

# An Intelligent Rehabilitation Assessment Method for Stroke Patients Based on Lower Limb Exoskeleton Robot

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**Abstract**—The 6-min walk distance (6MWD) and the Fugl-Meyer assessment lower-limb subscale (FMA-LE) of the stroke patients provide the critical evaluation standards for the effect of training and guidance of the training programs. However, gait assessment for stroke patients typically relies on manual observation and table scoring, which raises concerns about wasted manpower and subjective observation results. To address this issue, this paper proposes an intelligent rehabilitation assessment method (IRAM) for rehabilitation assessment of the stroke patients based on sensor data of the lower limb exoskeleton robot. Firstly, the feature parameters of the patient were collected, including age, height, and duration, etc. The sensor data of the exoskeleton robot were also collected, including joint angle, joint velocity, and joint torque, etc. Secondly, a gait feature model was constructed to deduce the walking gait parameters of the patient according to the sensor data of the exoskeleton, including the support phase to swing phase ratio, step length and leg lift height of the patient, etc. Then, the 6MWD and FMA-LE values were collected by traditional methods, feature parameters, gait parameters and human-machine interaction parameters

(joint torque) of the patient were adopted to train the rehabilitation assessment model. Finally, the assessment model was trained by a machine-learning based algorithm. The new stroke patients' the 6MWD and FMA-LE values can be predicted by the trained model. The experimental results present that the prediction accuracy for the 6MWD and FMA-LE values reach to 85.19% and 92.66%, respectively.

**Index Terms**—Intelligent rehabilitation assessment, 6MWD, FMA-LE, lower limb exoskeleton robot, machine learning.

## I. INTRODUCTION

STROKE is one of the top three causes of death worldwide and a leading cause of adult disability [1]. Studies have proved that up to 90% of the stroke patients have some kind of dysfunction, with motor dysfunction highly prevalent [2]. Asymmetric gait patterns, lower limb spasticity on the hemiplegic side, impaired ability to stand and shift center of gravity are observed in most of the stroke patients, thereby limiting their walking ability. 65% to 85% of the patients can regain basic walking ability within 6 months after stroke through early rehabilitation training [3].

With the development of exoskeleton technology, therapists are gradually replaced by robots in the rehabilitation training process. Upper limb exoskeleton robots have been adopted in rehabilitation training of the stroke patients [4], [5]. And several lower limb exoskeleton robots have been developed to promote gait rehabilitation for the patients, such as LOPES [6], Lokomat [7], WalkTrainer [8] and ALEX [9]. Moreover, some exoskeleton robots such as Indego [10], HAL [11], Exo [12] and BEAR-H [13], have been routinely adopted in hospitals and for individual patient.

Rehabilitation assessment is an important link to evaluate the training effect and guide the formulation of training programs [14]. Correct rehabilitation assessment provides guidance and help therapists formulate rehabilitation training process for the patients, so as to shorten their recovery procedure. Clinically, 6-min walk distance (6MWD) [15], [16] and Fugl-Meyer assessment lower-limb subscale (FMA-LE) [17], [18] are important measurements and reference indicators for evaluating the actual rehabilitation status of the stroke patients. 6MWD is the test that records the distance a patient walks in 6 minutes. The measurement process requires not only the cooperation of multiple therapists and medical

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of the First Affiliated Hospital of Nanjing Medical University under Application No. 2019-MD-43.

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staffs, but also a large area of space for a long time [19]. The traditional 6MWD measurement wastes vast manpower and resources of the hospital, which brings negative affects to the rehabilitation training of other patients. For the FMA-LE process, the patients are asked to complete the prescribed movements in turn. The therapist observes and scores the patients according to the difficulty of completing the movements. A certain subjectivity in the scoring process causes a negative impact on standardization [20]. Due to the subjective bias, therapists could obtain different assessment results and different rehabilitation plans for the same patient. Therefore, it is expected to propose a standard, convenient and effective method for intelligent rehabilitation assessment for the stroke patients.

Assessing patients' rehabilitation via exoskeleton is a convenient, efficient and economical approach with the relative technology being gradually applied in patients' rehabilitation training. Lu et al. [21], proposed an unsupervised learning approach to identify key features affecting the rehabilitation process of the stroke patients based on the data collected by rehabilitation robot sensors. Lee et al. [22], developed the Harmony upper limb rehabilitation exoskeleton to measure the arm and shoulder angles accurately. The accurate measurement of angles brings the exoskeleton the ability not only to perform rehabilitation training, but also to monitor training progress and improve the training efficiency. Grimm et al. [23] demonstrated the feasibility of effective assessment of upper limb range of motion for the severely impaired stroke patients by applying independent assessment of single joint motion via exoskeleton in clinical trials. Ding et al. [24] proposed a quantitative assessment system based on force feedback and machine learning algorithm for the rehabilitation robot, which provides refined and quantitative assessment for the wrist motion function of the stroke patients. In conclusion, it is feasible to evaluate the rehabilitation of the patients via sensor data on robotics. However, there is no case about direct rehabilitation assessment of the patients using exoskeleton robot in the field of lower extremity rehabilitation.

This paper presents a novel intelligent rehabilitation assessment method (IRAM) for the stroke patients based on lower limb exoskeleton robot. Firstly, the feature parameters of the patients were collected, including age, height, hemiplegic side and duration (in days). Secondly, the gait feature model was constructed based on the data collected by the sensors when the patient was training with the exoskeleton robot. The gait feature model deduces the gait parameters of the patient, including the support phase to swing phase ratio, step length and leg lift height, etc. Then, according to feature engineering, the main features that affecting 6MWD and FMA-LE values were analyzed and selected from the collected parameters of the patients, such as feature parameters, gait parameters and human-machine interaction parameters (joint torque). Finally, a machine learning algorithm was adopted to train a rehabilitation assessment model to predict the 6MWD and FMA-LE values of the stroke patients. With the proposed method, the 6MWD and FMA-LE values of a new stroke patient can be predicted by the robot as the patient walking smoothly on a flat surface for 30 seconds wearing the lower

limb exoskeleton. 66 stroke patients participated in the clinical trial, the prediction results by the robot were compared with the results collected in the clinical trials to verify the feasibility and effectiveness of the method.

This paper is organized as follows. In section II, we introduce the method of the IRAM. In section III, the experimental results for the rehabilitation assessment prediction using the IRAM will be presented. The discussion will be presented in section IV, and the conclusion will be drawn in section V.

## II. METHOD

The structure of the IRAM is presented in Fig. 1, which contains the following modules. 1) Data acquisition module. It collects and preprocesses patients' body feature parameters, sick condition and biomechanical parameters of motion. 2) Feature extraction module. A gait feature model is constructed to deduce the gait parameters of the patient based on the collected sensor data of the exoskeleton robot. 3) Model training module. XGBoost machine learning algorithm was adopted to train the rehabilitation assessment model based on the patients' feature parameters, gait parameters and human-machine interaction parameters. 4) Model application module. The rehabilitation assessment model predicts the 6MWD and FMA-LE values of stroke patients when working in the module-assessment mode.

### A. Data Acquisition

We firstly collected the basic body feature parameters and sick condition of the patient. Including the following 7 feature parameters, gender (GR), age (AG), height (HT)  $H$ , weight (WT)  $W$ , hemiplegic side (HS), stroke type (ST) and duration (DR). Then the therapists conducted lower limb gait rehabilitation training for the stroke patients with exoskeleton under clinical conditions. Meanwhile, the 6MWD and FMA-LE values of the patients after rehabilitation training were regularly collected via traditional methods.

The exoskeleton robot collected the biomedical parameters of motion of the patients during the rehabilitation training process with the following sensors. The collection of biomedical parameters in this paper utilized 15 sensors of the BEAR-H exoskeleton, including: two pressure sensors on the feet, six angle sensors, six torque sensors, and one IMU. More detailed description about the sensors will be presented in Chapter 3.1. Prototype of the Exoskeleton Robot.

### B. Feature Extraction

The effect of IRAM is determined by the feature factors hidden in the mobility of patients. However, it is critical to extract the feature factors of the stroke patients in order to input the feature factors into the rehabilitation assessment model. The feature parameters adopted in the rehabilitation assessment model affects the accuracy of the prediction results directly. Therefore, the feature parameters determine the upper limit of the accuracy of the prediction results, while the machine learning algorithm can only approach the upper limit in various paths.

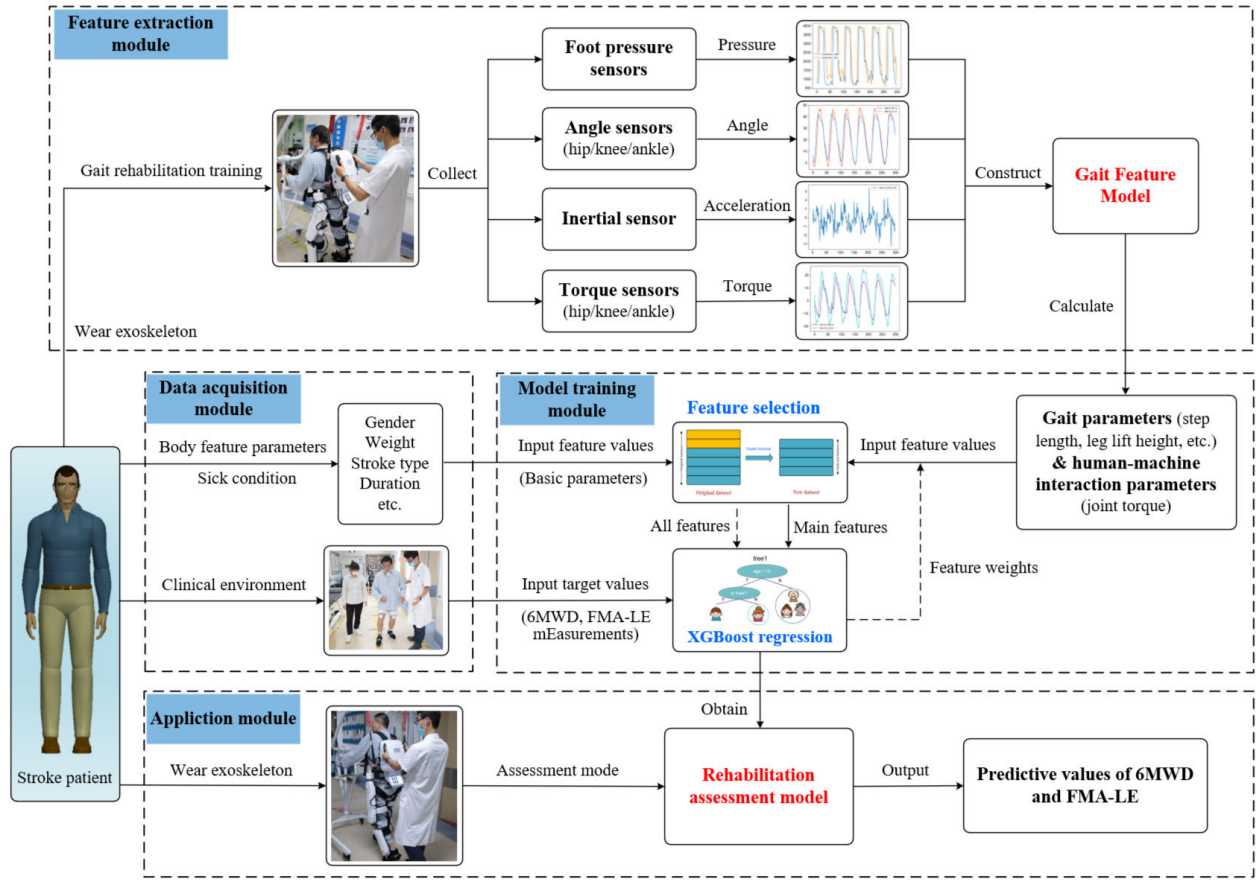


Fig. 1. Diagram of the working principle of the IRAM.

The gait feature model was constructed to calculate the feature parameters of the stroke patients during the rehabilitation training process, including the support phase to swing phase ratio, the average step length, the average leg lift height, the joint angles difference, the tilt angle and the pace, etc. The joint torque value can be used to analyze the patient's gait function and the degree of muscle recovery [25]. As shown in Table I, 42 selected feature parameters were adopted in constructing the model, including 7 (Index 1-7) basic feature parameters collected from the patients, 16 (Index 8-23) feature parameters collected by the sensors of the robot, and 19 (Index 24-42) feature parameters constructed by the gait feature model. The explanation of the following paragraphs will cover several critical feature parameters, while the rest of the parameters will be presented in Appendix.

#### 1) Construction of Parameter of the Support Phase to Swing Phase Ratio:

$$K = \frac{t_1}{t_2} \quad (1)$$

where  $t_1$  represents the time of support phase,  $t_2$  represents the time of swing phase. The ratio of the left/right side support matches with the ratio of the healthy/affected side support (HSSR, ASSR) according to the patient's specific condition.

2) Construction of Parameter of the Step Length: Step length represents the distance between two feet when standing. Step length is a critical parameter to evaluate the gait quality and stability [25]. There are significant differences of the step

length between the healthy side and the affected side of the stroke patients. Therefore, restoring the symmetry of step length is a common goal for the rehabilitation training. The feature parameter of the patient's step length is constructed by the gait model whose schematic diagram is presented in Fig. 2.

$$\begin{aligned} L_1 &= l_1 \sin \theta_1 + l_2 \sin (\theta_1 - \theta_2) \\ L_2 &= l_1 \sin \theta_3 + l_2 \sin (\theta_3 + \theta_4) \\ M &= W \cdot \sin \alpha \\ L &= L_1 \cos \alpha + L_2 \cos \alpha + M \end{aligned} \quad (2)$$

where  $l_1$  represents the thigh length of the exoskeleton robot, and  $l_2$  represents the calf length of the exoskeleton robot.  $\theta_1$  represents the angle of forefoot hip joint,  $\theta_2$  represents the angle of forefoot knee joint,  $\theta_3$  represents the angle of hindfoot hip joint, and  $\theta_4$  represents the angle of hindfoot knee joint.  $\alpha$  represents the hip joint rotation angle,  $W$  represents the hip joint length of the exoskeleton robot, and  $L$  represents the step length. The left/right step length ( $L_L$ ,  $L_R$ ) matches with the average healthy/affected step length (HSL, ASL) according to the patient's specific condition.

3) Construction of Parameter of the Leg Lift Height: There is a significant difference in the leg lift height between the healthy side and the affected side of the stroke patients. What's more, it brings a positive influence to assess the recovery situation of the patients with doing research on the change



TABLE I  
LIST OF FEATURE PARAMETERS OF THE REHABILITATION ASSESSMENT MODEL

| Index | Feature Parameters                             | Index | Feature Parameters                                                           |
|-------|------------------------------------------------|-------|------------------------------------------------------------------------------|
| 1     | Gender (GR)                                    | 22    | Right Jerk (RTJ)                                                             |
| 2     | Age (AG)                                       | 23    | Average Walking Frequency (WF)                                               |
| 3     | Height (HT)                                    | 24    | Healthy-Side Support Phase to Swing Phase Ratio (HSSR)                       |
| 4     | Weight (WT)                                    | 25    | Affected-Side Support Phase to Swing Phase Ratio (ASSR)                      |
| 5     | Hemiplegic Side (HS)                           | 26    | Average Healthy-Side Step Length (HSL)                                       |
| 6     | Stroke Type (ST)                               | 27    | Average Affected-Side Step Length (ASL)                                      |
| 7     | Duration (DR)                                  | 28    | Average Healthy-Side Leg Lift Height (HLLH)                                  |
| 8     | Average Healthy-Side Hip Joint Torque (HHT)    | 29    | Average Affected-Side Leg Lift Height (ALLH)                                 |
| 9     | Average Affected-Side Hip Joint Torque (AHT)   | 30    | Bilateral Hip Angle Difference (BHAD)                                        |
| 10    | Average Healthy-Side Knee Joint Torque (HKT)   | 31    | Bilateral Knee Angle Difference (BKAD)                                       |
| 11    | Average Affected-Side Knee Joint Torque (AKT)  | 32    | Bilateral Ankle Angle Difference (BAAD)                                      |
| 12    | Average Healthy-Side Ankle Joint Torque (HAT)  | 33    | Bilateral Hip Motion Range Difference (BHMD)                                 |
| 13    | Average Affected-Side Ankle Joint Torque (AAT) | 34    | Bilateral Knee Motion Range Difference (BKMD)                                |
| 14    | Front Tilt Angle (FTA)                         | 35    | Bilateral Ankle Motion Range Difference (BAMD)                               |
| 15    | Left Tilt Angle (LTA)                          | 36    | Hip Torque Ratio (HTR)                                                       |
| 16    | Right Tilt Angle (RTA)                         | 37    | Knee Torque Ratio (KTR)                                                      |
| 17    | Front Acceleration (FA)                        | 38    | Body Mass Index (BMI)                                                        |
| 18    | Rear Acceleration (RA)                         | 39    | Healthy-Side Support Phase to Swing Phase Ratio Difference (HSSRD)           |
| 19    | Front Jerk (FJ)                                | 40    | Healthy-Affected Side Support Phase to Swing Phase Ratio Difference (HASSRD) |
| 20    | Rear Jerk (RJ)                                 | 41    | Step Length Difference (SLD)                                                 |
| 21    | Left Jerk (LJ)                                 | 42    | Pace (PA)                                                                    |

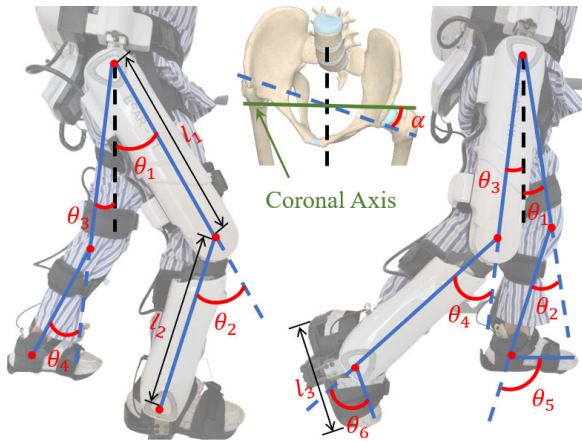


Fig. 2. Schematic diagram of the gait model.

of leg lift height [25]. The following formula represents the construction of parameter of the leg lift height.

$$\begin{aligned}
 H_1 &= l_1 \cos \theta_1 + l_2 \cos (\theta_1 - \theta_2) + l_3 \cos (\theta_1 + \theta_5 - \theta_2) \\
 H_2 &= l_1 \cos \theta_3 + l_2 \cos (\theta_3 + \theta_4) + l_3 \cos (\theta_6 - \theta_3 - \theta_4) \\
 H &= H_1 - H_2
 \end{aligned} \quad (3)$$

where  $l_3$  represents the foot length of the exoskeleton robot;  $\theta_5$  represents the angle of forefoot ankle joint, and  $\theta_6$  represents the angle of hindfoot ankle joint.  $H$  represents the leg lift height. The average left/right side leg lift height ( $H_L$ ,  $H_R$ ) matches with the average healthy/affected side leg lift height (HLLH, ALLH) according to the patient's specific condition.

### C. Construction of the Rehabilitation Assessment Model

Feature selection is an important problem in the field of feature engineering [26], whose goal is to find the optimal feature subset. Feature selection can improve the generalization ability of the model, reduce the possibility of overfitting, reduce the time cost of model training, and increase the interpretability between the feature and the target value by eliminating the

irrelevant or redundant features. The embedded approach [27] is adopted to screen all feature parameters and eliminate minor feature parameters. The mechanism of the embedding approach firstly trains the machine learning algorithm to obtain the weight coefficients of each feature. Then the features are selected according to the weight coefficients sorted from the largest to smallest. A total of 48 feature parameters were generated during the feature parameter construction process. After feature selection, the remaining 42 core feature parameters presented in Table I were adopted as the final input for the model training. Meanwhile, the 6MWD and the FMA-LE values of the patients were collected and set as the target values for model training in clinical trials. The feature parameters and the target values were input into the XGBoost regression algorithm [28] for training in order to obtain the rehabilitation assessment model. The trained model is able to predict the 6MWD and the FMA-LE values of the stroke patients.

The intelligent rehabilitation assessment method of the exoskeleton robot for the stroke patients proposed in this paper takes the XGBoost (eXtreme Gradient Boosting) regression algorithm [28] as the theoretical base. This algorithm solves the problem with the following advantages, including high accuracy, high flexibility, parallelism supported. What's more, it reduces the potential issue of overfitting and the quantity of computation by column sampling. A comparison of predictive performance based on other machine learning algorithms, such as random forests regression (RFRegressor), logistic regression (LRegressor), and multi-layer perceptual neural networks regression (MLPRegressor), is also presented.

As presented in Table I, a total of 42 feature parameters ( $X$ ) were collected and taken as the input of the rehabilitation assessment model, including the 7 body feature parameters of the patients, the 16 feature parameters collected by the sensors of the robot, and the 19 feature parameters constructed by the gait feature model. The 6MWD and the FMA-LE values were set as the target parameters ( $y$ ) which were collected from the patients in clinical trials. The 6MWD and FMA-LE values of the stroke patients predicted by the rehabilitation

assessment model represent the prediction results of the model ( $\hat{\gamma}$ ).  $t$  decision trees were constructed based on the feature parameters ( $X$ ) and the target values ( $\gamma$ ) of the model, thus the prediction result ( $\hat{\gamma}$ ) is generated via the decision trees.

The model dataset contains  $n = 2032$  samples and  $m = 42$  feature parameters. The integration of all the decision trees is applied for the IRAM, as presented in the following equation:

$$\hat{\gamma} = \hat{\gamma}^{(t)} = \sum_{i=1}^n f^{(t)}(\varphi^{(t)}(x_i)) \quad (4)$$

where  $f^{(t)}$  represents the node weight of an independent tree structure and the weight of the leaf node corresponding to the decision tree  $t$ .  $\varphi^{(t)}$  represents the sub-feature samples  $x_i$  which were selected from the feature parameters ( $X$ ) and contained 80% of the total quantity by the decision tree  $t$ . The samples of training data and feature parameters were randomly selected in order to maintain the variety of the input values and prevent the overfitting issue of the model.  $\gamma^{(t)}$  represents the 6MWD and FMA-LE values of the stroke patients collected in clinical trials which were extracted from the sample feature  $\varphi^{(t)}$ . To train the decision tree model, the mean square error (MSE) is adopted as the optimization function of the objective. As presented in the following equation:

$$l(\hat{\gamma}^{(t)}, \gamma^{(t)}) = \frac{1}{2} (\hat{\gamma}^{(t)} - \gamma^{(t)})^2 \quad (5)$$

The decision tree model may cause  $\hat{\gamma}^{(t)}$  splitting in the direction of approaching to  $\gamma^{(t)}$ , which could result in overfitting if only the mean square error is adopted as the optimization objective. Therefore, the regularization term  $\Omega(f_t)$  is introduced to reduce the complexity of the model. The additional regularization term smoothies the values of trained weight and avoids overfitting. The object of the regularization tends to select a model that adopts simple and predictive functions which reduce the possibility of overfitting. Finally, the equation of the objective function lists as following:

$$Obj^{(t)} = \sum_{i=1}^n l(\gamma^{(t)}, \hat{\gamma}^{(t-1)} + f_t(\varphi^{(t)}(x_i))) + \Omega(f_t) \quad (6)$$

$$\Omega(f_t) = \Upsilon T + \frac{1}{2} \lambda \|w\|^2 \quad (7)$$

In Taylor expansion form:

$$f(x + \Delta x) \simeq f(x) + f'(x)\Delta x + \frac{1}{2} f''(x)\Delta x^2 \quad (8)$$

Define:

$$\begin{aligned} g_t &= \partial_{\hat{\gamma}^{(t-1)}} l(\gamma^{(t)}, \hat{\gamma}^{(t-1)}) \\ h_t &= \partial_{\hat{\gamma}^{(t-1)}}^2 l(\gamma^{(t)}, \hat{\gamma}^{(t-1)}) \\ Obj^{(t)} &\simeq \sum_{i=1}^n \left[ l(\gamma^{(t)}, \hat{\gamma}^{(t-1)}) + g_t f_t(\varphi^{(t)}(x_i)) \right. \\ &\quad \left. + \frac{1}{2} h_t f_t^2(\varphi^{(t)}(x_i)) \right] + \Omega(f_t) \end{aligned} \quad (9)$$

$$\quad (10)$$

where  $T$  represents the number of the leaves of the decision tree model.  $w$  represents the weight values of the leaves.  $\Upsilon$

represents the difficulty of splitting the node.  $\lambda$  represents the coefficient of the regularization  $L_2$ .

Then, the greedy algorithm is adopted to optimize the objective function to obtain the decision tree model. More detailed derivation process is contained in [28].

#### D. Application and Performance Evaluation of Model

The exoskeleton robot will be able to predict the value of 6MWD and FMA-LE of the stroke patients working in the assessment mode, as long as the patients walk smoothly and continuously on the flat surface for 30 seconds. Despite being measured in supine position under clinical conditions, the value of FMA-LE exhibits a strong correlation with walking parameters. Similarly, walking function can indirectly serves as an indicator of the 6MWD and FMA-LE value [29].

The performance of the rehabilitation assessment model depends on the bias between the 6MWD and FMA-LE value  $\gamma$  of the patients collected in clinical trials and the predictive 6MWD and FMA-LE value  $\hat{\gamma}$ . We take two approaches to test the performance of the rehabilitation assessment model, mean absolute error (MAE) and root mean square error (RMSE).

Mean absolute error:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{\gamma}_i - \gamma_i| \quad (11)$$

Root mean square error:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{\gamma}_i - \gamma_i)^2} \quad (12)$$

where  $\gamma = \{\gamma_1, \gamma_2, \dots, \gamma_n\}$  represent the collected data,  $\hat{\gamma} = \{\hat{\gamma}_1, \hat{\gamma}_2, \dots, \hat{\gamma}_n\}$  represent the predictive value,  $n$  represents the number of samples.

### III. EXPERIMENT

#### A. Prototype of the Exoskeleton Robot

The Bilateral Exoskeletal Assistive Robot (BEAR-H) is adopted as the prototype for clinical trials in this paper, as shown in Fig. 3. BEAR-H is a product from Shenzhen MileBot Robotics Co., Ltd. The product has been certified by the National Medical Products Administration (NMPA) and has been adopted for rehabilitation in clinical trials for the stroke patients in several hospitals. Brief introduction of the BEAR-H's functions is as following:

- BEAR-H integrates a series of sensors to capture the changes of patient's limb and monitor the robot's posture. Specifically, angle sensors are adopted to measure the flexion/extension of the robot hip/knee/ankle. Inertial measurement units integrated in the circuit board are adopted to measure the angle and acceleration information of the lower limb. Pressure sensors embedded in the sole are used to inspect the contact status. The output torque/force can be obtained by measuring the deflection of the elastic element (as read by encoders at both ends of the flexible actuator).

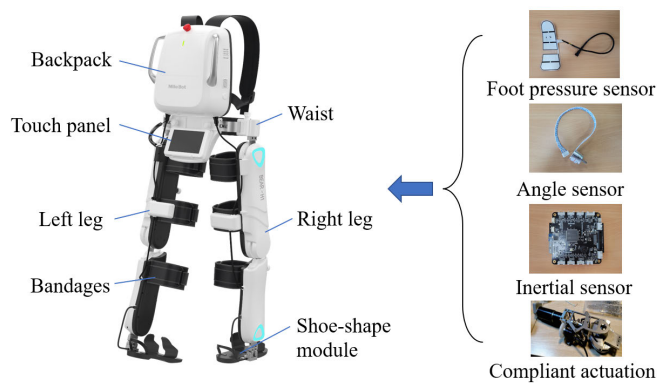


Fig. 3. Prototype of the exoskeleton robot.

- BEAR-H is the first commercial rehabilitation robot whose kinematic joints are fully driven by flexible actuators, making it flexible and safe for interaction from the hardware's perspective. The robot's functions of joint auxiliary mainly include: hip joint flexion/extension, knee joint flexion/extension and plantar flexion/ dorsiflexion.
- BEAR-H takes the adaptive impedance control algorithm to track the motion reference trajectory. It ensures the safety of human-machine interaction, also provides more voluntary movement space for the patients. Therefore, it improves the effect and the experience of the rehabilitation training [13], [30].
- BEAR-H includes three rehabilitation modes, i.e., weight support, training, and intelligent interaction. The weight support mode is designed for early stages of rehabilitation. In the training mode, the robot is controlled to follow a predefined trajectory to provide assistance for the patient. In the intelligent interaction mode, the level of assistance and frequency of the robot's trajectory is automatically adjusted online by monitoring the patient's walking pattern [13].

### B. Clinical Trials

The feasibility and effectiveness of IRAM were verified in clinical trials. As presented in Fig. 4, the stroke patients wore the exoskeleton robot for gait rehabilitation training, and the real values of 6MWD and FMA-LE were collected regularly after the training. The patients were informed of the purpose of the study and signed the informed consent forms before the formal clinical trials. Then several initial trainings were conducted to help the patients get familiar with the robot. Therefore, the patients were ensured being able to participate in subsequent formal trials. The initial trainings lasted 3-5 days, the formal trials lasted for 4 weeks, and 5 days each week. During the formal trials, the patients were asked to walk twice a day with the robot worn on, and each walking trial lasted about 30 minutes. This study was approved by the Ethics Committee of the First Affiliated Hospital of Nanjing Medical University (No. 2019-MD-43). The study was registered in the Chinese Clinical Trial Registry with the unique identifier: ChiCTR2100044475. 66 stroke patients participated in the formal clinical trials in total, with 49 male

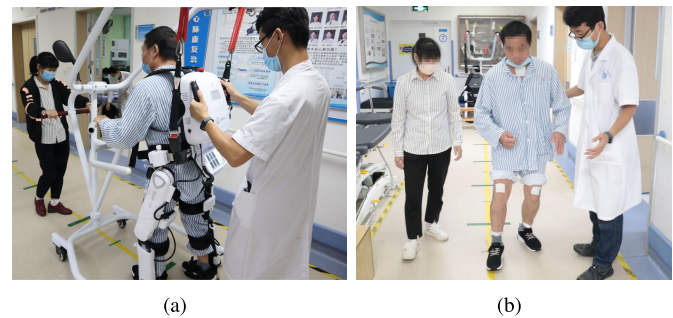


Fig. 4. Clinical trials for the stroke patients. (a) The patient receives the rehabilitation training with the exoskeleton robot. To ensure the safety and avoid secondary damage for the patients by safety braces and therapists. (b) The therapist collects the assessment metrics values of the patient after the training.

patients and 17 female patients. The standards of selecting the stroke patients are listed as following:

- The patients with stable vital signs and stable condition, and the exercise test is suitable for the patients.
- The patients with age over 18 years or older and 75 years or younger, weighting no more than 85kg, 1.55m-1.90m in height, with no limits in gender.
- The patients were confirmed as first-episode stroke with hemiplegia, including cerebral infarction and intracerebral hemorrhage. The condition lasted between 2 weeks and 6 months after the onset.
- The patients with the ability to walk under supervision, while the stability of walking decreased. The walking speed of the patients was significantly lower than that of person without disability of the same age.
- The patients with good cognitive function, who could understand and actively participate in the training program and agreed to sign the informed consent forms for the clinical trials.

The patients with the following conditions were excluded:

- The patients with severely limited range of motion, which limited the patients in walking movements.
- The patients with unhealed fractures or severe osteoporosis.
- The patients with skin lesions or infections on the lower limbs and the site where the robot was worn.
- The patients with other severe conditions.

The statistical data of physical feature parameters and sick condition of the patients participating in the clinical trials is presented in Table II. In Table II, the data of Duration represents the time interval since the patient was diagnosed. For example, a Duration of 15 means the patient was diagnosed 15 days ago. There are two types of strokes, cerebral hemorrhage (CH) and cerebral infarction (CI). The condition of hemiplegia is divided into left hemiplegia (LH) and right hemiplegia (RH). Table II presents that the patients were between 20 and 72 years old in age, 155 cm to 180 cm in height, and 45 kg to 83 kg in weight. Therefore, the stroke patients selected in the clinical trials are representative because most of the feature parameters have been covered. The selected patients in the clinical trials also covered the condition with



TABLE II  
STATISTICAL DATA OF THE PATIENTS

| PARAMETER      |    | COUNT | MEAN   | STD   | MIN | MAX |
|----------------|----|-------|--------|-------|-----|-----|
| Age(years)     | -  | 66    | 49.62  | 12.43 | 20  | 69  |
| Height(cm)     | -  | 66    | 167.77 | 6.60  | 155 | 180 |
| Weight(kg)     | -  | 66    | 65.15  | 8.60  | 45  | 83  |
| Duration(days) | -  | 66    | 89.56  | 43.66 | 15  | 176 |
| Types          | CI | 44    | -      | -     | -   | -   |
|                | CH | 22    | -      | -     | -   | -   |
| Side           | LH | 27    | -      | -     | -   | -   |
|                | RH | 39    | -      | -     | -   | -   |

diagnosed time between 15 and 176 days, with 27 patients of left hemiplegia (LH) and 39 patients of right hemiplegia (RH). Additionally, the number of patients with CI is as twice as the number of patients with CH, which matches the probability of clinical trials occurring.

The process of the formal clinical trial consists of 2 parts, gait training and data collection. The processes of gait training process are listed as following. 1) Doing the initial test for BEAR-H robot to ensure the functions of the robot system are normal. 2) Assessing the patient's condition by measuring blood pressure and heart rate, continue the procedures when the data readings are normal. 3) The patient wears the robot and fasten the safety belt of the stent with the help of the clinical staffs. Then the clinical staff input the patient's body parameters into the robot system. 4) The patient begins to walk after the robot is turned on. 5) The therapists and the clinical staff continuously monitoring and stop the procedure is any safety issues arise. 6) The patient takes off the robot after the walking phase. During clinical trials, BEAR-H adopts intelligent interaction mode to encourage stroke patients to exert voluntary efforts, so as to speed up the recovery and help patients regain the functionality of natural limb movement. The experiment lasted for 4 weeks and 5 days each week. The patients walked twice a day with the exoskeleton robot worn on, each walking test lasted about 30 minutes.

The data collection is divided into two parts. One part was to collect the 6MWD and FMA-LE data before the treatment, 2 weeks after the treatment, and 4 weeks after the treatment in the clinical trials. The other part was to obtain the motion biomechanical data generated by the robot sensor during the entire clinical rehabilitation experiment of the patients with the exoskeleton robot worn on.

The data of the 66 stroke patients was collected during the 11-month clinical trials. It contained 2032 pieces of rehabilitation training data of the exoskeleton robot, 736 pieces of the 6MWD and FMA-LE data in clinical trials, and constructed 42 feature parameters. The four-fold cross validation method was adopted to split the training data in order to verify the effectiveness of the rehabilitation assessment model. As presented in Fig. 5, 12 stroke patients in the testing set were randomly selected in one random cross-validation, the real values collected in the clinical trials and the values predicted by the model of the 6MWD and FMA-LE were analyzed. The evaluation indexes of the model performance including RMSE, MAE and accuracy present the statistical results after the average processing.

### C. Result

The 6MWD (in meters) values of the patients were compared under two conditions, in the clinical trials and predicted by the rehabilitation assessment model. The closer the predicted value of the rehabilitation assessment model of 6MWD reaches to the real value in the clinical trials, the more effective the model works in predicting 6MWD value, and vice versa. The experimental results are presented in Fig. 5 (a) and represent the distance deviation. It indicates the difference between the distance that the patients walk in the clinical trials and the distance predicted by the model after training. The prediction accuracy of the model reached 85.19% when the absolute value of the effective prediction deviation of the 6MWD was set as 20% of the real value.

Clinicians evaluate the effects of training by referring to FMA-LE (Marks), which has become a standard for assessing the rehabilitation efficacy after the stroke. Generally, the doctor asks the patient to perform a series of tasks and then assesses how hard the patient performs the task to calculate the value of FMA-LE. Comparing the performance before and after the rehabilitation training, the higher the score, the better the rehabilitation efficacy, and vice versa. The results of FMA-LE in the clinical trials and predicted by the model are presented in Fig. 5 (b). The closer the FMA-LE value predicted by the model reaches to the value collected in the clinical trials, the more effective the rehabilitation assessment model performs in predicting the FMA-LE value. The total score for FMA-LE is 34. The prediction accuracy of the model reaches 92.66% when the absolute value of the effective prediction deviation of FMA-LE is set to 20% of the real value.

Fig. 6 presents the change trend of the prediction accuracy of the rehabilitation assessment model in predicting the 6MWD and FMA-LE values of the patients with the change of the deviation value. In the situation of  $|\gamma - \hat{\gamma}| \leq \text{Deviation} * \gamma$ , the condition indicates the effectiveness of prediction when the absolute deviation value is set to a percentage of the real value (*Deviation*, in %). With the *Deviation* (in %) increases, the prediction accuracy of the model for the 6MWD and FMA-LE values of the patients gradually reaches to 100%. However, the larger the *Deviation* (in %) value was set, the lower the application value of the prediction model performs in the clinical trials. Considering both the clinical application value and the accuracy of the prediction model, the final *Deviation* (in %) value was set to 20 (in %). Moreover, the variance range of 6MWD and FMA-LE values of patients collected in clinical trials is between 15% and 25%, which indicates that it is acceptable to set the *Deviation* (in %) value to 20 (in %).

As the thermogram of correlation coefficient presented in Fig. 7, there is a strong correlation between Rear Acceleration (RA) with Average Healthy-Side Leg Lift Height (HLLH), Average Affected-Side Leg Lift Height (ALLH) with HLLH, Front Jerk (FJ) and Front Acceleration (FA), Rear Jerk (RJ) and FA, Right Jerk (RTJ) and FJ, RJ and FJ, RJ and RTJ, Left Jerk (LJ) and RTJ, Knee Torque Ratio (KTR) and Average Affected-Side Knee Joint Torque (AKT) according to their feature parameters ( $\rho > 0.85$ ). The other feature parameters present weak correlation or are basically irrelevant.

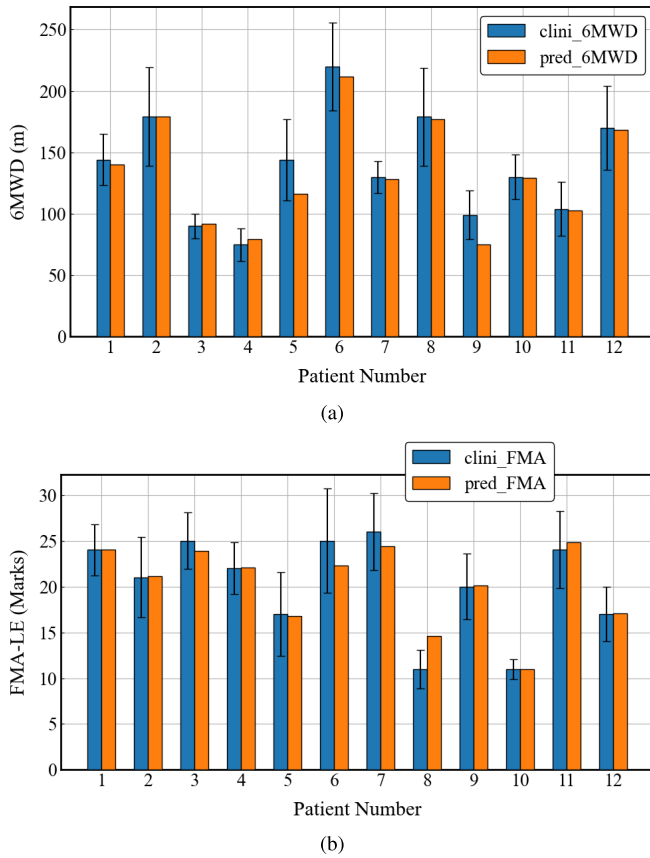


Fig. 5. Value deviation of the 6MWD and FMA-LE collected in clinical trials and predicted by the rehabilitation assessment model. (a) 6MWD (in meters) and (b) FMA-LE (in Marks).

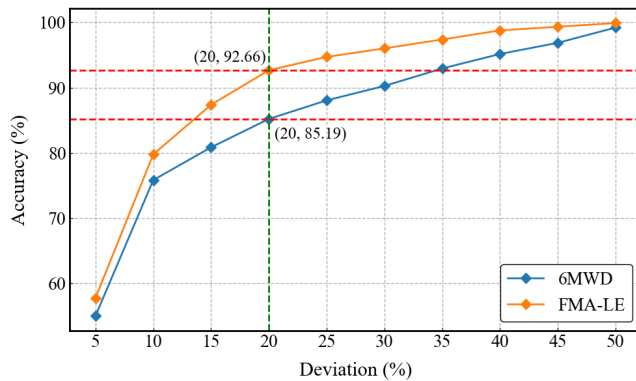


Fig. 6. The change trend of the accuracy of the intelligent rehabilitation assessment model in predicting the 6MWD and FMA-LE value of the patients when change the value settings of the Deviation (in %).

Fig. 8 (a) presents the influence of each feature parameter on the prediction results of the 6MWD value. Stroke Type (ST), Pace (PA) and Average Walking Frequency (WF) show higher influence on the rehabilitation assessment model. Additionally, Bilateral Knee Angle Difference (BKAD), Weight (WT), Age (AG), Average Affected-Side Leg Lift Height (ALLH), and Average Healthy-Side Leg Lift Height (HLLH) show decreasing influences on the model.

While Fig. 8 (b) presents the influence of each feature parameter on the prediction results of the FMA-LE value.

TABLE III

STATISTICAL RESULTS OF THE RMSE AND MAE IN PREDICTING THE 6MWD AND FMA-LE VALUES BASED ON DIFFERENT MACHINE LEARNING ALGORITHMS

|              | RMSE  |        | MAE   |        |
|--------------|-------|--------|-------|--------|
|              | 6MWD  | FMA-LE | 6MWD  | FMA-LE |
| RFRRegressor | 58.64 | 5.63   | 29.68 | 6.06   |
| LRegressor   | 41.33 | 3.21   | 20.10 | 3.93   |
| MLPRegressor | 45.51 | 2.84   | 21.42 | 2.06   |
| XGBoost      | 33.76 | 2.28   | 21.09 | 1.46   |

Stroke Type (ST), Gender (GR) and Hemiplegic Side (HS) are more important in the rehabilitation assessment model. Additionally, Body Mass Index (BMI), Weight (WT), Average Walking Frequency (WF), and Healthy-Affected Side Support Phase to Swing Phase Ratio Difference (HASSRD) show decreasing influences on the model.

In addition, Table III presents the statistical results of RMSE and MAE for predicting 6MWD and FMA-LE values based on different machine learning algorithms. It shows that the rehabilitation evaluation model based on XGBoost algorithm is effective in predicting 6MWD and FMA-LE values. Compared with RFRRegressor, LRegressor, and MLPRegressor algorithms, the XGBoost algorithm presents better predictive performance on this experimental dataset.

#### IV. DISCUSSION

##### A. Advantages

Experimental results presented in Fig. 5 prove that the IRAM proposed in this paper is feasible and effective in predicting the 6MWD and FMA-LE values of the stroke patients. As presented in Fig. 8, the main feature parameters that affect the value of the 6MWD and FMA-LE in the model match with the results in clinical trials. Among them, the value of 6MWD is mainly correlated with stroke type, pace and average walking frequency, etc. [31]. The value of FMA-LE is mainly correlated with stroke type, gender and hemiplegic side, etc. [32]. The proposed method can alleviate the work intensity of therapists and nursing staffs. It also increases the efficiency and reduces the cost of measurement. What's more, the proposed measurement method is easy, convenient and objective in execution.

The gait feature model constructed in this paper can solve the gait parameters of the healthy side and the affected side in the process of rehabilitation training. Clinically, analysis on gait parameters and analysis on gait symmetry are often included in the overall rehabilitation assessment of the stroke patients. Analysis on gait parameters contains of the time ratio of a single standing and swinging cycle, step frequency and gait cycle of the affected side [33]. In the analysis of gait symmetry, the swing phase symmetry rate (SPSR) and step length symmetry rate (SLSR) of the stroke patients were calculated by measuring the ratio of gait parameters between the affected side and the healthy side [34]. The gait parameters generated by the gait feature model can directly analyze the gait and symmetry of the patients. This model brings several advantages to the rehabilitation assessment procedures. Firstly, it simplifies the measurement process of the patients. Secondly,



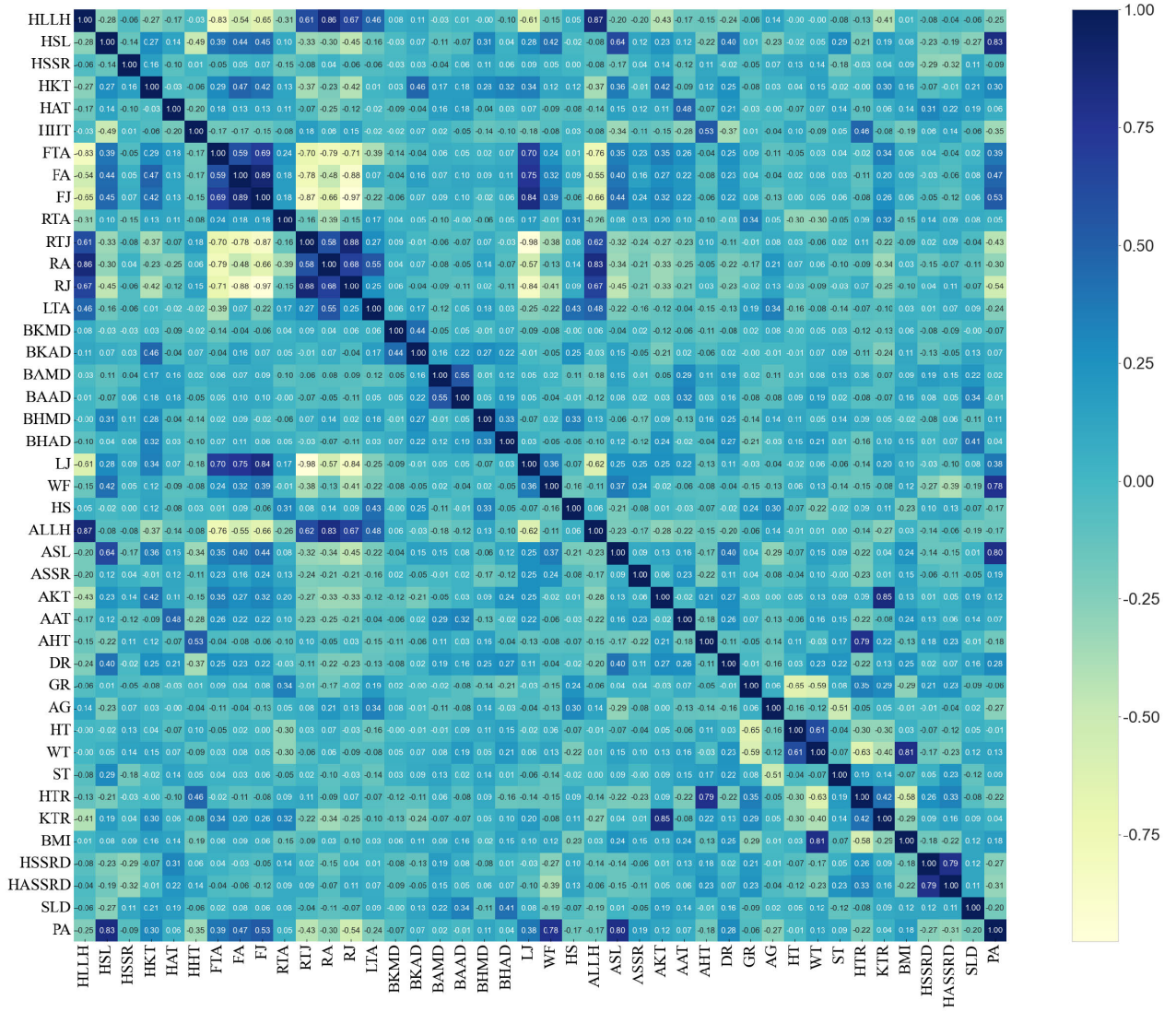


Fig. 7. The thermogram of correlation coefficient between the feature parameters.

it does not require much intervention of therapists and nurses in the process of collecting gait parameters of the patients. What's more, it saves the costs of the rehabilitation assessment and much space for medical usage.

The exoskeleton robot achieves a closed loop of rehabilitation training for the stroke patients. BEAR-H provides specific training modes for each stroke patient in different stages of rehabilitation, which meets the purpose of rehabilitation training - "Assisted As Needed (AAN)". Therapists diagnoses the rehabilitation stage of the patients based on the assessment indicators predicted by the rehabilitation assessment model and the gait parameters constructed by the gait feature model. With the generated parameters, therapists are able to adjust the training mode of BEAR-H to provide suitable assistance for the stroke patients.

### B. Limitations

To some extent, the more feature parameters being constructed, the more accuracy of the model prediction. However, more structural features mean more sensors are needed for the

exoskeleton system. The 42 features constructed in this paper utilize 15 sensors of the BEAR-H exoskeleton, including: two pressure sensors on the feet, six angle sensors, six torque sensors, and one IMU. We expect that the rehabilitation assessment model in this paper can be extended to existing exoskeleton robots. However, they, such as ALEX [9], Indego [10], etc., have fewer sensors than BEAR-H exoskeletons, resulting in fewer features constructed by these exoskeleton robots, thus affecting the accuracy of model prediction. Therefore, the method may not be directly applicable to existing rehabilitation exoskeletons. In the future, the corresponding sensors can be added to the new version of these exoskeletons, and then the rehabilitation assessment model in this paper can be used for intelligent assessment.

The quantity of the training data is insufficient for the rehabilitation assessment model. The rehabilitation assessment model proposed in this paper has only 2032 training data compared with the traditional machine learning models which construct millions of training data. Insufficient training data of machine learning algorithm could cause overfitting issues,

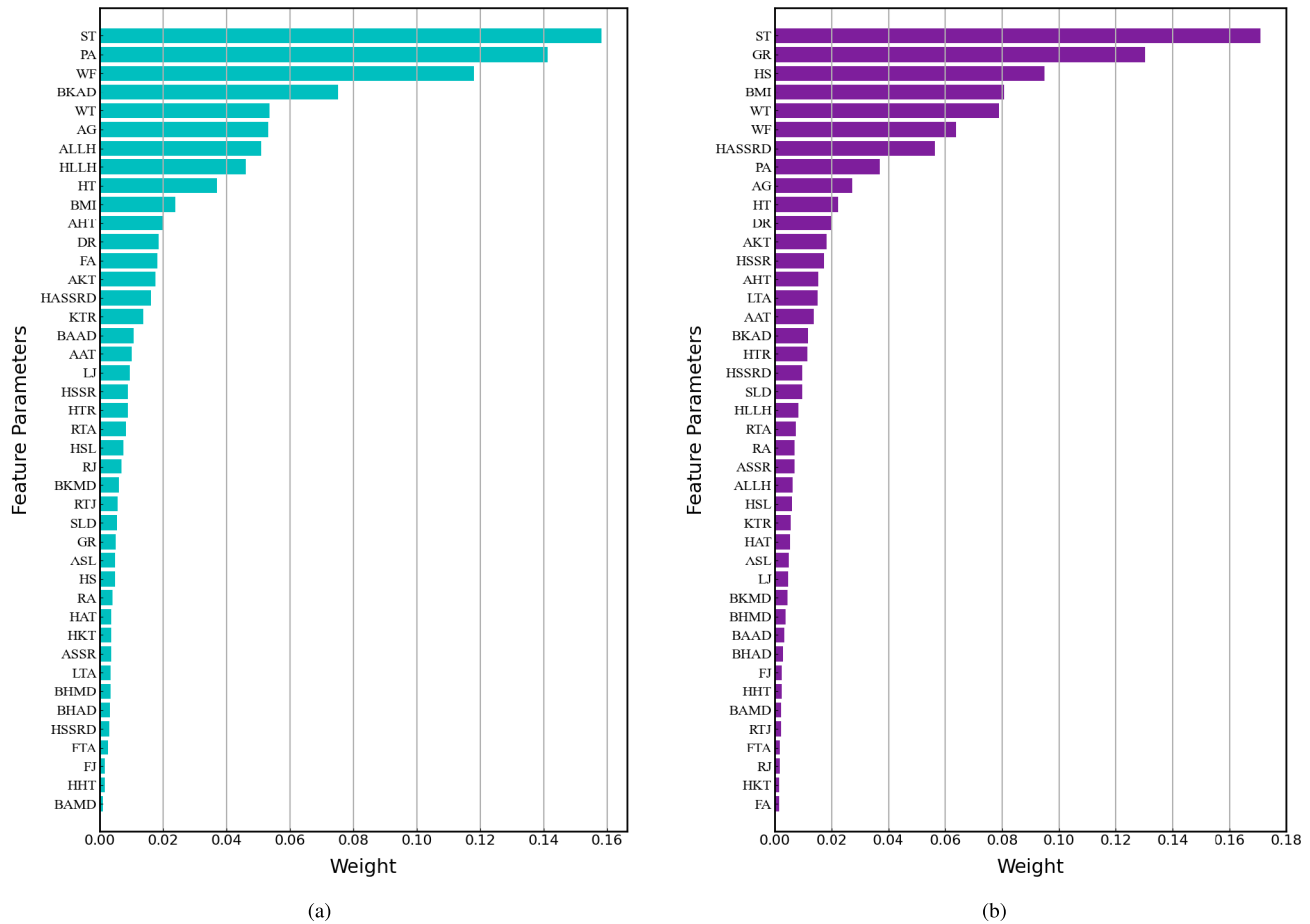


Fig. 8. The influence of each feature parameter on the prediction results of the 6MWD value and the FMA-LE value. (a) Weight relationship between 6MWD and feature parameters; (b) Weight relationship between FMA-LE and feature parameters.

which means the model performs well on the training set but generalizes poorly on the testing set. With the increase of clinical data of BEAR-H in the future, the training data of the model will also be constantly increased. Therefore, the rehabilitation assessment model will be constantly improved.

### C. Future Plans

The prediction of the 6MWD and FMA-LE values has been proved to be feasible and effective in clinical trials. However, a rehabilitation assessment report of the stroke patients is possibly directly generated based on the gait parameters constructed by the rehabilitation assessment model. The assessment report is able to score the stroke patient's rehabilitation status and provide suggestions for the subsequent rehabilitation training. The assessment report provides the therapists with quantitative gait parameters of the patient and predictive values of the rehabilitation assessment indexes. The therapists can have a qualitative understanding of the patient's status of rehabilitation based on the score given by the assessment report. Furthermore, the therapists would be able to formulate corresponding rehabilitation training plans for the patient with the advice given in the assessment report. The above content presents our research plans in the future.

### V. CONCLUSION

This paper presents a novel intelligent rehabilitation assessment method (IRAM) for the stroke patients based on lower

limb exoskeleton robot. The assessment model predicts the values of 6MWD and FMA-LE which are critical and necessary indicators for the stroke patients in rehabilitation assessment with minor involvement of therapists. The IRAM based on lower limb exoskeleton robot proposed in this paper actually extends the function of exoskeleton device. The proposed assessment model works more efficiently and objectively in obtaining the 6MWD and FMA-LE values than the traditional manual measurement method. What's more, the exoskeleton robot achieves a closed loop for the rehabilitation process of the stroke patients. The robot can be both adopted for gait rehabilitation assessment and rehabilitation training of the stroke patients at the same time. The results in clinical trials have proved and verified the effectiveness and feasibility of this proposed method. Additionally, the applications of the IRAM can also be expanded to the single joint exoskeleton robot, upper limb rehabilitation exoskeleton robot and prosthesis.

### APPENDIX

#### THE REST OF THE MENTIONED GAIT FEATURE PARAMETERS ARE AS FOLLOWING:

16 feature parameters are constructed directly by the sensors on the exoskeleton robot. Average Walking Frequency (WF)  $w$ ; hip, knee, ankle joint angle on the left/right side  $\theta_{L-h}$ ,  $\theta_{R-h}$ ,  $\theta_{L-k}$ ,  $\theta_{R-k}$ ,  $\theta_{L-a}$ ,  $\theta_{R-a}$ . The left/right hip, knee,

and ankle assisted torque  $T_{L-h}$ ,  $T_{Rhh}$ ,  $T_{L-k}$ ,  $T_{R-k}$ ,  $T_{L-a}$ ,  $T_{R-a}$  with respective to the patient's condition, which were matched with the average hip, knee, and ankle torque (HHT, AHT, HKT, AKT, HAT, AAT) on the healthy/affected side. Front Tilt Angle (FTA)  $\theta_{T-f}$ , Left Tilt Angle (LTA)  $\theta_{T-l}$ , Right Tilt Angle (RTA)  $\theta_{T-r}$ , Front Acceleration (FA)  $a_f$ , Rear Acceleration (RA)  $a_r$ , Front Jerk (FJ)  $J_f$ , Rear Jerk (RJ)  $J_r$ , Left Jerk (LJ)  $J_l$  and Right Jerk (RTJ)  $J_{rl}$ .

Bilateral Hip Angle Difference (BHAD)  $\Delta\theta_h$

$$\Delta\theta_h = |\theta_{L-h} - \theta_{R-h}| \quad (13)$$

Bilateral Knee Angle Difference (BKAD)  $\Delta\theta_k$

$$\Delta\theta_k = |\theta_{L-k} - \theta_{R-k}| \quad (14)$$

Bilateral Ankle Angle Difference (BAAD)  $\Delta\theta_a$

$$\Delta\theta_a = |\theta_{L-a} - \theta_{R-a}| \quad (15)$$

Bilateral Hip Motion Range Difference (BHMD)  $\Delta M_h$

$$\Delta M_h = |\max(\theta_{L-h}) - \max(\theta_{R-h})| \quad (16)$$

Bilateral Knee Motion Range Difference (BKMD)  $\Delta M_k$

$$\Delta M_k = |\max(\theta_{L-k}) - \max(\theta_{R-k})| \quad (17)$$

Bilateral Ankle Motion Range Difference (BAMD)  $\Delta M_a$

$$\Delta M_a = |\max(\theta_{L-a}) - \max(\theta_{R-a})| \quad (18)$$

Hip Torque Ratio (HTR)  $K_{T-h}$

$$K_{T-h} = \frac{T_{AHT}}{W} \quad (19)$$

where,  $T_{AHT}$  represents the Average Affected-Side Hip Joint Torque (AHT),  $W$  represents the weight of the patient (WT).

Knee Torque Ratio (KTR)  $K_{T-k}$

$$K_{T-k} = \frac{T_{AKT}}{W} \quad (20)$$

where,  $T_{AKT}$  represents the Average Affected-Side Knee Joint Torque (AKT),  $W$  represents the weight of the patient (WT).

Body Mass Index (BMI)

$$BMI = \frac{W * 10000}{H^2} \quad (21)$$

where,  $W$  represents the weight of the patient (WT),  $H$  represents the height of the patient (HT).

Healthy-Side Support Phase to Swing Phase Ratio Difference (HSSRD)  $\Delta K$

$$\Delta K = |K_{HSSR} - 51| \quad (22)$$

where,  $K_{HSSR}$  represents the Healthy-Side Support Phase to Swing Phase Ratio (HSSR).

Healthy-Affected Side Support Phase to Swing Phase Ratio Difference (HASSRD)  $\Delta K_{h-a}$

$$\Delta K_{h-a} = |K_{HSSR} - K_{ASSR}| \quad (23)$$

where,  $K_{HSSR}$  represents the Healthy-Side Support Phase to Swing Phase Ratio (HSSR),  $K_{ASSR}$  represents the Affected-Side Support Phase to Swing Phase Ratio (ASSR).

Step Length Difference (SLD)  $\Delta L_{h-a}$

$$\Delta L_{h-a} = |L_{HSL} - L_{ASL}| \quad (24)$$

where,  $K_{HSL}$  represents Average Healthy-Side Step Length (HSL),  $K_{ASL}$  represents Average Affected-Side Step Length (ASL).

Pace  $v$

$$v = (L_{HSL} + L_{ASL}) * w \quad (25)$$

where,  $K_{HSL}$  represents the Average Healthy-Side Step Length (HSL),  $K_{ASL}$  represents the Average Affected-Side Step Length (ASL),  $w$  represents the Average Walking Frequency (WF).

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