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INNOVATIVE APPLICATIONS OF MULTIMODAL SENSING TECHNOLOGY IN SPORTS REHABILITATION ASSESSMENT AND TRAINING

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Abstract. This study explores an innovative approach to evaluating the training effectiveness of lower limb exoskeleton robots by integrating multiple data types, including electrophysiological signals and kinematic measurements, to assess patients' walking ability quantitatively. Through precisely defined synergistic indicators, this method effectively combines different types of data and dramatically improves the efficiency and accuracy of rehabilitation assessment. First, the patient's lower extremity electro myoelectric activity and movement data were recorded while walking with exoskeleton assistance. Secondly, the key EMG and kinematic features are analyzed and extracted by a collaborative quantization algorithm based on the theory of muscle cooperative work. Then, this information from different levels is integrated to build a feature fusion model, based on which the lower limb motor function score is calculated. The development of multi-channel lower limb exoskeleton human-computer interaction technology for sports training can provide a variety of standardized and standardized auxiliary training for athletes and meet the human body's multi-sensory immersion. A multi-step, multi-degree-of-freedom motion planning algorithm is proposed to reproduce various activities the human body requires. Secondly, the lower extremity-oriented multi-modal human-computer interaction technology is studied to realize the display and guidance of standard movement in information space on the virtual reality competition training simulation platform. Build a motion database to assist and correct basic motion in physical space. The experimental results showed a significant correlation between the extracted myoelectric and kinematic synergistic features and the clinical evaluation tools, with the correlation coefficients reaching 0.832 and 0.859, respectively. The fusion features show a stronger correlation when applying the K-nearest neighbor (KNN) algorithm. This evaluation method cannot only optimize the training strategy of the exoskeleton robot according to the results but also provide the possibility to realize the "man in the ring" mode of evaluation and training simultaneously.

Key words: Rehabilitation assessment; Muscle coordination; Mode fusion; Machine learning; Stroke; Multimodal sensing technology.

1. Introduction. With an aging population and increasing incidence of chronic diseases, lower limb dysfunction has become a severe challenge in the field of global public health. Lower limb rehabilitation is related to individual quality of life and is an essential part of the rational allocation of social medical resources. Traditional rehabilitation assessment and training often rely on the experienced judgment of professionals and a single assessment means, which limits the accuracy and individuation of rehabilitation effects. Therefore, exploring more scientific and efficient lower limb rehabilitation assessment and training methods has become one of the hot spots in rehabilitation engineering.

The development of multimodal sensing technology provides a new opportunity to solve this problem. Multimodal sensing technology refers to integrating a variety of sensors, such as electromyography (EMG), accelerometer, gyroscope, pressure sensor, etc., to capture the electrophysiology, kinematics and dynamics of the human body simultaneously. This technology can provide more prosperous and detailed data in time and space to achieve a more comprehensive and in-depth understanding of the human movement function. In lower limb rehabilitation, applying multi-modal sensing technology can realize the accurate and quantitative assessment of patients' walking ability and provide a scientific basis for developing personalized rehabilitation training plans.

The paper [1] shows that EMG based on a single pathway can automatically evaluate the degree of damage

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in stroke patients and produce quantitative grading indicators corresponding to clinical scores. The researchers developed a portable exercise test bed. A comprehensive evaluation method of upper limb motor function was constructed by using an extreme learning machine. This method is suitable for clinical and home environments. In the paper [2], a neurorehabilitation evaluation method was constructed using the surface EMG signal of limbs. The paper [3] puts forward a new idea of quantitative evaluation of motor function using a mechanical arm's strength and trajectory characteristics. The research results will enhance the effectiveness and credibility of rehabilitation evaluation, expand its scope of application, and promote the broad application of rehabilitation robots. In addition, due to the rapid development of computer science and technology in recent years, machine learning has been paid more and more attention [4]. Current research on action evaluation based on machine learning usually divides behaviors into two categories: right and wrong. The result is only 0 or 1. This method can only be qualitatively described, unable to achieve a quantitative analysis of movement quality at each level and unable to identify incremental changes in patients' imagination. Moreover, the modeling process is relatively complicated, requiring specific training samples.

This project intends to research multi-source sensing data fusion of lower limb exoskeleton systems. In this project, real-time acquisition of lower extremity surface electromyography and movement information was carried out. Then, the patient is comprehensively evaluated from various aspects, such as movement and electrophysiology, to guide individual rehabilitation exercises and carry out guided rehabilitation exercises for the patient. A multi-step, multi-degree-of-freedom motion planning algorithm is proposed to reproduce various activities the human body requires [5]. Secondly, the lower extremity-oriented multi-modal human-computer interaction technology is studied to realize the display and guidance of standard movement in information space on the virtual reality competition training simulation platform. Build a motion database to assist and correct basic motion in physical space. Study the relationship between evaluation criteria and scale [6]. Finally, the score data are imported into the data fusion model to obtain the score of the machine test. The research results of this project will lay a foundation for applying the lower limb exoskeleton robot in stroke.

2. Lower limb exoskeleton multi-modal interaction system.

2.1. System Architecture. This project draws on the next generation of information-physical fusion technology (HCPS) to study the multi-modal interaction technology for the human body. In this process, the communication between man and machine and the control of the path is required, and it is required to accurately understand and implement the person's intention [7]. At the same time, it can meet the purpose of efficient information transmission and feedback. Under the background of the rapid development of the new generation of information technology, the digital intelligent technology represented by virtual reality and extended reality has laid the foundation for optimizing man-machine collaboration. Compared with the traditional CPS, the new generation of urban health management is a human-centered ternary system [8]. Its goal is to achieve cooperation and co-prosperity and guide the improvement of work efficiency. Figure 2.1 depicts the hierarchical structure of HPCS (image cited in A Triple Human-Digital Twin Architecture for Cyber-Physical Systems). It controls the entire physical system by sensing the user's presence, views and behaviors. The information system is added to the human-computer interaction process through the interactive cycle of pedestrian, information, and entity models. In this way, the profound combination of the trinity of "man-machine-thing" is gradually achieved.

2.2. System Functions. This project will study human-machine integration technology for lower limbs. It consists of three modules: a virtual reality simulator, a motion database, and a lower limb exoskeleton (Figure 2.2). Establish the information interaction model between the human endoskeleton and VR. The combination of reality and virtual provides more realistic movement training guidance for the human body to improve the training effect. The general applicability of the system is improved by collecting 4 motion nodes and transforming them into the limb movement of the training object [9]. The lower limb exoskeleton robot proposed in this project has the advantages of a simple structure, good adaptability and a flexible response mechanism. It can provide a variety of force feedback methods for all kinds of moving objects. The virtual body controller of the upper computer and the actual model of the lower limb exoskeleton robot arm of the slave foot constitute the whole control system. It mainly includes a virtual reality competitive training simulator and action data set design. Through the detection of virtual objects, the trajectory information of virtual objects

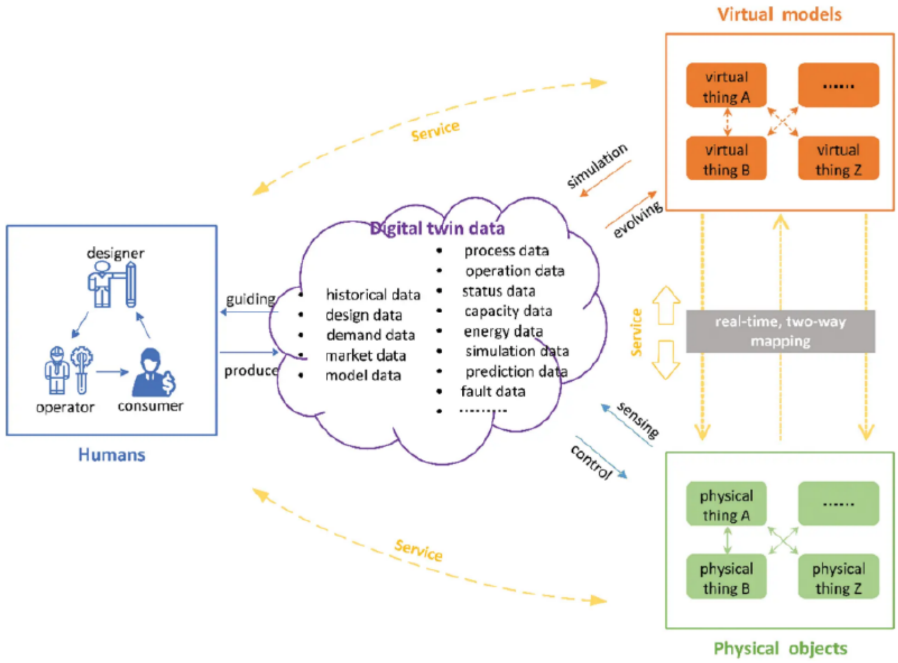

Fig. 2.1: *Human-information-physical system structure.*

is fed back to the actuator [10]. Then, the lower limb exoskeleton robot is supported by force perception, and VR simulators enhance the vision and hearing so students can obtain standardized and immersive exercise experiences in movement training.

Students wear an exoskeleton robot, virtual reality headset and motion capture tracker, and follow the instructor to do basic movements in virtual reality. Students can complete the standard sports training according to their own wishes through pre-programmed programming in the virtual simulation system. The lower limb exoskeleton robot arm adopts a force feedback device to realize the dynamic perception of the body [11]. The system ensures the standardization of the body and improves the training effect. The system helps students carry out basic competitive sports training using multi-sensory information such as vision, hearing and touch.

2.3. System Hardware. The system hardware completed the pressure feedback, including the motor drive and vibration two-force feedback. The hardware control scheme is given in Figure 2.3. The system comprises an STM32 development board, HC-05 Bluetooth module, MPU6050 module, vibration motor, EPOS drive, MAXON-Re35 motor, etc.

The athletes' hearing and force perception are enhanced by VR technology and lower limb exoskeleton technology. A method based on motor drive and vibration feedback is proposed to realize multi-mode human-computer interaction [12]. The first is to set the relevant parameters, and then put on the robotic arm and helmet on the leg. The Angle marker sensor is used to track the movement of the current trainer. The current motion orientation of the trainer and the changed reference motion orientation are determined. Figure 2.4 shows the multi-modal interactive execution process of the lower extremity exoskeleton.

3. Quantitative method of lower limb movement based on muscle synergy theory.

3.1. Muscle collaborative extraction. Muscle coordination, as an optimal central regulation mode, is clinically significant for recovery after a stroke. Studies have shown a high degree of consistency in healthy people's coordination of body movements [13]. This project seeks the mechanism of muscular coordination as universal neuromuscular coordination and to provide the temporal characteristics of the active-induced sEMG quantified muscle coordination. The existing decomposition methods mainly include factor analysis,

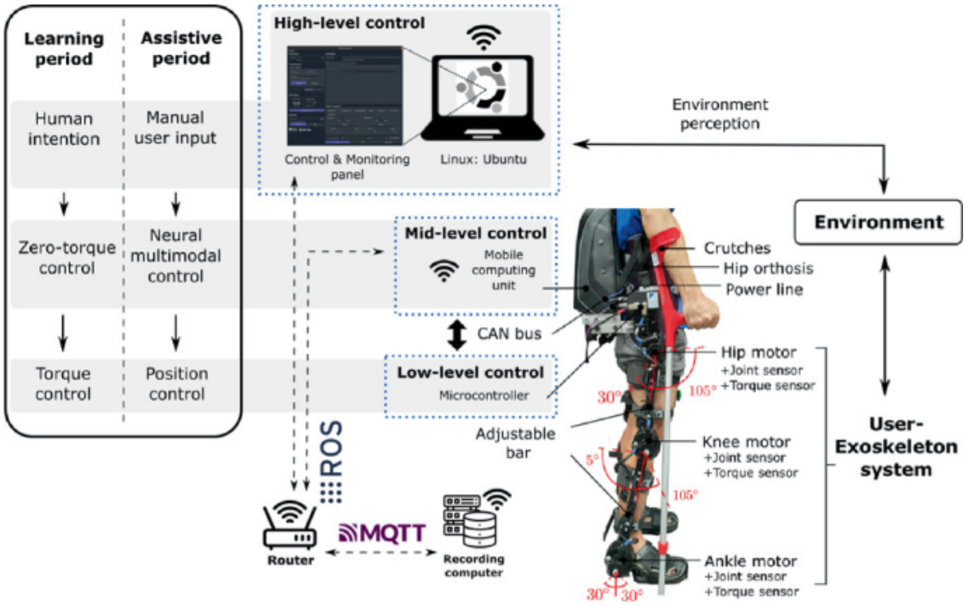

Fig. 2.2: *Framework of multi-modal interaction system for lower extremity exoskeleton.*

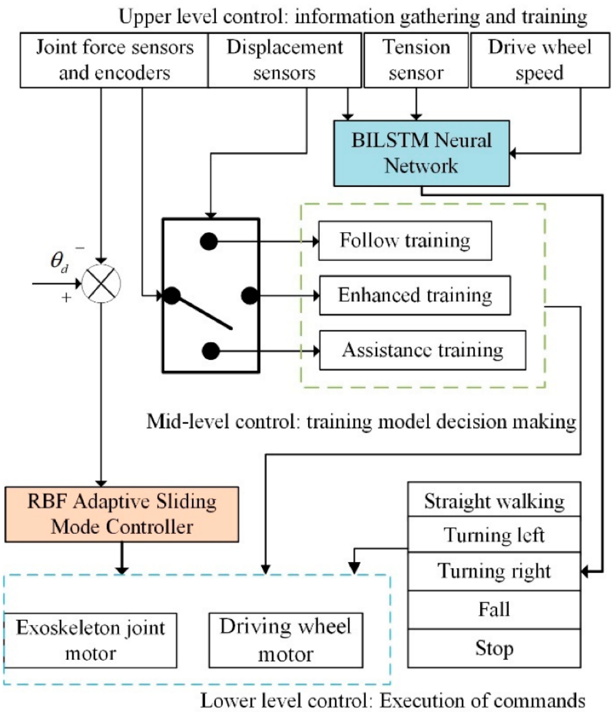

Fig. 2.3: *Hardware control block diagram of lower extremity exoskeleton multi-mode interaction system.*

non-negative matrix decomposition, principal component analysis, etc., which decompose multi-channel sEMG data and obtain fewer samples with high characterization ability. The basic mathematical model of code

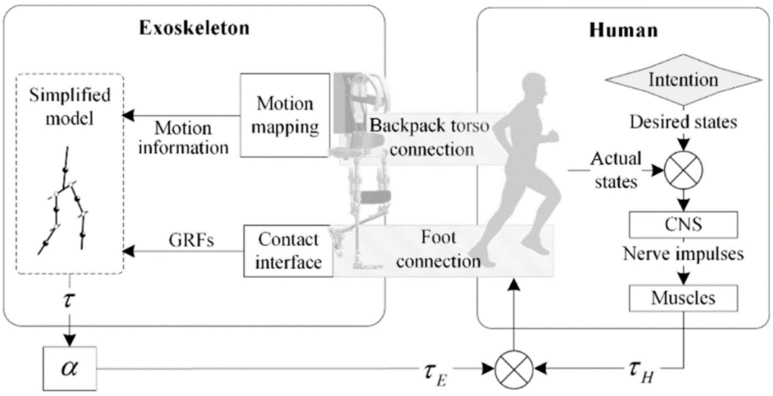

Fig. 2.4: *Multi-modal interactive execution flow.*

composition is expressed in formula (3.1):

$$Y_{n\cdot\tau}=R_{n\cdot\lambda}\times J_{\lambda\cdot\tau}=[R_1,R_2,\cdots,R_\lambda]\times[J_1,J_2,\cdots,J_\lambda]^T=\sum_{i=1}^{\lambda}R_iJ_i+D \tag{3.1}$$

It is known that the matrix $Y_{n\cdot\tau}$ can be divided into two parts: one is the coordination unit $R_{n\cdot\lambda}$, and the other is the excitation factor $J_{\lambda\cdot\tau}$. Where D is the error matrix that can be ignored. Where n represents the number of channels, τ represents the number of samples, λ represents the number of cooperative elements, T represents the exchange number, and i represents the number of matrices.

The traditional joint extraction method uses matrix decomposition to map the original sample to the lower dimension while maintaining the characteristic. Principal component analysis (PCA) is a typical feature extraction method based on probability distribution, which can effectively deal with samples containing redundant information [14]. It has significant application value in pattern recognition, machine vision, etc. By solving A linear orthogonal transformation of R matrix, the obtained data U is converted into an implicit low-dimensional matrix C :

$$C=R^TU \tag{3.2}$$

In equation (3.3), the method of obtaining each component of matrix C is expressed:

$$c_{ij}=r_i^Tu_j \tag{3.3}$$

where c_{ij} is the element of a low-dimensional matrix C, r_i is its orthogonal vector, u_j is the eigenvector, and T is the commutation sign. The loss function F is represented by the maximum value of the converted difference to obtain the orthogonal vector r_i :

$$\begin{aligned}&F=\max\frac{1}{N}\sum_{i=1}^{s}\sum_{j=1}^{N}\left(r_i^Tu_j-r_j^T\bar{u}\right)^2=\max\sum_{i=1}^{s}r_i^TBr_i\\&\text{s.t. } r_i^Tr_i=1\end{aligned} \tag{3.4}$$

where π represents the mean of u, and B represents the covariance matrix of U. The eigenvector refers to the local maximum eigenvalue on r_i. The corresponding eigenvalue δ_i and corresponding eigenvector v_i are obtained by the HSVD method, and then the orthogonal matrix $\tau\cdot\lambda$ is obtained. Here, U is the trained $\tau\cdot n$ dimension EMG signal (τ is 1 sample number of gait cycles, n is 8 channels), and R is the number of muscle coordination units in the human body (λ is the number of muscle coordination units). C is data converted to dimension $\lambda\cdot y$. The eigenvalues and eigenvectors after singular value decomposition are used to measure the similarity. When walking, the muscle group of the leg can be divided into 5 cooperative modes, so the cooperative unit λ is represented by 5 .

3.2. Collaborative Quantification. $Y = \{y_1, y_2, y_3, \cdots, y_n\}$ is the action data, where n is the number of extracted steps $y_i(i = 1, 2, \cdots, n)$, and is the data of a step. Through principal component analysis, the convector v_i, u_i is obtained, corresponding to the eigenvector δ_i, ξ_i. When two objects have similar motions in higher dimensions, their orbits should be similar. So, the sequence must also be the same when the corresponding action is similar. A joint decomposition method based on principal component analysis is proposed to realize the joint analysis of motion parameters [15]. In this way, the retrieval and classification of motion parameters are realized.

$$\mathcal{S}_i = \max_{\operatorname{din}(Z)} = \min_{a \in z} \frac{\|Bu\|_2}{\|u\|_2} \tag{3.5}$$

If two actions are similar, their conformal vectors v_1 and u_1 should be roughly parallel. There is $|v_1 \cdot u_1| = |v_1\|\|u_1\, \|\cos(\alpha) \approx v_1\|\, u_1| = 1.\alpha$ is the Angle of the two common vectors v_1 and u_1. The sEMG, and action sequences of different training segments were analyzed by weight similarity measure to evaluate patients' recovery status quantitatively.

$$\chi(A, Q) = \frac{1}{2} \sum_{i=1}^{n} \left(\left(\frac{\mathcal{S}_i}{\sum_{i=1}^{n} \mathcal{S}_i} + \frac{\eta_i}{\sum_{i=1}^{\pi} \eta_i} \right) |v_i \cdot u_i| \right) \tag{3.6}$$

Where n is the eigenvalue number, A is the baseline data set by the reference control group, and Q is the patient data. $\mathcal{S}_i, \eta_i$ is the i eigenvalue of the reference and experimental data. It corresponds to the i-cooperation vector v_e, u_i. In this way, only the convectors of the two action matrices and their corresponding eigenvalues are obtained without the influence of other action information [16]. The algorithm can capture the similarity between λ conformal vectors and use corresponding eigenvalues for weight calculation. χ is in the range from o to 1 . The closer it is to 1 , the better the patient fits the control group.

3.3. Modal fusion evaluation model. The most significant difference in each stage is the cooperation mode and the movement mode of each independent part. It focuses on gradually transforming the overall rehabilitation process to a standard and complex movement mode to achieve the brain reassembly effect [17]. This method is challenging to detect if a single sensor is used for detection, so additional characteristics are needed to classify each specific action more deeply. A joint coordination vector G_i is constructed to verify the practicality of this collaboration feature, expressed by the following formula (3.7)

$$G_i = [D_i, \cdots, D_n, \Lambda_i, \cdots, \Lambda_n] \tag{3.7}$$

Where D_i is the neurophysiological characteristic of cooperation, Λ_i is the motor coordination characteristic, and n is the number of cooperative characteristics. A predictive score Z_i for the patient's lower limb recovery can be obtained using a guided machine-learning model:

$$Z_i = I\left(G_i\right) \tag{3.8}$$

The KNN method is used to train 5 neighbors. The eigenvalue space U is defined as an n-dimensional vector space of real numbers $(u_i, u_j) \in U, u_i = \left(u_i^{(1)}, u_i^{(2)}, \cdots, u_i^{(n)}\right), u_j = \left(u_j^{(1)}, u_j^{(2)}, \cdots, u_j^{(n)}\right)$ .H is expressed as a function of the distance of (u_i, u_j). Using the formula (3.9) in Euclidean geometry:

$$H\left(u_i, u_j\right) = \left(\sum_{i=1}^{a} \left| u_i^{(i)} - u_j^{(n)} \right|^2 \right)^{\frac{1}{2}} \tag{3.9}$$

Here l is the dimension of the eigenspace U. The least squares support vector machine is regarded as a multi-layer feedforward neural network whose training model comprises 130 neurons. The quasi-Newton algorithm is used to optimize the weights and deviations, and the convergence efficiency of the algorithm is improved. Set the maximum depth of the RF to 5 . The radiation basis function is the core of the algorithm. Where Z_{i} is the result of the pattern, and does the evaluation value correspond to the result of the pattern, it is more detailed than the conventional category evaluation. From the 6 people, 60 cases were selected as experimental samples, and the other 4 cases were used as test data.

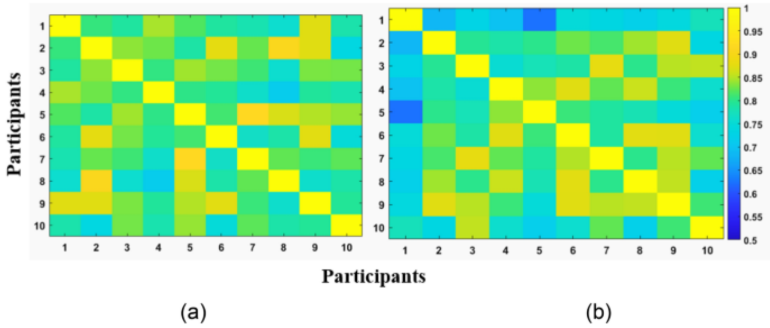

Fig. 4.1: *Weight comparison of synergies between healthy subjects and patients.*

4. Test results and analysis.

4.1. Comparison between healthy subjects and patients. The collaborative element weights of the healthy and patient sides were shown in Figure 4.1 for the BRS_3 stage subjects. This index ranges from o to 1 , indicating the strength of muscle activity from large to small. Due to the contraction of local muscles after stroke, the local myoelectric activity is reduced, so the weight of the affected limb is generally lower than that of the healthy side [18]. However, in the BRS_3 stage, the activation weight of the affected area of the left ventricle was significantly higher than that of the healthy area. This is due to increased limb strength caused by muscle spasms in the left ventricle.

The moving sample size tables BRS6 and BRS3 taken from the patient are shown in Figure 4.2. Patients in the BRS6 stage can walk independently, and their indicators are comparable to those of ordinary people. However, BRS3 stage patients often have instability due to limb pain and decreased ability to control movement. In particular, weakness of the hip flexors can significantly reduce the range of motion of the hip joint. The affected knee cannot fully flex and extend during both the upright and the rocking phases due to the weak flexor muscles of the knee flexor tendon, which prevents it from achieving normal hip flexion during both the upright and the rocking phases. Under normal circumstances, the maximum bending of the patient's foot occurs at the beginning of walking, but the degree of bending of the patient's knees is small, resulting in the patient's feet not being lifted from the ground. In addition, because the patient cannot fully lift the front ball of the affected side during the rocking phase, the initial contact appears to be on the flat ball of the foot rather than the heel.

The flexion and extension motion of the affected upper limb decreased significantly in the swaying period, and due to the lack of lower limb muscle strength, it could not independently complete its weight when standing. By studying sEMG and joint Angle, the cause of the limited range of limb movement after stroke. Grade 3 patients, due to their limited joint flexibility, will produce muscle convulsions and other symptoms, so their movements often end prematurely or deviate. The above two points can more directly reflect the shortcomings of patients in lower limb movement.

4.2. Research on the characteristics of the cooperation index.. The paper divided 10 patients into 4 different BRS stages. In Figure 4.3, there are significant differences in the characteristics of the joint index among patients with various BRS stages. Among them, the collaborative characteristics of SEMG appear more in Stage 6 and Stage 3. The S7 muscle twitching was more severe in BRS5 patients, so the cooperative properties of sEMG were very different from normal controls, with two abnormal values. During the same period, the data of the movement index were relatively stable. In terms of movement parameters, the data distribution of patients with the BRS3 stage is very different, and the variation is considerable compared with the average population, mainly because the symptom of patient S6 is that he is unable to speak in the right limb, and because his disease has only been over one month, there are a small number of movement samples. BRS3 stage patients have severe sports injury and spasmodic muscle tonia, and their motor and electromyographic coordination index is lower than usual. However, since the standard deviation of BRS6 stage patients was significantly lower than that of 3-5 stage patients, both sEMG and motor coordination index were relatively

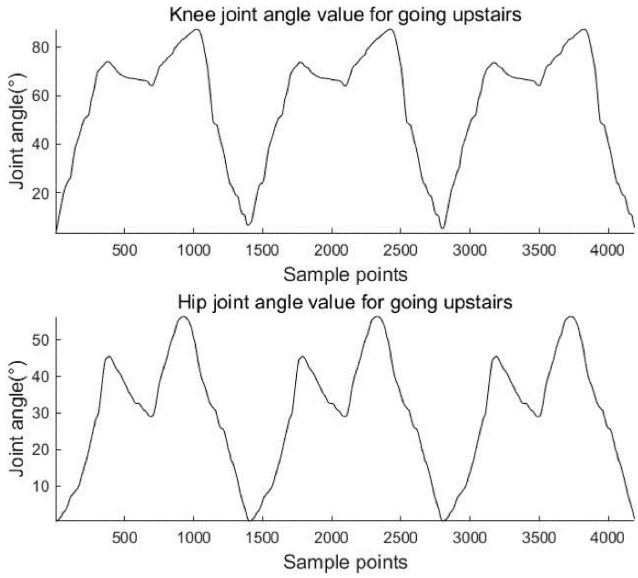

Fig. 4.2: *Comparison of subjects' lower extremity angles.*

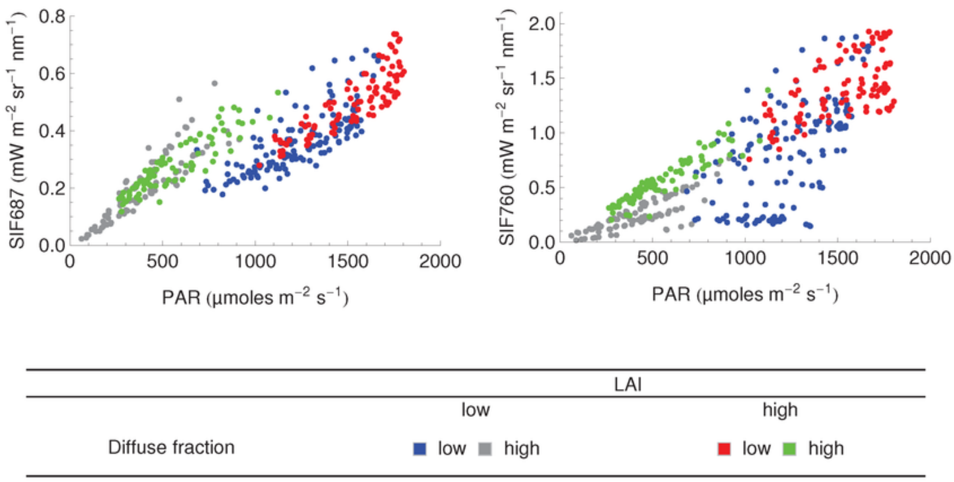

Fig. 4.3: *Data distribution of BRS staging coordination index.*

stable, suggesting that the muscle control function and Angle curve of BRS6 stage patients were relatively stable when walking.

5. Conclusion. This paper intends to construct a set of collaborative feature-based walking function assessment methods for stroke patients and combine this assessment method with BRS scale grading to verify the correctness of this method. Studies have shown that this scale is highly correlated with the conventional BRS scale. The research results can improve the accuracy of clinical evaluation and help update the motion trajectory of the lower limb exoskeleton in real time based on evaluation data. From the clinical level, the evaluation system proposed in this study can better meet the needs of newly admitted patients, provide evaluation indicators for newly admitted patients, and shorten the evaluation cycle of rehabilitation doctors. The research results of this paper provide a basis for rehabilitation doctors to make a reasonable rehabilitation plan.

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