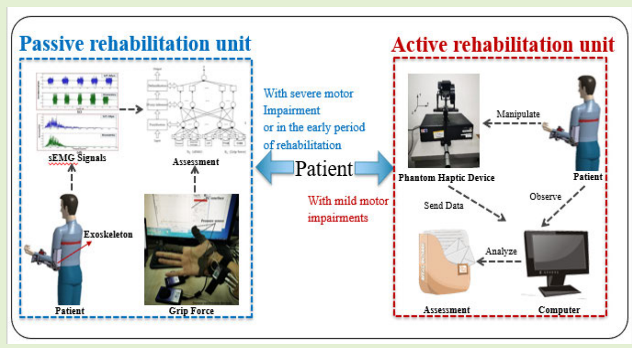
A Motor Recovery Training and Evaluation Method for the Upper Limb Rehabilitation Robotic System

Huimin Cai, *Student Member, IEEE*, Shuxiang Guo, *Fellow, IEEE*, Ziyi Yang, *Student Member, IEEE*, and Jian Guo, *Member, IEEE*

***Abstract*—Stroke can cause acute damage to blood vessels in the brain, which often leads to hemiplegia and imbalances in mobility. It is a challenge to develop a motor recovery training and evaluation method with less help of therapists. In this article, a motor recovery training and evaluation method for the upper limb rehabilitation robotic system is proposed. This system has two rehabilitation units, one is active, and the other is passive. The developed rehabilitation robotic system includes an exoskeleton rehabilitation robot and PHANTOM1.5. The patients do rehabilitation training with the help of a robot in the passive unit, and a virtual reality game is designed in the active unit. Patients with mild motor impairments observe the virtual reality game interface while manipulating the PHANTOM to do rehabilitation training. Three experiments are proposed in this paper. The fuzzy neural network (FNN), spring-damper model, and the method to evaluate the training trajectory are designed and validated. The surface electromyography (sEMG) signals and grip force during rehabilitation training are collected to set up an FNN and achieve evaluation. The accuracy of the network is 0.96 which is calculated in validation set. In Section IV, the rehabilitation evaluation method is compared with the state of art on rehabilitation evaluation method. The method proposed in this article can reach high accuracy. It is easy to use and understand for patients even without the help of therapists. The problem of lacking therapists can be solved to some extent by the proposed upper limb rehabilitation system.**



***Index Terms*—Force feedback, fuzzy neural network (FNN), motor recovery training and evaluation, upper limb rehabilitation robotic system, virtual reality.**

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I. Introduction

STROKE is a growing threat to the people all over the world. Over 2 million poststroke patients in China have difficulty taking care of themselves each year [1]. More than half of poststroke patients are unable to live independently [2].

Although the damage in the brain cannot be healed completely, patients can do rehabilitation exercises to stimulate the recovery of damaged blood vessels and cells based on “neuroplasticity” theory [3]. The traditional rehabilitation training evaluation method relies on the experience of therapists. Mostly, they use the Brunnstrom scale, the Fugl-Meyer scale, the National Institutes of Health Stroke Scale, and the modified Rankin Scale [4]. The Brunnstrom scale was proposed by a Swedish therapist. It is based on the analysis of the patients’ ability, coordination of synergistic movements, and the synergy of flexors and extenders. The Fugl-Meyer Assessment (FMA) is another widely used scale. The FMA scale consists of five scales related to various aspects of the upper and lower limbs of patients. The National

Institutes of Health Stroke Scale is a score calculated from 11 components and is used to quantify the severity of strokes. These 11 components are summed and the score correlates with stroke severity. The modified Rankin scale is used to classify levels of functional independence with reference to prestroke activity. In general, the traditional rehabilitation evaluation method is based on the scale in terms of reflex response, synergy, balance, sensory function, and pain.

These methods lack efficiency and can barely reflect subtle progress. And the number of therapists can hardly keep up with the demand. Recently, the problem has been improved to some extent [5], [6]. The rehabilitation evaluation method is carried out in recent studies. In 2016, Chen et al. [7] proposed a wavelet-based method to analyze the local band spectral entropy of the surface electromyography (sEMG) signals. The research is helpful to describe the variation of joint angles. Antonella et al. [8] proposed a multiparameter approach to evaluate poststroke patients based on electroencephalogram (EEG) signals, sEMG signals, and some scales. The author compares the result with traditional scales, the trend agrees. In 2022, Tamantini et al. [9] proposed a patient-tailored control architecture for upper-limb robot-aided orthopedic rehabilitation. The controller was capable of tracking the planned path and managing a position error according to the tuned stiffness parameters. However, the research lacks sufficient rehabilitation evaluation methods. Recent research still largely relies on the assistance of therapists. In addition, EEG signals and sEMG signals vary from person to person. These kinds of signals are unstable and easy to be disturbed [10], [11], [12], [13]. It is a challenge to develop a motor recovery training and evaluation method without therapists. Periodic rehabilitation evaluation can help to enhance patients' confidence. In addition, patients can adjust the rehabilitation plan to improve the efficiency of the rehabilitation training, but the number of therapists is far from enough [14], [15], [16], [17]. Early in 2002, many experiments indicates that virtual reality exercises can improve the motor skills of stroke patients [18]. Virtual reality shows great potential in rehabilitation, especially with the development of haptic feedback device [19]. In this article, a motor recovery training and evaluation method is proposed for upper limb rehabilitation robotic system which can work without the help of therapists. It does not mean the whole rehabilitation process does not require therapists. This research aims to design a rehabilitation system that is easy to control and understand for patients. So that therapists will be able to help more patients.

In general, there should be a new rehabilitation system. First, it should be easy to use and understand for patients. And there should be rehabilitation evaluation unit. So that therapists would be able to help more patients. Second, it can be used by patients in different injury levels. Third, the training should be enjoyable and easy to adjust the difficulty.

The contribution of this article is shown as follows. First, a novel home-based rehabilitation system is set up where patients can do rehabilitation training and get evaluation results without the help of therapists. Second, rehabilitation training and evaluation are suitable for patients in different injury levels. Third, the evaluation method is related to

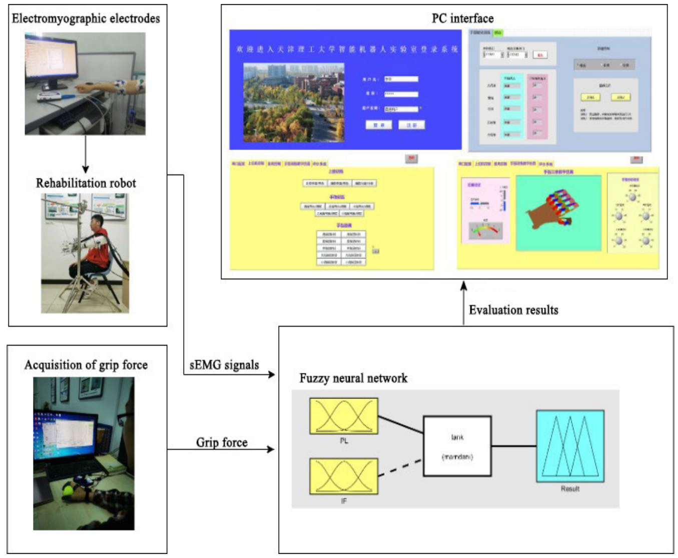

Fig. 1. Overall block diagram of passive rehabilitation unit.

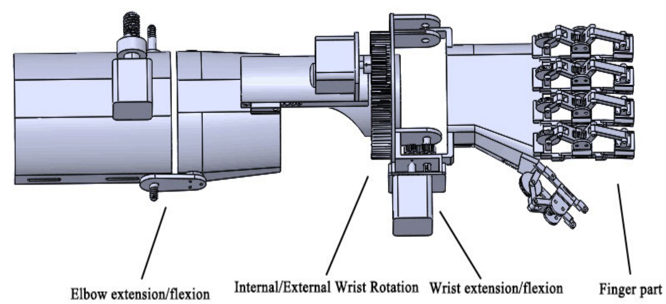

Fig. 2. Three-dimensional model of exoskeleton upper limb rehabilitation robot.

the Brunnstrom scales, patients and therapists can easily understand the current rehabilitation stage. And in active rehabilitation unit, haptic device based on spring-damper model can provide feedback force in VR games. It can make the training more enjoyable and the difficulty can be adjusted by changing the feedback force.

II. System Design

A. Rehabilitation Training Method

This system has two rehabilitation units, one is active, and the other is passive. The passive rehabilitation unit is for patients with severe motor impairment or in the early period of rehabilitation. The active rehabilitation unit is for patients with mild motor impairment or in the later period of rehabilitation.

The overall block diagram of passive rehabilitation unit is shown in Fig. 1. The exoskeleton upper limb rehabilitation robot drives the patient to perform rehabilitation exercises in the passive rehabilitation unit. The structure of the exoskeleton upper limb rehabilitation robot is based on the joints of the human hand, with 2 degrees of freedom for the thumb and 3 degrees of freedom for the remaining four fingers. Fig. 2 shows the 3-D model of the rehabilitation robot. The components of the passive unit are shown in Fig. 3. The robot module consists of motor, driver, flex sensor, and power converter. The passive unit of the developed rehabilitation robotic system mainly contains the exoskeleton robot, sEMG signals acquisition equipment, and grip force acquisition

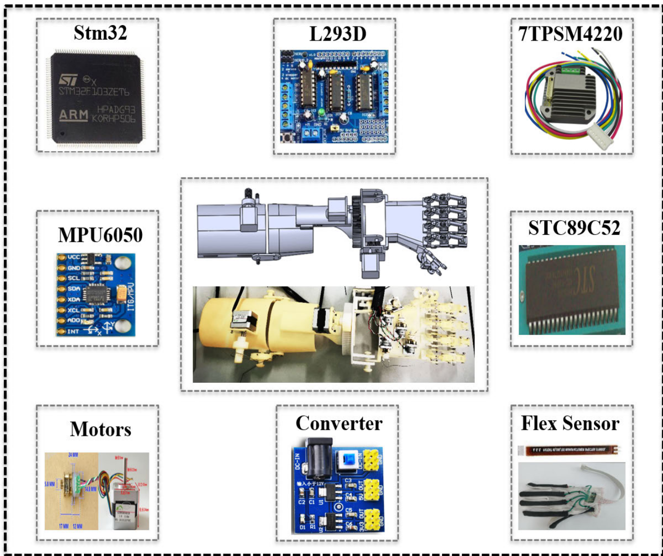

Fig. 3. Components of the rehabilitation robot.

equipment. Patients will be guided by the rehabilitation robot to do rehabilitation training. There will be PC interface for patients to select the training mode or control the robot. Information like time, training mode, username, and sEMG signals will be saved. Grip force and sEMG signals will be sent into fuzzy neural network (FNN) to evaluate patient's motor ability.

The length of the robot can be adjusted to suit different persons. It is easy and comfortable to wear. The rehabilitation training mainly includes internal and external rotation of the wrist, internal and external rotation of the elbow, extension and flexion of the elbow, and grip training.

The active unit of the developed rehabilitation robotic system mainly uses PHANTOM Premium 1.5, which has 6 degrees of freedom. PHANTOM from 3-D systems company is a haptic device that can fulfill the requirements of a vast range of research and commercial applications. It is widely used in the fields of rehabilitation [10], [12], [20]. PHANTOM can be programmed to move along the x-, y-, and z-axes and generate feedback forces. The user can feel the collision force, reaction force, and traction rotation during the movement. The feedback force is generated by spring-damper model. In this article, the patient controls the PHANTOM to do VR games. A haptic device will provide feedback force during the rehabilitation training. The block diagram of active rehabilitation unit is shown in Fig. 4. VR rehabilitation game can not only make the training more enjoyable but also easily set different difficulties of VR games [18], [19]. The resolution in rotation can reach 0.0023°, 75 cm in the x-axis, 75 cm in the y-axis, and 40 cm in the z-axis are the maximum displacement distances. For patients with mild motor impairment who need to enhance strength, this project develops a virtual reality game. The patients do rehabilitation training by playing the virtual reality game. Then, the rehabilitation evaluation method is performed based on time, accuracy, and stability of the trajectory. After the patient completes the VR game, the trajectory can also reflect the rangehe can reach. Time and

TABLE I
LEVELS OF MOTOR ABILITY

Level	Explain
ZO	No signals, completely driven by the robot
SO	Slight force, the force is very weak
MO	The patient can do rehabilitation training with the assistance of robot
NO	The patient can do rehabilitation training with the resistance of robot
LO	Almost the same as a normal person

stability of the trajectory are related to patient's muscle strength [10]. The complexity of the rehabilitation training game and the strength required to complete the game can be adjusted according to the patients' injury levels.

The spring-damper model is widely used to calculate the feedback force in the field of rehabilitation [20], [21]. Suppose the surface of the virtual object has a series of springs and dampers. When the patients manipulate the PHANTOM and collide with the surface of the virtual object, the feedback force is calculated according to Hooke's law and Newton's law of viscosity.

In active rehabilitation unit, haptic devices based on spring-damper model can provide feedback force in VR game. It can make the training more enjoyable and the difficulty can be adjusted by changing the feedback force. The spring is used to simulate the mutual force when contacting the virtual object surface. And the damper is used to simulate the energy dissipation during the deformation of the spring, which makes the model have some viscoelastic properties. The cursor of the PHANTOM is considered a mass point. At any moment t, let the external force $f(t)$ be the input and the displacement $x_0(t)$ after contacting the virtual object surface be the output. Assuming the viscous damping force generated by the damper is $f_B(t)$ and the elastic force generated by the spring is $f_K(t)$. Then, the equations of motion are established in (1)–(3), where K is the spring stiffness, B is the viscous damping coefficient, and m is the mass of the point.

When the mass is neglected and only springs and dampers are considered, the equation is the first-order constant coefficient differential equation

$$f(t) - f_K(t) - f_B(t) = m\frac{d^2x_0(t)}{dt^2} \quad (1)$$

$$m\frac{d^2x_0(t)}{dt^2} + B\frac{dx_0(t)}{dt} + Kx_0(t) = f(t) \quad (2)$$

$$B\frac{dx_0(t)}{dt} + Kx_0(t) = f(t). \quad (3)$$

The model of feedback force is established, and the feedback force can be modified by changing K and B. The tactile feel of the virtual surface can be adjusted to be hard or elastic. The motor ability of patients can be calculated from time, accuracy, and stability of the trajectory and other parameters. Time, accuracy, and stability will each correspond to a score, and the result will be determined by calculating the sum of the scores.

B. Rehabilitation Evaluation Method

During the rehabilitation training, sEMG signals of the biceps, triceps and brachioradialis muscles, and grip force will

TABLE II
MOTOR ABILITY SCORE

Score	0	1	2	3	4
AT	Unable to Complete	>10	8-10	6-8	4-6
FF	<1	1-2	2-3	3-4	>4
SA	<50%	50%-70%	70%-80%	80%-90%	>90%

AT: Average Individual Node Completion Time/s, FF: The repulsive and attractive forces of nodes/N, SA: Stability and accuracy of the trajectory

TABLE III
TOTAL SCORE

Level	Description	Score
A	Normal	10-12
B	Mild Dyskinesia	7-9
C	Moderate Dyskinesia	4-6
D	Severe Dyskinesia	0-3

be collected. The detail of filters and features is explained in this part, and some picture of sEMG signals before and after filter is shown in the experiment part. The motor skill of the patient is divided into five levels. The training data are obtained by simulating rehabilitation training according to Table I, which is based on manual muscle testing (MMT) scale [22].

Empirical mode decomposition (EMD) algorism is used to do the denoising. Specifically, the signals are decomposed as a superposition of the intrinsic mode function (IMF). In (4), $r_i(t)$ is the residual component of the decomposition. Finally, the components are reconstructed to obtain the preprocessed sEMG signal

$$x(t) = \sum_{i=1}^{n} \mathrm{imf}_i(t) + r_n(t). \quad (4)$$

After several experiments, from the previous study, the following three features were selected to evaluate the sEMG signals [23], [24].

The mean absolute value (MAV) reflects the fluctuation of sEMG signal intensity with time. It also reflects the contraction characteristics of the muscle. The MAV is calculated by

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=0}^{N-1} |x(i)|. \quad (5)$$

The variance (S) is often used to reflect the state of muscle activity, and the variation of it is also related to the strength of muscle contraction. The function of variance is calculated by

$$S = \sqrt{\frac{1}{N-1}\sum\nolimits_{j=1}^{N}\left(x_{ij} - \overline{x_i}\right)^2}. \quad (6)$$

The mean power frequency (MPF) is selected as a feature from the frequency domain [25]. The function of MPF is

$$\mathrm{MPF} = \frac{\int_0^\infty f p(f) df}{\int_0^\infty p(f) df}. \quad (7)$$

During the rehabilitation, patients should try to do the grip training on a tennis ball shown in Fig. 5. The equipment in Fig. 6 is used to collect grip force. The curve in Fig. 7. shows the data of a single grip and relaxation on a tennis ball.

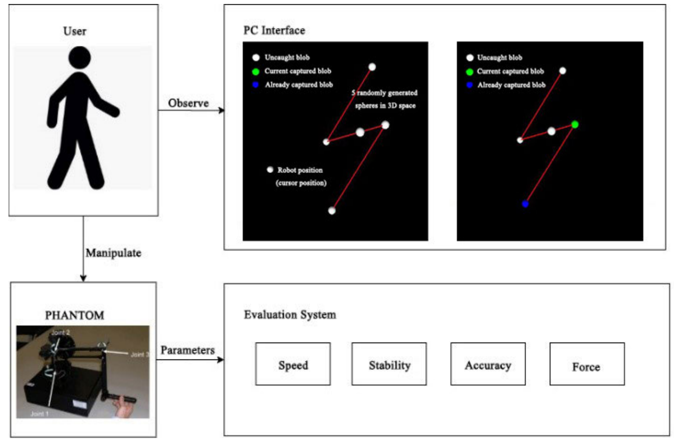

Fig. 4. Block diagram of active rehabilitation unit.

Fig. 5. Grip training on a tennis ball.

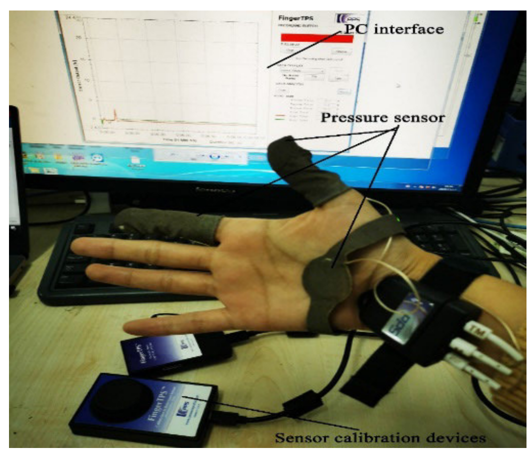

Fig. 6. Grip force acquisition equipment.

FNN is a multilayered feed-forward network. It combines the fuzzy system with the neural network. Entering sEMG and grip force features to the input layer, and the output is the result of rehabilitation evaluation. When a patient did rehabilitation training completely passive, the sEMG signals will be very weak. On the contrary, if a patient could actively participate in the rehabilitation training, the sEMG signals will be different from that of the former patient [26], [27], [28], [29].

The framework diagram of FNN is shown in Fig. 8. The first layer is the input layer, x_1 represents the sEMG signals and x_2 represents the grip force. The input layer contains the

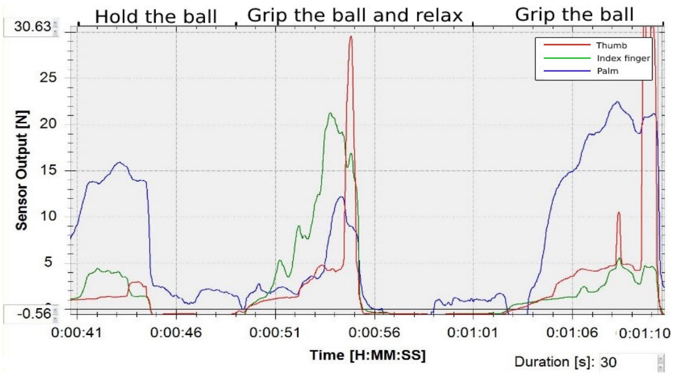

Fig. 7. Grip force signals.

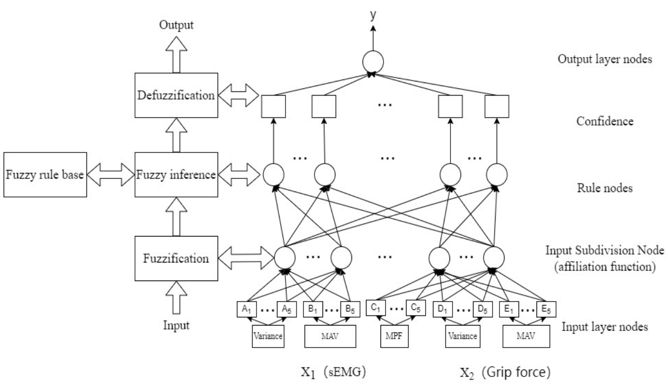

Fig. 8. Framework diagram of FNN.

MAV, the variance, and the MPF of the sEMG signals as well as the mean value and standard deviation of the grip force.

The second layer is the affiliation function layer to fuzzify the input variables. Each input variable contains five fuzzy sets, which are assumed to be set to A_i–E_i, and then the output after fuzzification is A_1–A_5, B_1–B_5, C_1–C_5, D_1–D_5, and E_1–E_5, they represent the probability of each fuzzy set, respectively. The higher the value, the more likely x belongs to that fuzzy set.

The third layer of the FNN is the fuzzy rule layer. The number of nodes in this layer is the same as the number of fuzzy rules, which is $m \times n$. It is the strength release layer of the rules, and each node in this layer is connected to only one of the m nodes and one of the n nodes in the second layer. This layer can be expressed as, with j, k, l, o, p = 1, 2, 3, 4, 5

$$O_i^{(3)} = A_j B_k C_l D_o E_p. \tag{8}$$

The fourth layer is confidence layer. The number of nodes in this layer also represents the division of the fuzzy degree in the output layer. The connection between this layer and the third layer is fully interconnected, assuming that the connection weight is W_{kj}, with $k = 1, 2, \ldots,$ $j = 1, 2, \ldots, m \times n$, $i = 1, 2, \ldots, 55$. The confidence level is

$$O_i^{(4)} = \overline{\omega_i} = w_i \Big/ \sum_{i=1}^{5^5} w_i. \tag{9}$$

The fifth layer is the defuzzification layer, a fixed node that calculates the total output in (10), where i = 1, 2. This layer

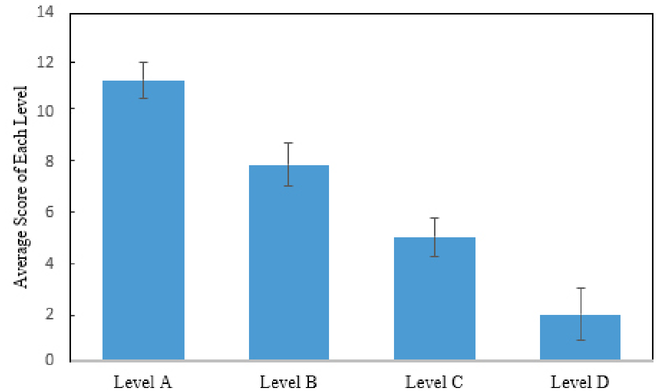

Fig. 9. Average score of each level.

transforms the output of each node in the fourth layer into an exact value

$$O_i^{(5)} = \sum \overline{\omega_i} f_i. \tag{10}$$

The network is trained the same as the BP neural network, the antecedent parameters are adjusted, and the affiliation function is modified to achieve the best result. The final FNN established in this project divides the signal strength into five fuzzy sets from small to large: $I = \{Z, S, M, N, L\}$, and the evaluation results into five fuzzy sets $U = \{ZO, SO, MO, NO, LO\}$. The output of the network is a number between 0 and 4, representing five rehabilitation stage. The closer the output is to an integer, the higher the confidence.

Another evaluation method only for the active rehabilitation unit is designed. Combining the two methods can reach evaluation in different aspects. This method is based on time, feedback force, stability, and accuracy of the trajectory during the virtual reality game. The score of each stage is shown in Table II. Twenty healthy volunteers play the virtual reality game; the time, stability, and feedback force are recorded as the standard of healthy people. Average score of each level is shown in Fig. 9. The scores were summed according to Table III. Then divide the data into 5 stages to evaluate the motor ability of the patients in different injury levels.

III. Experiment

Twenty volunteers were selected to do rehabilitation training. First, wipe the skin surface with medical alcohol and then stick surface electrodes on the biceps brachii, triceps brachii, and brachioradialis. Each volunteer was required to perform traditional rehabilitation movements including elbow extension and flexion, wrist extension and flexion, and wrist internal and external rotation [30]. The motor ability levels are shown in Table I. Second, performed grip training and acquired the force signals. Each group of training was performed three times and then rested for 30 s. After one level, rest for 30 min and then prepared for the next level [31], [32]. The relationship of each level in this paper is compared with Brunnstorm scale in Table IV.

Figs. 10–12 show sEMG signals in different muscles. All experiments were conducted within the experimental requirements of the Institutional Review Board (IRB) in the Faculty of Engineering Kagawa University (Ref. No. 01-011)

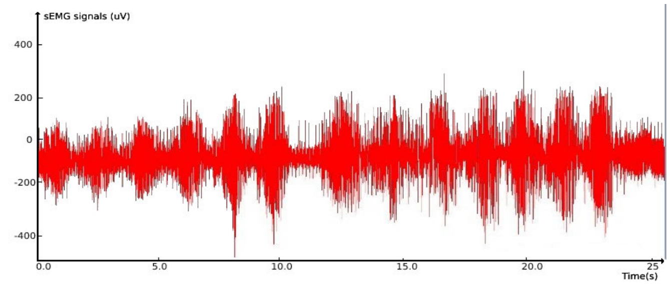

Fig. 10. sEMG signals of bicipital muscles.

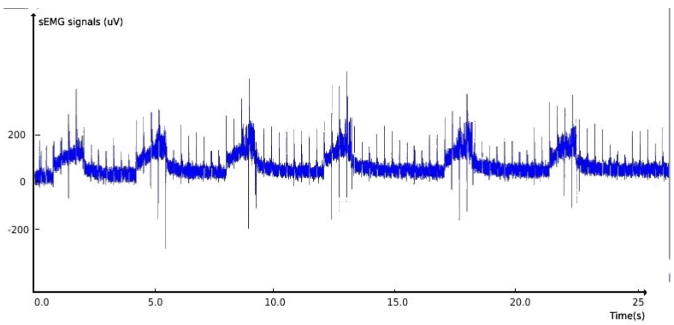

Fig. 11. sEMG signals of triceps brachii muscle.

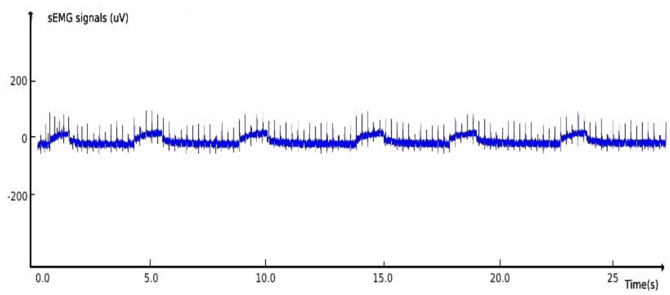

Fig. 12. sEMG signals of brachioradialis.

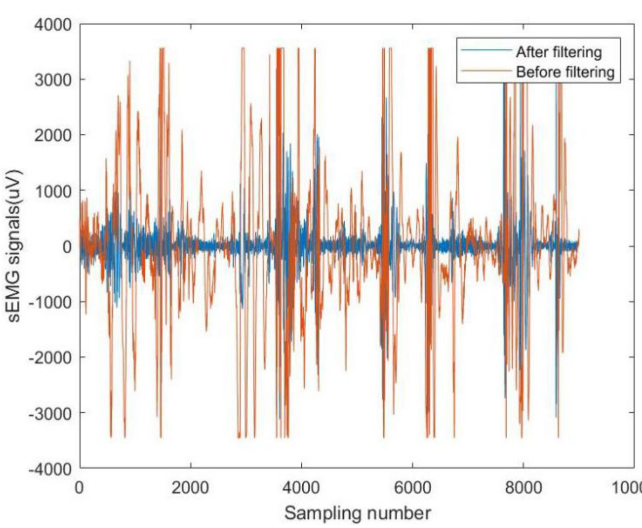

Fig. 13. Comparison of sEMG signals before and after filtering.

The sEMG signals before and after denoising are shown in Fig. 13. The sEMG signals and grip force are saved for the training of FNN. The data will be split into training set and validation set to train the network and calculate the accuracy. The accuracy rate is 0.96. It is compared with the state of art on

TABLE IV
CHOICE OF REHABILITATION MODALITY

Grade	Upper Limb	Hand	Scores corresponding to each subsystem	Recommended rehabilitation methods
I	Relaxed, no movement	Relaxed, no movement	Exoskeleton: ZO Phantom: 0-3	Passive rehabilitation
II	There is only a common movement pattern	Only slight flexion and extension	Exoskeleton: SO Phantom: 0-3	Passive rehabilitation
III	Can produce common movement at will	Hook grip, no finger extension	Exoskeleton: MO Phantom: 0-3	Passive rehabilitation
IV	1. When the shoulder is 0 ° and the elbow is 90 ° flexion. Forearm can be pronated and supinated 2.The elbow can be straightened by bending the shoulder forward 90 degrees 3. The back of the hand can touch the lumbosacral region	The thumb can be pinched and released, and the fingers can be extended in a small range	Exoskeleton: NO Phantom: 4-6	Passive rehabilitation or Active rehabilitation
V	1. Elbow extension, shoulder abduction 90° 2. Elbow extension, shoulder flexion 30°-90° and forearm pronation and supination 3. Elbow straight position, forearm neutral position, upper limbs raised above the head	It can be grasped in spherical and cylindrical shape, and fingers can be extended at the same time, but not alone	Exoskeleton: NO Phantom: 7-10 points	Active rehabilitation
VI	The movement coordination was close to normal, the finger and nose had no obvious bad, but the speed was slightly slower than that of the healthy side	All grasping can be completed, but the speed and accuracy are worse than that of the healthy side	Exoskeleton: LO Phantom: 10-12	Active rehabilitation

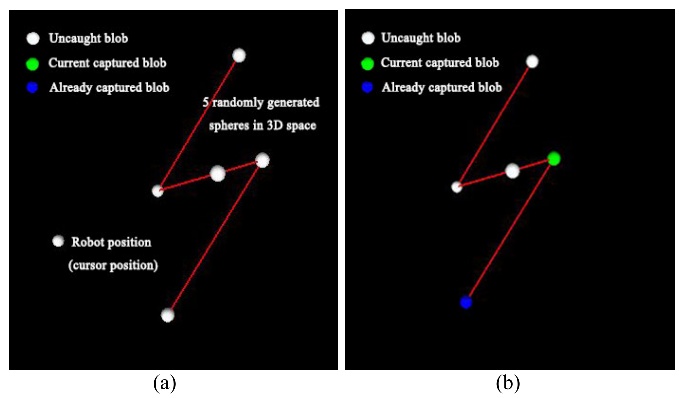

Fig. 14. Rehabilitation training operation interface. (a) Initial interface. (b) In-training interface.

rehabilitation evaluation method in Table V. For patients with mild motor impairment or in the later period of rehabilitation, the active rehabilitation unit is designed. Patients will play a virtual reality game for rehabilitation and evaluation. The rehabilitation game is shown in Figs. 14 and 15. Randomly generate serial points in 3-D space, with a red line to guide the trajectory of the movement. The patients manipulate PHANTOM to control the cursor move according to the path and capture each node in turn. When the cursor is close to the node, patients will feel the elasticity and need to apply enough force to make the cursor coincide with the node. When the cursor leaves, patients will feel the attraction. The force can be adjusted to increase or decrease the difficulty of the rehabilitation game. The white node is untouched, and the blue node is the node which is already captured. When the cursor coincides with the node, it will be green.

In this rehabilitation stage, patients already have basic motor ability and need to enhance their strength. The virtual reality game with feedback force can not only make the training more enjoyable but also easily set different difficulties of VR games. This game can meet the need for range of motion and strength training. Completing one small goal after another through continuous movement helps motivate patients to complete the entire rehabilitation game [33].

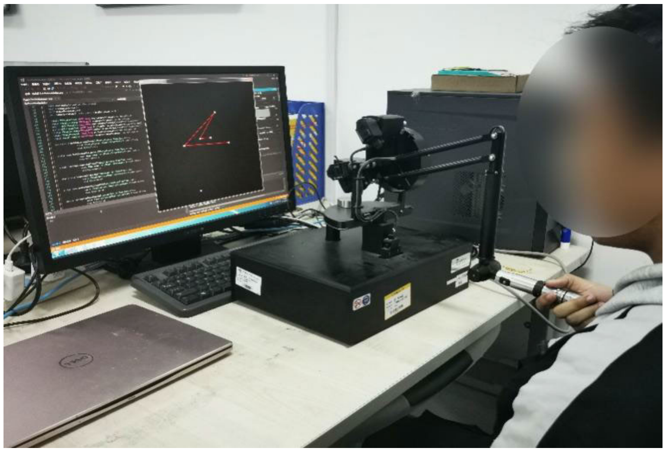

Fig. 15. Doing the active rehabilitation training.

A photograph during the training is shown in Fig. 15. All target nodes are within 225 dm^3 of the PHANTOM's end-effector. The user manipulates the PHANTOM to move the cursor for rehabilitation movement by continuously observing the visual feedback provided by the computer. The collision detection process and the feedback force thread will detect whether the cursor touches the ball and then update the image of the computer.

Although the game is displayed on the computer screen, the game is not planar. The virtual ball is generated in 3-D space within the range that the PHANTOM can reach, which is 75 cm in the x-axis, 75 cm in the y-axis, and 40 cm in the z-axis. The patient can drag the screen to rotate the perspective. However, as the range is only 225 dm^3, volunteers can easily find the virtual ball and only observe the interface with default angle. They can feel the hard surface of virtual ball when the cursor is close to it. The process of finding the ball is also a small challenge for the user.

The smoothness of the trajectory was analyzed by (11). First, fit the discrete points into a curve. The coordinates in 3-D space are x, y, z, and time is t. The distance of two destinations is s. The smoothness of the curve represents the stability of the trajectory. We defined a smooth function (Smo) which is calculated as (11)

$$\mathrm{Smo} = \sqrt{\frac{1}{2}\int\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2 + \left(\frac{d^3z}{dt^3}\right)^2 dt\left(\frac{t^5}{s^2}\right)}. \tag{11}$$

Table IV describes the relationship of each level in this article to the Brunnstrom scale. It establishes a link between the rehabilitation evaluation, classification, method in this article, and the traditional rehabilitation evaluation method. It is convenient for patients in each rehabilitation stage to understand their rehabilitation status and what rehabilitation exercises are most suitable for them.

The complete process of rehabilitation training and evaluation is as follows. First, introduce the experimental platform and environment to the patients. When they are familiar with the environment and manipulation, the training will begin. Second, figure out which mode should they use based on Table IV, if they are in the early period of rehabilitation, they need to do passive rehabilitation training. And the active rehabilitation training is for those who have mild motor impairment or are in the later period of rehabilitation. In the passive rehabilitation training, patients are guided by the robotic system. In the active rehabilitation training, patients could see a spherical cursor and five white virtual balls which are connected by red lines. Then, patients move the PHANTOM, doing it as straight as possible along the line, and overcome the repulsive force when it touches the virtual balls. The virtual ball's color will turn to green, then overcome the attractive force and leave the virtual ball, go for the next target. The ball turns from green to blue after the cursor breaks away. When all the balls turn blue, it means that the training is completed. Finally, the program will automatically record the data and do the rehabilitation evaluation.

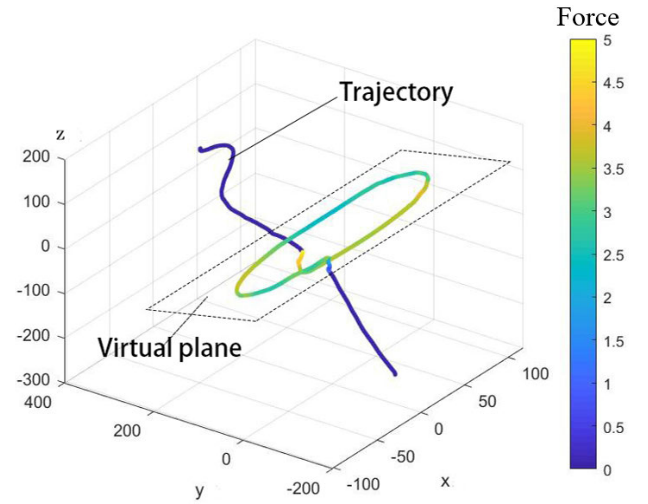

Fig. 16. Verification experiments of surface stiffness and feedback force.

IV. Discussion

An experiment is set to inspect the result of spring-damper model. Generate a virtual plane in 3-D space, the curve shown in Fig. 16 means the trajectory and the color means the force.

In the experiment, smaller result of Smo indicates that the patient has a better performance in trajectory and finishing time. For example, the curve in Fig. 17 is the trajectory of a smooth movement and a trembling movement. The result of red curve from A to B is 459.64, and the result of green curve from C to D is 889.98. That means the red curve is smoother than the green curve, and it has a better performance during the movement. Twenty volunteers simulated the rehabilitation, according to Table IV. The average value was obtained to do the rehabilitation evaluation.

By recording the feedback force, the results show that the feedback force can meet the requirements. The results in Fig. 18 also show that there is a linear relationship between the curve of feedback force when moving one unit from the plane and the feedback force curve when moving five units, which is consistent with the model.

A comparison of the rehabilitation evaluation method with the state of art on rehabilitation evaluation method is shown

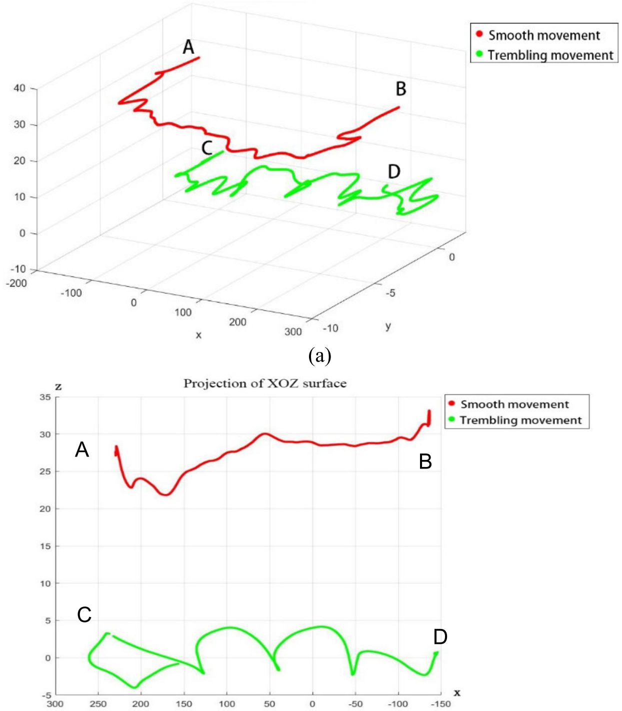

Fig. 17. Trajectory of a smooth movement and a trembling movement. (a) Trajectory in 3-D space. (b) Projection of *XOZ* surface of the trajectory.

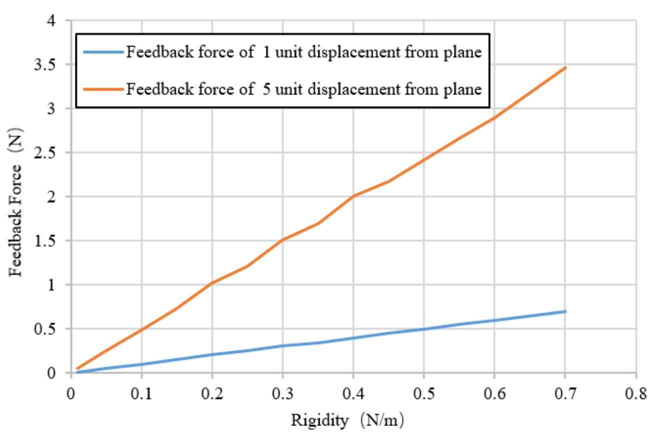

Fig. 18. Data from verification experiments of rigidity and feedback force models.

TABLE V
COMPARISON WITH THE STATE-OF-THE-ART

Research	Joints	Feature	Other parameters	Method	Results
[8]	Elbow	Temporal Components	EEG	ICA	Correlations (>0.79)
[34]	Elbow	K-WAS, PCA	No	BPNN	0.90
				SVM	0.87
This work	Elbow	MAV, MPF, Std, S^2	Grip force	FNN	0.96

in Table V. Antonella et al. [8] proposed a multidomain method analysis, including EEG, sEMG, kinematics, and scales. The results show that quantitative description has the same trend with traditional scales. However, it only shows the trend and did not present a method to get rehabilitation evaluation by these parameters. Wang et al. [34] present a method to get rehabilitation evaluation with sEMG signals. Two features were chosen in this method, and then the author compares support vector machine (SVM) and back propagation neural network (BPNN) as the model. The accuracy rate is 0.87 and 0.90. However, only use sEMG signals in the rehabilitation assessment is unstable. And the method still largely relies on therapists. This research combines grip force and sEMG signals to evaluate muscle strength to achieve better rehabilitation evaluation.

A motor recovery training and evaluation system is proposed in this article. Two training unit is provided so that patients in different injury levels can use this training system. The virtual reality game can enhance the interests and motivation of patients. The evaluation method is based on muscle strength and can work without therapists and achieve high accuracy. So that therapists will be able to help more patients.

V. CONCLUSION

A robotic system that consists of two rehabilitation units is proposed in this article. The passive rehabilitation unit includes signal acquisition, filtering, feature extraction, and establishment of an FNN for rehabilitation evaluation. Finally, the accuracy of the FNN is verified, and the accuracy rate is 0.96. The active rehabilitation unit includes PHANTOM and virtual reality rehabilitation games on a computer. The active rehabilitation training unit combines virtual reality, force feedback, collision detection, and other methods. Patients manipulate PHANTOM to complete the rehabilitation training according to the virtual reality game. Three experiments are proposed in this article, the FNN, spring-damper model, and the method to evaluate the trajectory are designed and validated. The rehabilitation evaluation method is compared with the state of art on rehabilitation evaluation method. The method proposed in this article can reach high accuracy and does not require the participation of a therapist. The upper limb rehabilitation training and evaluation robotic system designed in this article achieves the expected results. The rehabilitation training and evaluation in robotic system has a broad development prospect, it solves the problem of insufficient rehabilitation physicists, and brings hope to more patients.

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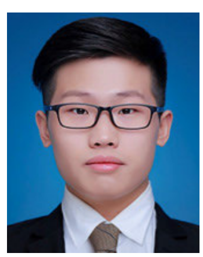

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