as a type of auxiliary monitoring devices. As another hot topic in the mainstream trend of technological development, wearable devices are versatile and applied in various fields. They make an outstanding contribution in health management, motion assistance, rehabilitation, as well as education monitoring. Rehabilitation and motion monitoring are two pivotal topics in the contemporary medical industries. For the conventional treatment methods, hospital monitoring is ubiquitous worldwide. It normally requires doctors, nurses and other nursing staff to execute long-term nursing on the patients. For patients who need home-based rehabilitation, long-term and continuous door-to-door visits are necessary. However, this method possesses confines intrinsically, especially for the monitoring continuity and precision. It cannot also provide valid and rapid response to emergencies. Therefore, as an ideal platform for distant monitoring, wearable devices are the optimum choice because in the domain of real-time monitoring and data collection, they possess dominant superiority.

Relevant technologies in the field of rehabilitation and motion monitoring have been widely applied in the rehabilitation of injuries and the treatment of specific diseases. The majority of demand originates from manual workers, professional athletes, the elderly population and patients with movement disorder diseases. Take China as an example. It is confronted with challenges including the aging population, the increase in the number of patients with chronic diseases and disability and the post-operative rehabilitation. The rising demand for rehabilitation treatment requires a more comprehensive and advanced technique to serve as the foundation. By the end of 2024, the population aged 65 and above accounted for 15.6% of the total population. Even though this data had decreased by 3.1 percent compared with that in 2020, the quantity still remained substantial. Therefore, countries with a relatively large proportion of aging population have a greater demand for rehabilitation technologies. (By 2022, the proportion of aging population in Japan was 29.1%) [1, 2]. So, accompanied by the increasing demand for such technologies, wearable devices start to demonstrate unique advantages, especially for the retarding of the deterioration of neurodegenerative diseases (e.g. Parkinson's disease) and the improvement on patients' living quality [3]. For example, they are able to monitor disease dynamically. Wearable devices have been applied to the diagnosis and rehabilitation process of movement disorder, Huntington's disease and Parkinson's disease [4]. Motion monitoring is pivotal alongside rehabilitation. It's essential for the treatment and continuous monitoring of athletic injuries. Relevant technologies can assist determine the recovery progress precisely and formulate the next step of the medical plan. Wearable devices are also widely applied in this process, including the real-time monitoring of musculoskeletal disorder patients [5].

In conclusion, the development of wearable devices is currently in a rising stage. Through summarizing the application of AI-assisted wearable devices systematically in the field of rehabilitation and motion monitoring, this review is aimed to provide directive guidance for the future technical innovation and product development of such devices. It is also aimed to facilitate further research in relevant fields. In content, this article begins by introducing the application monitoring technology for wearable devices, including techniques based on sensors and visual aid and the data processing methods combined with AI technology. Then, this article will discuss the application in rehabilitation which combines wearable devices and AI technology, including rehabilitation on gait and upper limbs, as well as the application in exoskeletons and VLA (vision-language-action) technology. Finally, this article will summarize and carry out an outlook on the research content, in order to provide theoretical support for further research in relevant fields.

2. Motion Tracking Technology in Wearable Devices

2.1. Sensor-Based Tracking Technology

Wearable devices usually need to monitor the wearer's physical signs in real time, among which motion tracking technology is the most prominent to determine the wearer's activity status. Wearable devices for motion tracking mainly rely on Inertial Measurement Units (IMU), surface Electromyography Sensors (sEMG), and pressure sensing arrays. For IMU, a typical application is the IMU in the Empatica E4, which controls errors through a temperature compensation algorithm. Such a configuration enables accurate detection in motion studies of Parkinson's disease patients, referring to the research by the University of Oxford on using wearable devices to detect the progression of Parkinson's disease, where the IMU is a key data collection component [6].

Secondly, regarding the patients' muscle movements, the sEMG plays a crucial role. By focusing on monitoring the electromyographic activity of the sternocleidomastoid muscle and the tibialis anterior muscle, the sEMG observes postural control and gait swing. It can collect abnormal data of the electromechanical energy spectrum before the occurrence of freezing of gait (FOG), efficiently monitor the patients' muscle movements, and provide effective data for evaluating the condition.

Finally, the pressure sensing array is used to monitor the patients' movement direction. Devices are worn on the plantar and wrist respectively. By analyzing the changes in the direction of plantar pressure and the fluctuation frequency of tremor pressure at the wrist, it can distinguish between resting tremor and intention tremor, facilitating the acquisition and analysis of the patients' condition during movement.

In the field of sensor innovation research, a number of breakthrough achievements have emerged in recent years. In terms of IMUs, scholars such as Meng (Meng Lin and Pang Jun's team from the Institute of Medical Engineering and Translational Medicine, Tianjin University) innovatively constructed a five-dimensional evaluation model covering "gait spatiotemporal parameters, joint motion parameters, variability, asymmetry, and stability" by deploying IMU sensors at 11 joint points including the head, upper chest, pelvis, upper arms, thighs, lower legs, and feet. They focused on incorporating 180-degree turning gait analysis, and finally increased the AUC value for early Parkinson's disease detection to 0.879. In particular, the recognition accuracy for patients with postural instability and gait difficulty (PIGD) was 23% higher than that of the traditional linear gait model. This study confirmed that the range of motion (RoM) and stability parameters of joints such as the neck and pelvis during turning are key biomarkers for the early diagnosis of PIGD [6].

In terms of sEMG, the research team of Nanjing Medical University selected 12 Parkinson's disease patients with FOG, 13 Parkinson's disease patients without FOG, and 11 healthy controls. By using sEMG to monitor the electrical activity of the tibialis anterior muscle and gastrocnemius muscle during linear walking, they found that the normalized root mean square (RMS) amplitude of the sEMG in the pre-swing phase of patients with FOG was significantly reduced, and the RMS of the gastrocnemius muscle was strongly negatively correlated with the severity of FOG ($r=-0.758$, $p=0.007$). This provides electromyographic biomarkers for the analysis of the pathological mechanism of FOG and early warning [7].

Meanwhile, medical wearable devices need to accurately capture microvolt-level electromyographic signals and low-frequency tremor signals of Parkinson's disease patients in complex electromagnetic environments such as hospital Wi-Fi, 5G signals, and medical equipment. The anti-interference hardware ensures data quality through a three-layer architecture of "source suppression - signal correction - physical isolation" for the design of anti-interference hardware and device materials.

In terms of signal correction hardware, integrating the hardware of "adaptive Kalman filtering + IMU motion compensation" can realize real-time correction of tremor interference in sEMG signals, increasing the accuracy of extracting electromyographic features from 78% (traditional method) to more than 92%.

In terms of material selection, medical-grade silicone substrates with a Shore hardness of approximately 30A and a magnetic charging design (such as the Apple Watch Ultra Medical Edition) are adopted. These materials have passed biocompatibility tests to adapt to the skin and activity characteristics of people of different ages, improving the wearing experience of patients.

2.2. Vision-Assisted Tracking Technology

The core design principle for wearable devices is "miniaturization with low power consumption". First, for the miniature camera module, the most widely used one currently is the VGA resolution (640*480) global shutter camera with an 85-degree wide-angle lens, which is integrated into wearable devices. Through human posture key point detection algorithms such as MediaPipe Pose, the coordinates of key nodes such as the hip joint and knee joint are extracted. Similar visual detection technology has also been applied in some clinical auxiliary diagnostic equipment to capture the dynamic information of patients.

Second, in gait analysis-related scientific research projects, structured light sensors can obtain more accurate spatial position data. For example, some high-end devices integrate miniature Time-of-Flight (TOF) sensors to construct a 3D gait model, quantify step width asymmetry and posture tilt angle, and make up for the limitations of IMUs in spatial position perception.

In complex movements, vision and sensors complement each other. The core reason lies in the difference in their perception dimensions: sensors (IMU, sEMG, pressure sensors) are good at capturing the dynamic characteristics of local movements (such as acceleration, electromyographic activity, and pressure changes), but they lack global perception of the overall spatial posture and are easily affected by the deviation of the wearing position; the visual module obtains the spatial relationship of the whole-body movement through an external perspective and can provide absolute position and geometric parameters, but its accuracy decreases in scenarios of rapid movement or occlusion.

This complementary characteristic of "local dynamics + global space" is particularly important in complex movement scenarios of Parkinson's disease patients. Common types of complex movements in clinical practice include: Turning gait, characterized by rigid trunk and continuous small-step turning, involving limb coordination and balance control. Posture transition movements, such as standing up from a sitting position and going up and down stairs, which require the simultaneous activation of the trunk and limb muscles; Fine motor execution, such as unbuttoning and holding objects, accompanied by the superposition of tremor and bradykinesia [6].

In these scenarios, a single sensor has obvious limitations: the IMU is prone to errors in gait cycle calculation due to heading angle drift when turning; pressure sensors cannot capture the spatial information of trunk tilt. The sEMG is difficult to distinguish the electromyographic characteristics between muscle rigidity and bradykinesia [7]. However, the fusion of visual sensors can achieve complementary advantages: During turning movements, the IMU monitors the swing acceleration of the lower limbs, and the visual module measures the turning angle and step width asymmetry. After fusion, the evaluation accuracy of turning efficiency is increased by 40%; During posture transition, the sEMG monitors the activation sequence of the sternocleidomastoid muscle, and the visual module tracks the trajectory of the center of gravity shift, increasing the early warning sensitivity of postural instability from 79% (single sensor) to 94%. In the evaluation of fine movements, the pressure sensor captures the pressure fluctuation of hand tremor, and the visual module records the movement completion time. The combination of the two makes the accuracy of bradykinesia grading reach 89% [8].

2.3. Data Processing Technology

The table below systematically presents the quantitative analysis schemes for the four core motor symptoms of Parkinson's disease. Through a four-layer architecture of "sensor type - key parameters - algorithm chain - quantitative accuracy", physical signals are converted into clinically interpretable pathological indicators. The design logic of the table is based on the pathological characteristics of Parkinson's disease: resting tremor and bradykinesia are local movement abnormalities, mainly relying on high-frequency data from IMUs and sEMG; FOG and postural instability involve whole-body coordination and require the fusion of multi-sensor and visual data. The selection of algorithms follows the principle of "signal characteristic matching": the periodicity of tremor signals is suitable for wavelet transform decomposition, the temporal characteristics of gait are compatible with deep learning models, and the dynamic changes of posture require the combination of visual positioning and filtering calculation. Finally, the quantitative parameters of each symptom are accurately corresponding to the clinical scales. The initial data is converted into clinical indicators through the algorithm chain in Table 1.

Table 1. The data of clinical indicators

Pathological Feature	Key Parameters	Algorithm Chain	Quantitative Accuracy
Resting Tremor	Amplitude, Frequency, Intermittency	Wavelet Transform > Peak Detection > Time-Domain Statistics	Frequency: ±0.1Hz, Amplitude: ±0.2mm
Bradykinesia	Completion Duration, Movement Delay	Sliding Window Feature Extraction > Support Vector Machine Classification	Time: ±0.05s
Freezing of Gait (FOG)	Occurrence Frequency, Interruption Duration	Acceleration Mutation Detection > CNN-LSTM Fusion Model	Recognition Accuracy: 95.3%
Postural Instability	Center of Gravity Deviation Angle, Recovery Time	Visual Key Point Positioning > Attitude Calculation	Angle: ±0.3 Degrees

"IBM Collaborates with Pfizer to Develop AI Algorithm for Remote Diagnosis of Parkinson's Disease Severity" [9].

These algorithms are widely used in the processing of motion data of Parkinson's disease patients. In the project jointly developed by IBM (International Business Machines Corporation) and Pfizer, which uses AI to remotely analyze human motion data to determine the severity of Parkinson's disease, similar algorithms are used to process the data obtained by wearable devices.

3. Applications of Wearable Devices based on Artificial Intelligence

3.1. AI Technology in Gait Rehabilitation

Gait abnormalities are a common rehabilitation challenge in patients with stroke, Parkinson's disease and spinal cord injury, affecting their ability to move in daily life. In traditional clinical rehabilitation methods, patients need to undergo rehabilitation training under the guidance of doctors or professionals through instrument guidance or other ways. However, there are real-time changes in the continuous rehabilitation process. Patients may suffer from inadequate training and practice errors, which can slow their recovery process and even make the disease worse. In addition to other factors, it is also because the traditional method is fixed and cannot adapt well to the continuous and real-time changes.

Wearable devices with AI-assisted technology can achieve personalized and continuous rehabilitation training programs through accurate tracking, intelligent analysis and real-time feedback. On the other hand, not only physical rehabilitation, but also mental health should be paid attention to, because the inconvenience of activity often gives patients negative psychological suggestion, thus reducing the efficiency of training or even inducing danger. For example, when designing the rehabilitation training system for optic neuritis, Zhang Shuai and others also emphasized the monitoring of patients' psychological state when correcting their training posture. Through AI vision, feedback is timely, differentiated, guided, and traceable. A system with a strong interactive sense can not only guide in real time, but also optimize the psychological experience.

Gait rehabilitation devices typically employ sensors such as IMU (Inertial Measurement Units) and smart insoles to continuously monitor parameters including step length, step frequency, and gait symmetry. By analyzing gait patterns through AI algorithms, these devices can promptly detect abnormalities and provide corrective recommendations. Some devices can also predict the risk of falling and give real-time warnings, providing comprehensive support for patients' rehabilitation. For example, Chen and his team have designed a wearable sensor to monitor muscle fatigue, falls and emotional states in real time. By integrating multi-source EMG signals and employing an attention mechanism to optimize the Long Short-Term Memory (LSTM) network for extracting muscle fatigue-related features, this solution enables precise monitoring of muscle fatigue. By integrating convolutional neural networks (CNN) with Long Short-Term Memory (LSTM) networks, we extract spatial and temporal domain features to monitor patients' emotional states, thereby significantly reducing risks in rehabilitation training [10]. In addition, the long-term accumulation of gait data not only provides data support for clinical evaluation, but also provides a basis for the optimization of rehabilitation programs, helping patients to recover their motor ability and reduce secondary injury.

3.2. Integration of Upper Limb Rehabilitation with AI Technology

Different from the lower limb rehabilitation equipment, which focuses on the spine and legs, the upper limb rehabilitation training mainly involves the coordinated movement of the shoulder, elbow and wrist, and is widely used for stroke or nerve injury patients. Traditional upper limb rehabilitation methods rely on physicians to manually assess the completion and specification of movements, but this method is not only inefficient, but also lacks personalized training. With the application of smart wristbands, gesture sensors and visual tracking systems, upper limb rehabilitation training has been significantly improved. Through real-time analysis of AI models, these systems can assess the completion, specification and deviation of patients' movements, and provide real-time feedback and training suggestions based on the evaluation results, thereby improving the science of training and patient participation.

For example, MediaPipe can calculate joint angles in real time and score training movements to help personalize rehabilitation training. This method improves the scientificity of training and patient participation, and reduces the dependence on clinical manpower, but it is not effective for some patients with severe motor impairment or visual impairment. Because it is difficult to predict and recognize only visual image signals due to special movements, wearable devices and AI that process non-image signals are needed. At the same time, non-wearable AI is also being studied. The characteristics of this type of wearable device are to use cameras or some optical sensors for perception. After receiving image signals, these devices use machine vision algorithms to recognize human motion. Combined with cameras, they can be used in many situations. However, environmental sensors require installation in the home, which is costly [11], while visual systems rely on cameras for recognition, which are often considered invasive devices. Wearable AI is characterized by the collection of signals provided by wearable sensors. These AI systems process electrical signals to capture features that images struggle to represent, enabling more accurate prediction and recognition. However, the integration of EMG technology and related equipment makes the system relatively more expensive.

Compared with non-wearable AI, wearable AI system is characterized by collecting signals through wearable sensors and capturing motion features that are difficult to capture by image signals through processing of electrical signals. Such a system could better predict and identify a patient's movements, especially complex ones that can't be predicted by visual signals. Although the cost of wearable devices is relatively high and they are often combined with technologies such as electromyography (EMG), they provide more continuous and objective data support for clinical rehabilitation and can provide patients with more scientific and quantifiable rehabilitation paths. For instance, Li Jiaming and colleagues applied support vector machines (SVM), random forests (RF), decision trees (DT), and K-nearest neighbors (KNN) algorithms to a wearable scoliosis rehabilitation training system, enabling patients to perform rehabilitation exercises without professional medical supervision [12]. The first is the support vector machine (SVM), a supervised learning algorithm commonly used for classification problems. The fundamental principle is to identify an optimal "hyperplane" that separates data points into distinct categories. The key feature is to achieve excellent classification performance by maximizing the margin. For instance, Pazit Levinger et al. applied Support Vector Machines (SVM) to clinically assess post-knee replacement rehabilitation outcomes. The SVM classifier effectively identified preoperative gait parameter changes caused by osteoarthritis and detected postoperative gait function improvements at 2 and 12 months [13].

Therefore, this method can help improve the rehabilitation training effect of patients. The second, random forest is an ensemble learning method that builds multiple decision trees and votes (classification) or averages (regression) to get the final prediction. The characteristic is that it can reduce the risk of overfitting and improve the generalization ability of the model. For example, Venkatesan S et al. applied a random forest classifier to rehabilitation assessment, which achieved an accuracy of 85% and an AUC-ROC value of 0.90, confirming the reliability of the model in predicting rehabilitation outcomes and optimizing discharge plans. This enables medical staff to quickly assess and update the diagnosis and treatment plan, and ensure that each patient's rehabilitation plan is unique [14]. Third, a decision tree is a supervised learning algorithm used for classification and regression tasks. It builds a tree structure by recursively dividing the data into different subsets, with each leaf node representing a category label or numerical prediction. Each internal node represents a decision based on a feature value. Features are easy to understand and visualize, and require less preprocessing of data. For instance, Jackson H. Allen and colleagues discovered through research that clinical decision trees can help better understand the connections between concussion-related factors. This model provides a clear and reasonable prognosis for patients, which is conducive to the subsequent rehabilitation treatment [15]. Fourthly, KNN is an instance-based learning algorithm. During classification, it votes based on the labels of the K nearest neighbors of the input sample, while regression predictions are made by averaging the values of the K nearest neighbors. The advantage is that there is no training phase and all the calculations are done during the prediction. Shane Shahrestani et al. employed a KNN model incorporating socioeconomic status (SES) factors to effectively assist in patient screening and management, optimize resource utilization, and formulate preoperative surgical plans, while also predicting postoperative length of stay (LOS) [16]. This greatly helps hospitals predict and develop rehabilitation plans for each patient.

3.3. Exoskeleton and auxiliary equipment in rehabilitation

The exoskeleton device, which combines wearable sensors with AI control algorithms, can identify the user's movement intention in real time and adjust the size of the assistance, thus achieving active rehabilitation training. This technique is especially suitable for patients with paralysis and severe motor dysfunction. By controlling based on electromyography (EMG) signals, exoskeleton devices can help patients reshape neuromuscular connections and promote motor function recovery. The real-time prediction and adjustment function of AI model makes the training more personalized, and can dynamically adjust the training strategy according to the needs of patients to improve the rehabilitation effect.

Typically, the use of exoskeleton devices requires the loading of efficient real-time algorithms. They typically demonstrate higher accuracy and F1 scores, metrics commonly used to evaluate model performance. Algorithms can be categorized into two types: traditional machine learning methods represented by the random forest algorithm, and deep learning algorithms represented by artificial neural networks. Traditional machine learning methods have shown good performance in wearable motion recognition. Leng Hansong et al. applied the random forest algorithm to human gait recognition. By analyzing the voltage waveform and peak value of the collected signals and establishing a model, they could accurately identify whether a person was running or walking [17]. The model developed by Karam Kumar Sahoo and colleagues was designed to accurately classify daily human activities. After feature extraction, the classification of the optimal feature set was performed using a K-nearest neighbors (KNN) classifier. In evaluations across various datasets, the F1 scores reached 0.94,0.93, and 0.93 [18]. It can be seen that these traditional methods are highly accurate and reliable in identifying and classifying problems, and can be applied to process information of common wearable devices, such as spectral image information and electrical information. In summary, traditional machine learning methods are still worth using for wearable devices.

The representative of deep learning algorithm is artificial neural network, which imitates the working mechanism of the human nervous system, stacks neurons layer by layer, and simulates the processing mode of human thinking. This structure gives the neural network the ability to automatically learn and extract features. In deep learning, features usually refer to representations extracted from input data that have an impact on prediction or classification results. Each feature reflects an aspect of the data, and through the multi-layer processing of the neural network, the model can gradually abstract high-level features that are helpful for the task from simple to complex. Therefore, one of the advantages of deep learning technology is the automatic learning of features, which avoids the tedious process of manual feature extraction in traditional machine learning. The limitation of traditional machine learning algorithms is that they require a large amount of time-consuming manual extraction of features. In contrast, deep learning techniques are better suited for classifying complex human behaviors because they can automatically learn features from data. Shibo Zhang et al. demonstrated that deep learning approaches outperform traditional machine learning methods in human activity recognition (HAR). Compared with rigid classical models, neural networks can adjust parameters more flexibly and adapt to different application scenarios [19]. At the same time, because the neural network is constructed layer by layer, it is easier to be improved than other kinds of algorithms. It only needs to replace different layers or stack and arrange them, so as to alleviate the problems of gradient disappearance and gradient explosion, and further improve the effect of the model. For instance, Ravi Kumar Athota et al. proposed the Convolutional Memory

Fusion Algorithm (CMFA), which employs the ReLU activation function and adds a 0.1 dropout layer after the third Conv1D layer [20]. The ReLU function helps mitigate gradient explosion, while the dropout layer prevents overfitting by randomly disabling neurons, thereby enhancing the model's generalization performance. Obviously, neural networks are adjustable. By flexibly adjusting each layer, it is easier to get a better performing model.

3.4. Multimodal Information Fusion Technology for Wearable Devices

In the rehabilitation application of wearable devices, the quality and accuracy of data directly affect the rehabilitation effect. One-dimensional data sources often fail to fully reflect the patient's motion status, especially in complex and difficult rehabilitation training. Therefore, multimodal information fusion technology has emerged. The combination of different types of data often contains more effective features, providing more comprehensive and rich input for AI models, so as to improve the accuracy and reliability of motion recognition and rehabilitation feedback. Multimodal information fusion technology combines data sources from different sensors, such as images, sounds, electromyography (EMG), pressure sensing, acceleration, and angle sensing, which can be analyzed and understood from different angles to analyze and understand the patient's movement patterns and rehabilitation status. For example, Wang's team significantly improved the accuracy of human gesture recognition by combining visual data (such as camera images) and motion sensing data (such as stretchable strain sensors made of carbon nanotubes) [21]. This shows that it is often difficult for single-mode data to fully capture the dynamic state of patients, and multi-modal data fusion can effectively supplement the shortcomings of each sensor and improve the comprehensive judgment ability of the model. For instance, the Riera team developed a pressure detection fusion system that achieved only 79% classification accuracy when trained exclusively on EEG datasets. After integrating EEG and EMG data with the fusion tree structure, the average accuracy of pressure detection can reach more than 97%, which indicates that even in the case of poor data set or more noise, the data fusion technology can effectively extract features and improve the prediction accuracy [22]. Furthermore, Wang's team demonstrated that combining visual data (e.g., camera images) with motion data e.g., stretchable strain sensors significantly improved gesture recognition accuracy compared to using a single data type [21], as shown in Figure 1. This further proves the importance of multimodal data fusion, which can extract more useful features from multiple sensors to improve the overall recognition effect. Clearly, in addition to image information processing, other types of data are also critical to the functionality and performance of wearables.

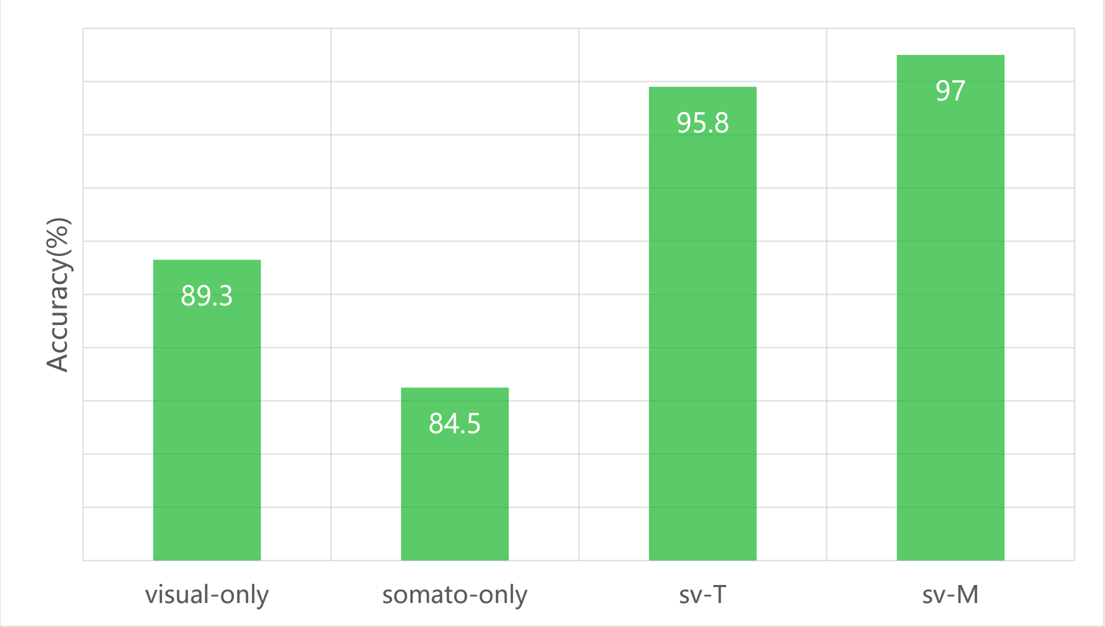

Fig 1. Fused vision and sensor data

In the multimodal information fusion technology of wearable devices, different algorithms or models perform differently. Therefore, it is also important to select the appropriate model to adapt to the processing of multimodal information. As Xiao Kai et al. have noted, numerous algorithms such as LDA and ANN (artificial neural networks) have demonstrated strong predictive performance. However, their optimal data characteristics vary slightly across algorithms. For example, SVM is particularly effective for handling small sample sizes and high-dimensional nonlinear data [23]. Therefore, according to the characteristics and adaptability of different algorithms, the selection of the most suitable algorithm for optimization is the key to improving the application effect. In the application of multimodal data processing, model selection often depends on the characteristics of the data and the type of equipment. For instance, R. San-Segundo et al. compared features from traditional hand-designed methods with those extracted by convolutional neural networks (CNNs), and applied hidden Markov models (HMMs) and long short-term memory networks (LSTMs) for activity classification. The evaluation results indicate that the LSTM model outperforms in smartphone-based activity recognition (HAR) applications, while the HMM model demonstrates superior performance in smartwatch HAR scenarios [24]. This discovery shows that testing and selecting the best algorithm according to different application environments is an effective way to realize efficient multimodal information fusion. Another optimization idea is to improve the existing algorithm. With the increasing requirements, the original algorithm can not meet the requirements of multimodal information processing. Therefore, further improvement of the algorithm is an important direction of optimization application to improve its performance. Common strategies include the fusion of different algorithms, or the addition of features from other algorithms. For example, Zhao Ju et al. employed Long Short-Term Memory (LSTM), a time-recurrent neural network, by implementing three types of gating mechanisms. This approach effectively resolved the gradient explosion or vanishing gradient issues in traditional recurrent neural networks, achieving over 97% accuracy [25]. The scheme fully combines the advantages of threshold method and deep learning method, and has different individual adaptability, eliminating the disadvantage of single threshold method, which has a relatively high false alarm rate due to the inaccuracy of manual extraction of features. MST. ALEMA KHATUN and colleagues developed a depth CNN-LSTM self-attention network model for wearable sensors integrating triaxial accelerometers, gyroscopes, and linear accelerometers, achieving 98.76% and 93.11% classification accuracy on the MHEALTH and UCI-HAR datasets respectively. It not only effectively reduces the dependence on traditional machine learning techniques and avoids the limitations of manual feature extraction process, but also achieves the same effect as other sensors such as global positioning system (GPS) or pressure sensor [26]. The CNN-GRU hybrid model proposed by Saurabh Gupta et al. combines a one-dimensional convolutional neural network (CNN) with a gated recurrent unit (GRU), where the output of the previous layer is processed and then fed into the next layer. The results are shown in the following Table 2. Compared with other models, the hybrid model has higher accuracy whether applied to smartwatches or smartphones [27]. It can also extract spatial and temporal features from the original sensor data of different modes at the same time, so as to effectively identify complex human activities such as eating, drinking, brushing teeth and dribbling.

Table 2. Model comparing

model	Smartwatch (accuracy)	Smartphone (accuracy)
CNN-GRU	96.54%	90.44%
Inception Time	95.79%	88.50%
LSTM	87.65%	75.31%

In conclusion, the hybrid algorithm is a very effective strategy, which can overcome the limitations of a single algorithm and significantly improve the accuracy of the model. By combining the advantages of different algorithms, the hybrid model can better deal with complex multimodal data and further improve the effect of prediction and classification.

4. Conclusion

Compared with traditional wearable rehabilitation devices, AI-assisted wearable devices show significant advantages in the field of rehabilitation. Different from traditional rehabilitation methods that rely on manual evaluation and fixed training programs, AI technology can provide personalized and continuous training programs. Through accurate tracking, intelligent analysis and real-time feedback, AI can dynamically adjust the rehabilitation plan according to the actual situation of the patient, which significantly improves the training effect and efficiency. Unlike traditional rehabilitation methods that rely on manual assessment and fixed training programs, AI-assisted wearables can adapt to changes in the patient's condition in real time, providing a more flexible and accurate rehabilitation path. Although these devices are expensive, they are able to collect a variety of physiological data that is difficult for visual AI to access, providing more comprehensive support for the patient's rehabilitation process.

While AI-assisted wearables have great potential in the field of rehabilitation, there are still some challenges. First, data privacy issues need to be addressed, as these devices need to collect sensitive health information about patients, and ensuring secure transmission, storage and processing of data is key to their adoption. Second, although AI models perform well in a laboratory environment, their ability to generalize across different patient groups still needs to be improved, especially in complex rehabilitation situations. In addition, the comfort of the device and the long-term compliance of the patient are still a problem to be solved. The comfort and ease of use of the device will directly affect the wearing time of the patient and the treatment effect. Future trends include the combination of flexible electronics and multimodal data fusion to develop lighter, more portable devices to improve patient wearability and compliance. At the same time, with the continuous progress of deep learning and multimodal data processing technology, AI-assisted wearable devices will become more and more personalized, able to provide customized rehabilitation programs, and further improve the effect of rehabilitation. Ongoing clinical validation and optimization will also drive the use of these devices in rehabilitation therapy and health management, ensuring that they provide a safer, more scientific and continuous rehabilitation experience.

In conclusion, AI-assisted wearables have great potential to revolutionize rehabilitation by providing patients with more scientific and personalized rehabilitation paths. Despite current challenges such as data privacy, algorithmic generalization, and comfort, these devices will play an increasingly important role in improving patient rehabilitation efficiency and quality of life as technology advances and clinical applications deepen.

Authors'Contributions

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

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