Rehabilitation Evaluation of Upper Limb Motor Function for Stroke Patients Based on Belief Rule Base

Shuang Li, Zhanli Wang, Xiaojing Yin, Zaixiang Pang, and Xue Yan

***Abstract*— In the process of rehabilitation treatment for stroke patients, rehabilitation evaluation is a significant part in rehabilitation medicine. Researchers intellectualized the evaluation of rehabilitation evaluation methods and proposed quantitative evaluation methods based on evaluation scales, without the clinical background of physiatrist. However, in clinical practice, the experience of physiatrist plays an important role in the rehabilitation evaluation of patients. Therefore, this paper designs a 5 degrees of freedom (DoFs) upper limb (UL) rehabilitation robot and proposes a rehabilitation evaluation model based on Belief Rule Base (BRB) which can add the expert knowledge of physiatrist to the rehabilitation evaluation. The motion data of stroke patients during active training are collected by the rehabilitation robot and signal collection system, and then the upper limb motor function of the patients is evaluated by the rehabilitation evaluation model. To verify the accuracy of the proposed method, Back Propagation Neural Network (BPNN) and Support Vector Machines (SVM) are used to evaluate. Comparative analysis shows that the BRB model has high accuracy and effectiveness among the three evaluation models. The results show that the rehabilitation evaluation model of stroke patients based on BRB could help physiatrists to evaluate the UL motor function of patients and master the rehabilitation status of stroke patients.**

***Index Terms*— Rehabilitation robot, belief rule base, rehabilitation evaluation.**

I. Introduction

STROKE is one of the common diseases of the elderly, which is a disease of necrosis of brain cells and tissues [1]. Stroke patients usually have unilateral or bilateral limb weakness, unclear speech, cognitive impairment and other symptoms, may die in severe cases [2]. It is clinically proved that patients can recover limb motor function by rehabilitation training [3], [4]. The rehabilitation evaluation is an important part of rehabilitation medicine in the process of rehabilitation treatment for stroke patients. When patients receive rehabilitation treatment, the rehabilitation physiatrist will assess the patient's rehabilitation and current physical condition [5], [6]. According to the rehabilitation evaluation results, the rehabilitation treatment plan will be formulated for the patients to achieve the best treatment and recovery effect.

In clinic, physiatrists evaluate the rehabilitation level of stroke patients according to the Medical Stroke Assessment Scale [7]. Traditional clinical rehabilitation evaluation methods include Bobath, Brunstrom, Fugl-Meyer Assessment (FMA), improved Ashworth, Motor Status Scale (MSS) [8], [9], [10]. The traditional rehabilitation evaluation needs to be accomplished by well experienced physiatrist and the evaluation results are influenced by the physiatrist and the evaluation process needs more time [11]. Traditional rehabilitation evaluation is to be evaluated by well-experienced physiatrist [12]. The one-to-one evaluation between rehabilitation doctors and patients takes a long time, and the evaluation result will be affected by the subjective of the physiatrist. Therefore, it is necessary to apply advanced theories and methods to the field of rehabilitation medicine, establish an evaluation model for patients' motor function, and help their doctors obtain rehabilitation level of patients accurately. Combining advanced theoretical methods with medical combined rehabilitation methods and auxiliary rehabilitation resources can not only optimize the rehabilitation effect and rehabilitation resource allocation, but also provide important theoretical support for intelligent medical treatment [13], [14], [15].

At present, many researchers try to intelligentize rehabilitation assessment [16], [17], [18]. Takehito Kikuchi developed a 6 degrees of freedom rehabilitation robotic system and combined with the evaluation function software to establish three evaluation modes: Rhythmic Stabilization, FNF and GUR. The patient's rehabilitation status and training quality were displayed through the virtual reality system [19]. Fan and Yin used multisource information fusion technology to study the early rehabilitation of active and passive exoskeleton, which improved the safety and efficiency of exoskeleton assisted rehabilitation training [20]. Reddy et al. detected the three-dimensional workspace surface area according to the data collected by Kinect and evaluated the UL function of patients with shoulder musculoskeletal dysfunction [21]. Kim et al. proposed a method to judge the degree of elbow

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spasticity and used machine learning algorithm to classify the level of elbow spasticity [22]. Zhang et al. proposed a rehabilitation evaluation system for desktop rehabilitation training robot, which can quantitatively assessment the UL motor function of patients and grasp the degree of rehabilitation of patients [23].

The existing intelligent rehabilitation evaluation method is quantitative evaluation [24]. According to the information collected from the patients, the researchers use the quantitative scoring method to evaluate the rehabilitation of the patients and there was no involvement of physiatrist in the assessment process. However, in clinical practice, the physiatrist obtains the patient's information and evaluates the patient's rehabilitation based on the evaluation scale and their experience. The experience of physiatrist plays an important role in the rehabilitation evaluation of patients.

The BRB model is proposed by Yang which is a nonlinear model based on semi-quantitative information [25]. It can address both qualitative knowledge and quantitative information. The characteristic of this model is that it incorporates expert knowledge and can fully utilize quantitative knowledge. Especially, when the model is combined with expert knowledge, it exhibits excellent performance when dealing with the small-scale samples. In the rehabilitation assessment model, expert knowledge is the clinical experience of the physiatrist.

Therefore, in this paper, a rehabilitation robot with 5 DoFs is designed to assist patients in rehabilitation training and acquire motion data of stroke patients. In order to better measure the patient's movement data, surface electromyography (sEMG) signal measurement is added. The rehabilitation evaluation method of stroke patients is established by fusing the acquired information and expert knowledge based on BRB theory. The relationship model between rehabilitation characteristic quantity and rehabilitation degree is established to simulate the rehabilitation evaluation of patients by physiatrist to the greatest extent. In the modeling process, aiming at the uncertainty of expert knowledge, the updating and optimization method of model parameters is studied to provide more accurate rehabilitation evaluation results for physiatrist.

II. Rehabilitation Robot Design

A. Structure of Rehabilitation Robot

The proposed rehabilitation robot for stroke patients is shown in Fig. 1, which can help patients complete the rehabilitation actions of upper limbs, including active and passive movements. The robot can complete the adduction and abduction of the shoulder joint directly in the coronal plane, which can help patients better complete the rehabilitation of the shoulder joint. The rehabilitation robot is composed by a base station and five models, which can help the stroke patients do rehabilitation exercises in their middle and late stages of rehabilitation. The module I, II and III can accomplish the movement of shoulder joint. The module IV accomplishes the flexion/extension of the elbow joint, and module V accomplishes the radial/ulnar deviation of the wrist.

In module III, a gravity compensation device is designed, which consists of a parallel four link mechanism and cable. The gravity compensation device can bear the axial load

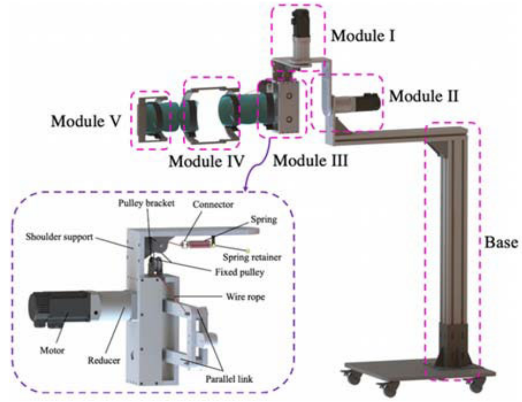

Fig. 1. The overall structure of rehabilitation robot.

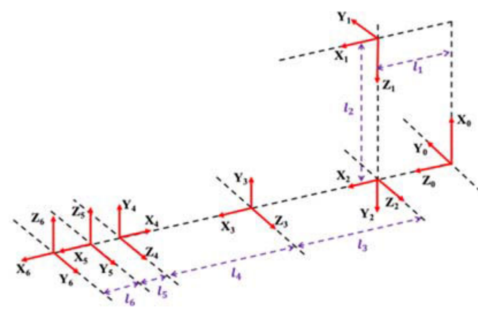

Fig. 2. Mechanism diagram of ULRR.

of the shoulder joint mechanism and improve the stability when shoulder joint is moving. When patients use robots for rehabilitation training, it is necessary to connect the patient's upper limbs to the robot through flexible straps, aligning the patient's upper limb joints with the robot joints. The robot drives the patient's upper limbs for rehabilitation movement by actuators which are driving the joint movement of the robot.

B. Forward Kinematics of Rehabilitation Robot

The forward kinematics (FK) is to address the pose of the end effector of robot by inputting the values of θ_i. In this paper, the FK of the robot is derived based on the D-H parameter method. The kinematics model of the ULERR based on the kinematics theory, as shown in Fig. 2. Each link of the robot can be represented by the four parameters of D-H which are the length a_i of the link, the twist α_i, the offset d_i and the joint angle θ_i, respectively. The TABLE I shows D-H parameters of robot.

According to the robotics knowledge, the coordinate transformation systems of the robot can be expressed as:

$$ {}^{i-1}T_i = \begin{bmatrix} C_i & -S_i c\alpha_i & S_i s\alpha_i & a_i C_i \\ S_i & C_i c\alpha_i & -C_i s\alpha_i & a_i S_i \\ 0 & s\alpha_i & c\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1} $$

where, $C_i = \cos\theta_i$ $\mathrm{c}\theta_\mathrm{i} = \cos\theta_\mathrm{i}$, $\mathrm{s}\theta_\mathrm{i} = \sin\theta_\mathrm{i}\mathrm{S}_\mathrm{i} = \sin\theta_\mathrm{i}$, $\mathrm{c}\alpha_\mathrm{i} = \cos\alpha_\mathrm{i}\mathrm{c}\alpha_\mathrm{i} = \cos\alpha_\mathrm{i}$, $\mathrm{s}\alpha_\mathrm{i} = \sin\alpha_\mathrm{i}\mathrm{s}\alpha_\mathrm{i} = \sin\alpha_\mathrm{i}$.

The pose matrix of the coordinate system at the end of the robot relative to the base coordinate

TABLE I
D-H PARAMETERS OF THE ROBOT

Link /i	*Joint angle/*θ_i	*Link length/*a_i	*Link offset/*d_i	*Link twist/*α_i
1	θ_1	0	l_1	90°
2	θ_2	0	l_2	90°
3	θ_3	l_3	0	0°
4	θ_4	l_4	0	0°
5	θ_5	l_5	0	90°
6	θ_6	l_6	0	0°

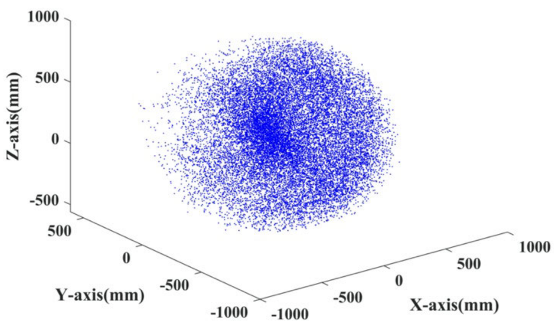

Fig. 3. Cloud map of the robot workspace.

system is:

$$ {}^0_5T = {}^0_1T\,{}^1_2T\,{}^2_3T\,{}^3_4T\,{}^4_5T\,{}^5_6T = \begin{bmatrix} n_x & o_x & a_x & p_x \\ n_y & o_y & a_y & p_y \\ n_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2) $$

where, n, o, a, are the posture of the robot and $p_x p_x$, $p_y p_y$, $p_z p_z$ are represent the end position coordinate vector.

C. Workspace of Rehabilitation Robot

In order to know whether the designed robot meets the rehabilitation needs of patients, it is necessary to know the workspace of the robot. The workspace needs to include the max range of upper limb activity for the patient. The workspace is obtained by combining Monte Carlo method and D-H parameter method. As shown in Fig. 3 of the simulation results, the range of workspace of the end of the robot is: $-730\text{mm} \leq X \leq 730\text{mm}$, $-730\text{mm} \leq Y \leq 730\text{mm}$, $-556\text{mm} \leq Z \leq 556\text{mm}$. According to the ergonomics, the limit position of the robot is near to the limit position of the upper limb of the human body. Therefore, the designed robot fulfills the requirements for the range of motion (ROM) of the upper limbs.

D. Experiment of Rehabilitation Robot

To realize the control of robot using the computer, and Fig. 4 shows the diagram control system of the robot. Using the sensors on the robot to collect the human motion data, and the information is transmitted to the data acquisition card, and finally uploaded the data to the computer.

The purpose of the patient by using robot for rehabilitation is that the patient can complete the basic activities in daily life. Therefore, it is necessary the patients complete the multi-joint compound movements by robot. Taking the action of drinking water and touching the left shoulder as examples, and multi-joint compound exercises rehabilitation training experiment are carried out. The Fig. 5 shows the participant completes the movement of drinking water and touching the left shoulder by using the robot.

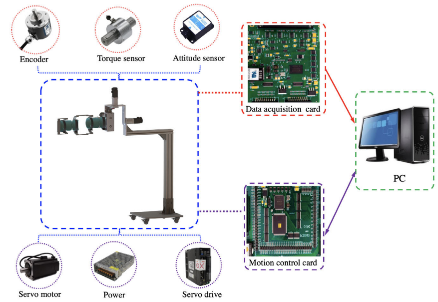

Fig. 4. The rehabilitation robot system.

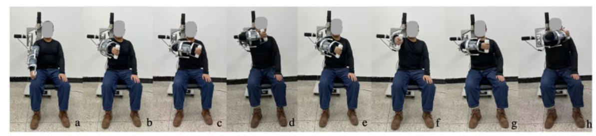

Fig. 5. The participant completes the movement by using robot.

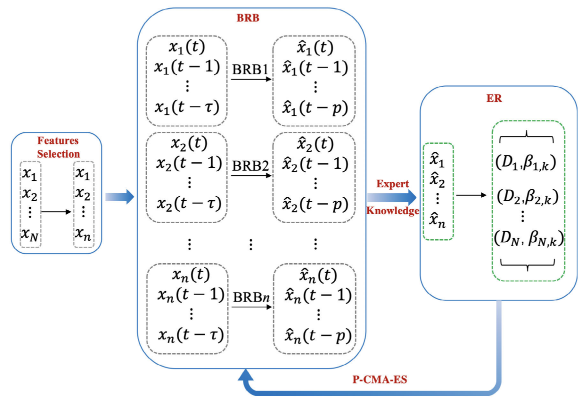

Fig. 6. The structure of the model.

III. EVALUATION METHOD

The evaluation model of UL rehabilitation for stroke patients based on BRB proposed in this paper mainly includes three parts. First, the features are selected to represent the UL rehabilitation characteristics of the patients. Secondly, the time series evaluation model of rehabilitation characteristics based on BRB is established. Finally, ER algorithm is used to fuse these rehabilitation features. The UL rehabilitation status of stroke patients was evaluated. Fig. 6 shows the structure of the model.

A. Features Selection

At present, the main methods used in the evaluation of UL motor function are the method based on the change of limb motion mode and muscle strength. In the method based on the motion mode of the limbs, the ROM is a motion feature that can be directly observed and detected. ROM refers to the motion arc through which the joint moves, usually expressed in degrees, which can be used as an indicator to reflect the motor function level of stroke patients with motor disorders [26]. Muscle force refers to the ability of a muscle to generate tension to make it produce static or dynamic contraction, which can also be regarded as muscle contraction force. With the development of detection technology, muscle strength can also be reflected by sEMG. sEMG signal is the most important physiological parameter of human muscle activity. It is a small electrical signal generated by human muscle during contraction. The research shows that the amplitude of sEMG signal is related to the size of muscle force, movement speed and acceleration, and the Root Mean Square (RMS) of sEMG reflects the number of motor units activated during muscle activity [27], [28]. Therefore, in this paper, the ROM and sEMG signals are selected as features to evaluate the UL motor function of stroke patients.

B. Establishment of BRB Rehabilitation Evaluation Model

To evaluate the health status of UL of patients, the nonlinear relationship between the health status of patients' UL and the characteristic quantity should be established first. The specific relationship model is as follow:

$$H = f\left(x_{1t}, x_{2t}, \cdots, x_{Mt}, V\right) \tag{3}$$

where, H represents the health status of the patient's UL, f is the nonlinear BRB model, $x_{Nt}(N = 1, 2, \ldots, M)$ is one of the characteristics of the evaluation system, V is the model parameters. In this paper, the nonlinear model f between the features and the evaluation state will be established by using such features as the ROM and sEMG based on BRB theory.

The health status evaluation model of stroke patients based on BRB considers both expert knowledge and feature information. In the process of rehabilitation evaluation, considering the uncertainty of expert knowledge, P-CMA-ES is used to update the initial parameters of BRB respectively, and a simpler and more accurate rehabilitation evaluation model is established. The specific process of modeling is as follows:

The first step:

Assuming that a total of i features can be used to represent the health status of UL of stroke patients, based on the evaluation scale and the professional knowledge of rehabilitation physicians, the kth BRB rule of rehabilitation evaluation is:

R_k : *If* $a_1 is A_1^k \wedge a_2 is A_2^k \wedge \cdots \wedge a_M is A_{M_k}^k$, *Then* $\{(D_1, \beta_{1,k}), (D_2, \beta_{2,k}), \ldots, (D_N, \beta_{N,k})\}$ *with a rule weight* θ_k *and attribute weight* $\delta_{1,k}, \delta_{2,k}, \ldots, \delta_{M_k,k}$.

where,

R_k the k-th confidence rule.

a_i—— the i-th premises attribute, i represents the number of feature quantities of system, $i = 1, 2, \cdots, M_k$.

A_i^k—— the reference value of the i-th premises attribute in the k-th rule, $i = 1, 2, \cdots, M_k, k = 1, 2, \cdots, L$, $A_i^k \in A_i$, and $A_i = \left\{A_{i,j} j = 1, 2, \cdots, J_m\right\}$ represents the set composed of J_i reference values of the i-th prerequisite attribute.

M_k—— the number of prerequisite attributes in the k-th rule.

D_j—— the j-th evaluation result, $j = 1, 2, \cdots, N(N$ is the number of evaluation results).

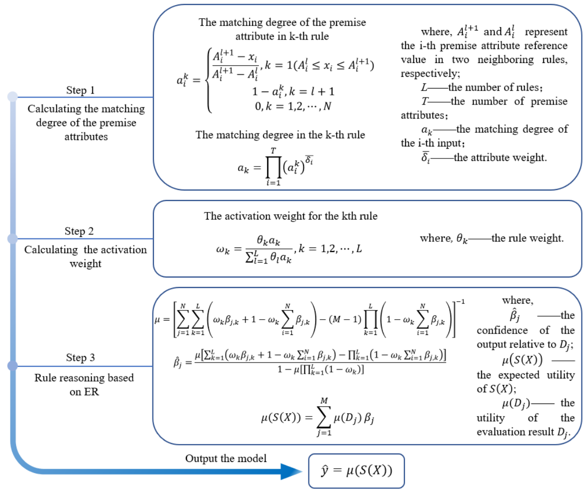

Fig. 7. Reasoning process based on ER.

$\beta_{j,k}$—— the confidence of the k-th result D_j, $j = 1, 2, \cdots, N, k = 1, 2, \ldots, L$.

If there are M prerequisite attributes in BRB, then $\delta_i = \delta_{i,k}$, $\bar{\delta_i} = \frac{\delta_i}{\max\limits_{i=1,2,\ldots,M}\{\delta_i\}}$, $(i = 1, 2, \cdots, M_k, k = 1, 2, \ldots, L)$.

$$\text{If} \sum_{j=1}^{N} \beta_{j,k} \neq 1,$$

then k-th rule is incomplete; Otherwise, it is complete.

The second step: To get the final system output in the BRB model, Evolutionary Reasoning (ER) algorithm is used to perform combined reasoning on the confidence rules. The reasoning process is as shown in Fig.7. The third step:

In the rehabilitation evaluation model for stroke patients based on BRB, the initial parameters of the model are given by experts, which is highly subjective and the accuracy of the evaluation model is low. The initial BRB parameters are optimized based on P-CMA-ES to improve the accuracy of the evaluation model [29]. In the process of parameter optimization of BRB rehabilitation evaluation model, the following optimization objective function is established:

$$\begin{aligned} & min\xi\left(V\right) \\ & s.t. \sum_{n=1}^{N} \beta_{n,k} = 1, \\ & \qquad 0 \le \beta_{n,k} \le 1, \quad k = 1, 2, \cdots, L \\ & \qquad 0 \le \delta_i \le 1, \quad i = 1, 2, \cdots, M \\ & \qquad 0 \le \theta_k \le 1 \end{aligned}$$

where,

$$\xi\left(V\right) = \frac{1}{t - \tau} \sum_{t=\tau-1}^{T} \left(y\left(t\right) - \hat{y}\left(t\right)\right)^2$$

$y\left(t\right)$—— output results of actual rehabilitation state of stroke patients.

$\hat{y}\left(t\right)$—— output of rehabilitation evaluation model for stroke patients.

T—— the amount of data.

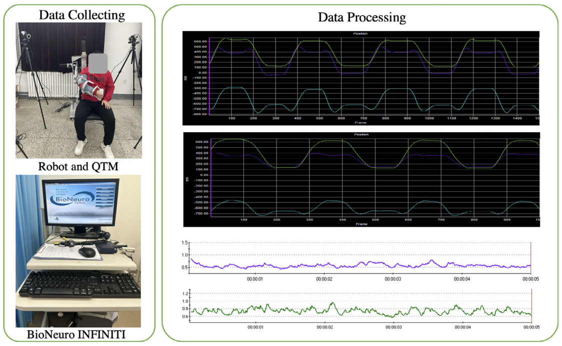

Fig. 8. Data collecting systems.

IV. Case Study

To verify the effectiveness and accuracy of the rehabilitation evaluation model for stroke patients proposed in this paper, the model is used to evaluate the health status of UL of stroke patients. When collecting joint angle data, the first step is to place markers on the patient's UL joints and connect the patient's UL to the robot through protective covers. This facilitates guiding the patient through a series of joint movements, such as shoulder adduction and abduction. The UL rehabilitation robot and the QTM system are used to collect the patient's UL motion data. When collecting sEMG signals, the first step is to clean the designated areas with alcohol swabs. After the cleaning process is completed, electrode pads are applied to the patient's upper limb. BioNeuro INFINITI is used to collect sEMG data during human joint movements. Each subject is required to perform six sets of movements, including adduction/abduction, internal/external rotation and flexion/extension of shoulder joint, flexion/extension of elbow joint, flexion/extension and radial/ulnar deviation of wrist joint. Each movement is to be repeated ten times.The ROM and sEMG of patients' UL were collected using the rehabilitation robot, Qualisys Track Manager (QTM) and BioNeuro INFINITI, as shown in the Fig. 8. The UL motion data of 30 patients with different rehabilitation levels and 5 normal persons are collected to establish the rehabilitation evaluation level data. The collection of exercise data from patients and participants is agreed upon by them. The basic information of the patients (15 males and 15 females, mean age of 57.8±10.4 years) is shown in Table II.

Because the MSS adopts a 6-level scoring mode, which provides a detection method for the separation movement of a single joint of the UL, this paper establishes a database of different rehabilitation levels for different patients based on the MSS and expert knowledge. Based on the quantitative data of joint ROM and sEMG obtained, and qualitative knowledge such as expert knowledge and MSS, a rehabilitation evaluation model for UL of stroke patients is established.

According to the MSS and expert knowledge, the ROM selects 6 reference values:

N = no contraction or motion
C = contraction or initiating first few degrees of motion
PP = performs partly movement
L = lacking few degrees of movement
CF = completes full range or decreased control
PF = performs faultlessly
And the $A_1^k \in \{N, C, PP, L, CF, PF\}$.

TABLE II
The Basic Information of the Patients

Subject	Age	Sex	Etiology	Side	Mss
1	52	Male	Hemorrhagic	Right	1+
2	46	Female	Ischemic	Left	1+
3	66	Male	Ischemic	Right	0
4	78	Female	Ischemic	Right	1-
5	63	Male	Ischemic	Right	2-
6	45	Female	Ischemic	Left	0
7	48	Male	Ischemic	Right	1-
8	71	Female	Ischemic	Right	1+
9	77	Male	Ischemic	Right	1-
10	68	Female	Ischemic	Right	1
11	64	Male	Ischemic	Left	1
12	66	Female	Ischemic	Right	0
13	54	Male	Ischemic	Right	2-
14	52	Female	Ischemic	Left	1-
15	50	Male	Hemorrhagic	Right	1+
16	47	Female	Ischemic	Left	1-
17	42	Male	Ischemic	Right	2-
18	43	Female	Hemorrhagic	Right	0
19	74	Male	Ischemic	Right	2
20	65	Female	Ischemic	Right	1
21	42	Male	Hemorrhagic	Left	2
22	64	Female	Ischemic	Right	1
23	53	Male	Ischemic	Right	2
24	57	Female	Ischemic	Left	0
25	50	Male	Hemorrhagic	Right	1+
26	58	Female	Ischemic	Right	2
27	66	Male	Ischemic	Right	2-
28	62	Female	Hemorrhagic	Left	2
29	55	Male	Ischemic	Right	2-
30	57	Female	Ischemic	Right	1

For sEMG, six reference values are selected the same as ROM [30], [31], namely $A_2^k \in \{N, C, PP, L, CF, PF\}$.

According to the MSS evaluation scale, the rehabilitation status of stroke patients is divided into six grades, which are respectively expressed as (N, I, II, III, IV, V):

$\{T_1, T_2, T_3, T_4, T_5, T_6\} = \{N, I, II, III, IV, V\}$

The input features of BRB have six reference values respectively, so 36 initial confidence rules can be established to evaluate the rehabilitation level of patients. If the quantitative data of ROM is qualitative semantic expression "N", and the qualitative semantic expression of sEMG is respectively "N, C, PP, L, CF, PF", the following rules are established according to expert knowledge:

R_1 : *If (ROM is N)∧ (sEMG is N), Then {(0.9,0.1,0,0,0,0)}*
R_2 : *If (ROM is N)∧ (sEMG is C), Then {(0.1,0.8,0.1,0,0,0)}*
R_3 : *If (ROM is N)∧ (sEMG is PP), Then {(0, 0.1,0.9,0,0,0)}*
R_4 : *If (ROM is N)∧ (sEMG is L), Then {(0,0,0.1,0.8, 0.1,0)}*
R_5 : *If (ROM is N)∧ (sEMG is CF), Then {0,0,0,0,0.9,0.1)}*
R_6 : *If (ROM is N)∧ (sEMG is PF), Then {0,0,0,0, 0.1,0.9)}*

Taking the above rules as an example, a systematic BRB rehabilitation evaluation model is established. The k-th rule is as follows:

R_k : *If Range of motion is* $A_1^k \wedge$ *sEMG is* A_2^k , *Then Rehabilitation condition is* $\{(N,\beta_{1,k}), (I,\beta_{2,k}), (II,\beta_{3,k}), (III,\beta_{4,k}), (IV,\beta_{5,k}), (V,\beta_{6,k})\}$ *with a rule weight* θ_k , *attribute weight* $\delta_1, \delta_2, \ldots, \delta_6$

TABLE III
THE ATTRIBUTE REFERENCE VALUE OF ROM

Referential points	N	C	PP	L	CF	PF
Referential values	180	150	120	90	60	30

TABLE IV
THE ATTRIBUTE REFERENCE VALUE OF sEMG

Referential points	N	C	PP	L	CF	PF
Referential values	40	35	30	25	20	15

TABLE V
THE REFERENCE VALUE OF REHABILITATION STATUS

Referential points	N	I	II	III	IV	V
Referential values	5	4	3	2	1	0

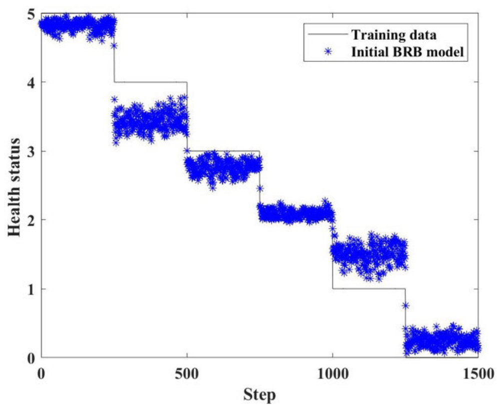

Fig. 9. The rehabilitation evaluation results by initial BRB model.

The attribute reference value of ROM and sEMG are shown in Table III and Table IV, respectively. The reference value of rehabilitation status is shown in Table V.

In the rehabilitation evaluation model, since there are 6 reference values for each feature, there are 36 rules in total when evaluating the health status of the features. According to expert knowledge, the initial confidence of two characteristic quantities is given in Table VI.

This paper has obtained 2100 sets of data, including 1500 sets as training data and 600 sets as test data. According to the initial parameters given by experts, the weight of characteristic quantity is not considered. θ_k and δ_i are both set to 1, and the rehabilitation evaluation results are shown in Fig. 9. The results show that that the fitting degree between the evaluation results and the training data is not high.

In the rehabilitation evaluation model for stroke patients based on BRB, the initial parameters of the model are given by experts, which is highly subjective and the evaluation model is inaccurate. To improve the accuracy of the evaluation model, the initial BRB parameters need to be optimized. In this paper, P-CMA-ES optimization algorithm is used to optimize BRB model parameters. The optimized BRB parameters are shown in Table VII. Fig. 10 illustrates the evaluation results which is shown that the updated output of parameters can well fit the training data.

V. COMPARATIVE ANALYSIS

To verify the effectiveness and accuracy of the methods proposed in this chapter, this section conducts a comparative

TABLE VI
THE INITIAL PARAMETERS OF BRB

Rule number	Attributes		Fault-degree distribution $\{T_2, T_3, T_4, T_5, T_6\} = \{5, 4, 3, 2, 1, 0\}$
	ROM	sEMG	
1	N	N	{(0.9, 0.1,0,0, 0,0)}
2	N	C	{(0.1, 0.8,0.1,0, 0,0)}
3	N	PP	{(0, 0.1,0.9,0, 0,0)}
4	N	L	{(0, 0,0.1,0.8, 0.1,0)}
5	N	CF	{(0, 0,0,0.1, 0.8,0.1)}
6	N	PF	{(0, 0,0,0, 0.9,0.1)}
7	C	N	{(0, 0.9,0.1,0, 0,0)}
8	C	C	{(0, 0.1,0.8,0.1, 0,0)}
9	C	PP	{(0, 0,0.1,0.8, 0.1,0)}
10	C	L	{(0, 0,0,0.1, 0.9,0)}
11	C	CF	{(0, 0,0,0.2, 0.7,0.1)}
12	C	PF	{(0, 0,0,0, 0.2,0.8)}
13	PP	N	{(0, 0.1,0.9,0, 0,0)}
14	PP	C	{(0, 0,0.1,0.8, 0.1,0)}
15	PP	PP	{(0, 0,0,0.7, 0.3,0)}
16	PP	L	{(0, 0,0,0.6, 0.4,0)}
17	PP	CF	{(0, 0,0.7,0.3, 0,0)}
18	PP	PF	{(0, 0,0.1,0.7, 0.2,0)}
19	L	N	{(0, 0,0.8,0.2, 0,0)}
20	L	C	{(0, 0,0.1,0.7, 0.2,0)}
21	L	PP	{(0, 0,0.1,0.6, 0.3,0)}
22	L	L	{(0, 0,0,0.6, 0.4,0)}
23	L	CF	{(0, 0,0.1,0.5, 0.4,0)}
24	L	PF	{(0, 0,0,0.4, 0.6,0)}
25	CF	N	{(0, 0,0.1,0.5, 0.4,0)}
26	CF	C	{(0, 0,0,0.4, 0.5,0.1)}
27	CF	PP	{(0, 0,0,0.2, 0.6,0.2)}
28	CF	L	{(0, 0,0,0.1, 0.6,0.3)}
29	CF	CF	{(0, 0,0,0, 0.7,0.3)}
30	CF	PF	{(0, 0,0,0, 0.8,0.2)}
31	PF	N	{(0, 0,0,0, 0.5,0.5)}
32	PF	C	{(0, 0,0,0, 0.4,0.6)}
33	PF	PP	{(0, 0,0,0, 0.3,0.7)}
34	PF	L	{(0, 0,0,0, 0.2,0.8)}
35	PF	CF	{(0, 0,0,0, 0.1,0.9)}
36	PF	PF	{(0, 0,0,0, 0,1)}

analysis. First, the Back Propagation Neural Network (BPNN) is used for comparative analysis. BPNN is widely used in diagnosis, classification and prediction. As with the BRB model simulation analysis, the 1500 groups of data are also used for training in the BPNN evaluation model, and the remaining data are used as test data. Evaluation results based on BPNN are shown in Fig. 11. To further verify the progressiveness of the proposed model, Support Vector Machines (SVM) is used to evaluate and analyze the data. The previous 1500 groups of data are also used for training, and the rest are used as test data. The results are shown in Fig. 12. Table VIII lists the Mean Square Error (MSE) of BRB, BPNN and SVM health status evaluation model. Through comparative analysis, it can be known that the rehabilitation evaluation model based on BRB proposed in this paper has high accuracy and effectiveness.

VI. DISCUSSION

This paper presents a rehabilitation evaluation model based on BRB for stroke patients which combine the assessment scale and the expert knowledge of physiatrist. To verify the accuracy of the proposed model, BPNN and SVM are

TABLE VII
THE OPTIMIZED BRB PARAMETERS

Rule number	Attributes		Fault-degree distribution $\{T_1, T_2, T_3, T_4, T_5, T_6\}$ = {5, 4, 3, 2, 1, 0}
	ROM	sEMG	
1	N	N	{(0.7335,0.0301,0.0438,0.0501,0.0473,0.0952)}
2	N	C	{(0.0693,0.6547,0.0869,0.0759,0.0439,0.0693)}
3	N	PP	{(0.0802,0.0381,0.8442,0.0063,0.0218,0.0094)}
4	N	L	{(0.0126,0.0852,0.0411,0.7651,0.0562,0.0398)}
5	N	CF	{(0.0719,0.0923,0.0561,0.0445,0.6580,0.0772)}
6	N	PF	{(0.0129,0.0651,0.0369,0.0187,0.8607,0.0057)}
7	C	N	{(0.0156,0.9086,0.0204,0.0117,0.0437,0)}
8	C	C	{(0.0143,0.2414,0,0,0.7323,0.0130)}
9	C	PP	{(0.0763,0.0431,0.0118,0.7228,0.0537,0.0923)}
10	C	L	{(0.0886,0.0057,0.0675,0.0235,0.7820,0.0327)}
11	C	CF	{(0.3612,0.0151,0,0,0.6104,0.0133)}
12	C	PF	{(0.0267,0.0765,0.0193,0.0938,0.0489,0.7348)}
13	PP	N	{(0.0013,0.0175,0.542,0,0.0157,0.4235)}
14	PP	C	{(0.0374,0.0883,0.0855,0.7251,0.0065,0.0572)}
15	PP	PP	{(0.0093,0.0416,0.0264,0.8647,0.0413,0.0167)}
16	PP	L	{(0.0400,0.0636,0.0300,0.7510,0.0278,0.0876)}
17	PP	CF	{(0.0508,0.0998,0.0414,0.6875,0.0984,0.0221)}
18	PP	PF	{(0,0.0179,0.0113,0.9547,0.0132,0.0029)}
19	L	N	{(0,0,0,0.7023,0.0189,0.2788)}
20	L	C	{(0.0632,0.0410,0.0109,0.7818,0.0267,0.0764)}
21	L	PP	{(0.0727,0.0314,0.0420,0.8274,0.0198,0.0067)}
22	L	L	{(0.0444,0.0803,0.0051,0.7970,0.0544,0.0188)}
23	L	CF	{(0.0673,0.0926,0.7675,0.0553,0.0036,0.0137)}
24	L	PF	{(0,0.0024,0.0052,0.0023,0.9894,0.0007)}
25	CF	N	{(0.0256,0.0429,0.0596,0.7607,0.0927,0.0185)}
26	CF	C	{(0.7647,0.0874,0.0268,0.0388,0.0636,0.0187)}
27	CF	PP	{(0.0990,0.0671,0.0204,0.0841,0.6396,0.0898)}
28	CF	L	{(0.0764,0.0473,0.0130,0.0234,0.7646,0.0753)}
29	CF	CF	{(0.0494,0.0409,0.0611,0.0854,0.7430,0.0202)}
30	CF	PF	{(0,0.0862,0.0103,0.0013,0.8037,0.0985)}
31	PF	N	{(0.1140,0,0.3786,0,0.5074,0)}
32	PF	C	{(0.0381,0.0350,0.0204,0.0484,0.0015,0.8566)}
33	PF	PP	{(0.0900,0.0857,0.0288,0.0053,0.0929,0.6973)}
34	PF	L	{(0.0005,0.0140,0.0723,0.0338,0.0905,0.7889)}
35	PF	CF	{(0.0804,0.0612,0.0067,0.0506,0.0816,0.7195)}
36	PF	PF	{(0.0304,0.0917,0.0067,0.0006,0.0019,0.8687)}

TABLE VIII
THE MSEs OF DIFFERENT MODELS

Models	Training	Testing
BRB	0.0298	0.0325
BPNN	0.1736	0.2410
SVM	0.2844	0.3975

used to evaluate. Three different evaluation models are established based on BRB, BPNN and SVM algorithms which are evaluated the UL motor function of stroke patients. The experimental results show that the MSE of the BRB, BPNN, and SVM model in UL motor function are 0.0325, 0.2410 and 0.3975, respectively. Comparison of the BPNN and the SVM model, the MSE of BRB model is small, which indicate that the evaluation model based on BRB has better performance. The reason why the BRB assessment results are more accurate is that the expert knowledge of doctors has been added in the model. In the rehabilitation process, the period of rehabilitation is long, and the staged data of patients collected is less, so the purely data-driven evaluation will have disadvantages and be inaccurate. The addition of expert knowledge can make up for the lack of data and evaluate the rehabilitation of patients better. Physiatrists play an important role in rehabilitation evaluation. With the addition of expert knowledge, the model can better simulate physiatrists' rehabilitation evaluation of patients. BRB is an excellent modeling method based on semi quantitative information, which can effectively use various uncertain information and quantitative knowledge to model nonlinear systems.

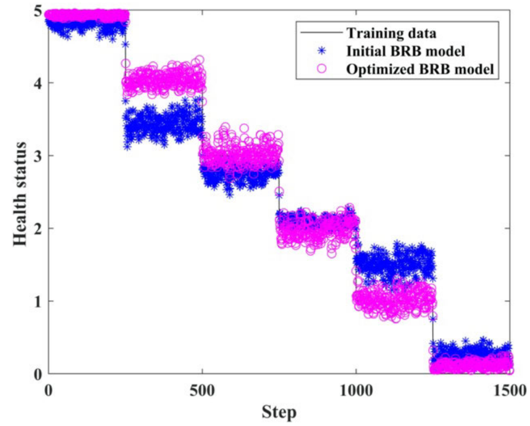

Fig. 10. The rehabilitation evaluation results by optimized BRB model.

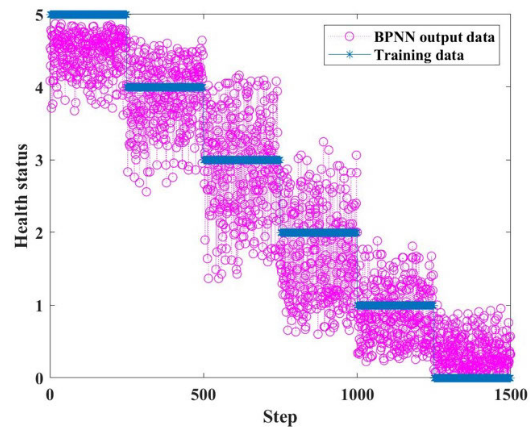

Fig. 11. Evaluation results based on BPNN.

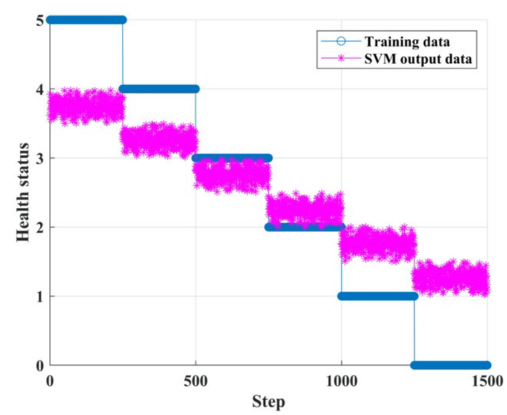

Fig. 12. Evaluation results based on SVM.

VII. Conclusion

In this paper, a rehabilitation robot has been designed which can help patients exercise their upper limbs. A model based on BRB has been proposed to evaluate the rehabilitation status of stroke patients which can be applied to rehabilitation robots. A new method of rehabilitation evaluation based on BRB has been proposed. A time series evaluation model of rehabilitation health characteristics based on BRB has been established. Representative characteristic values have been taken as health characteristics. Finally, these rehabilitation features have been fused by ER algorithm which realizes that the comprehensive evaluation of UL rehabilitation status of stroke patients. In the process of using BRB for rehabilitation evaluation, P-CMA-ES has been used to optimize the model parameters in order to solve the subjectivity of expert knowledge. The case study shown that the model can be used to evaluate the rehabilitation of UL of patients. The results shown that the evaluation model of UL rehabilitation state of patients based on multi features had high effectiveness and accuracy, compared with BPNN and SVM. The rehabilitation evaluation applied to rehabilitation robots is helpful for the physiatrist to evaluate the UL motor function of patients. In the future, we will add more features in BRB model, carry out large-scale clinical trials, and improve the rehabilitation evaluation model. By adding new features, the UL rehabilitation status of patients can be more comprehensively evaluated, and the accuracy of the model can be further improved.

References

[1] C. W. Tsao et al., "Heart disease and stroke statistics—2022 update: A report from the American heart association," *Circulation*, vol. 145, no. 8, pp. e153–e639, 2022.

[2] M. R. Yochelson, A. C. Dennisonsr, and A. L. Kolarova, *Stroke Rehabilitation*, 6th ed. Maryland Heights, MO, USA: Elsevier, 2021, pp. 2–47.

[3] B. Delpont, C. Blanc, G. V. Osseby, M. Hervieu-Bègue, M. Giroud, and Y. Béjot, "Pain after stroke: A review," *Revue Neurologique*, vol. 174, no. 10, pp. 671–674, Dec. 2018.

[4] J. Bernhardt, E. Godecke, L. Johnson, and P. Langhorne, "Early rehabilitation after stroke," *Current Opinion Neurol.*, vol. 30, no. 1, pp. 48–54, 2017, doi: 10.1097/wco.0000000000000404.

[5] D. B. Gandhi, A. Sterba, H. Khatter, and J. D. Pandian, "Mirror therapy in stroke rehabilitation: Current perspectives," *Therapeutics Clin. Risk Manage.*, vol. 16, pp. 75–85, Feb. 2020, doi: 10.2147/TCRM.S206883.

[6] N. Shimamura et al., "Rehabilitation and the neural network after stroke," *Transl. Stroke Res.*, vol. 8, no. 6, pp. 507–514, Dec. 2017, doi: 10.1007/s12975-017-0550-6.

[7] X.-J. Wei, K.-Y. Tong, and X.-L. Hu, "The responsiveness and correlation between Fugl–Meyer assessment, motor status scale, and the action research arm test in chronic stroke with upper-extremity rehabilitation robotic training," *Int. J. Rehabil. Res.*, vol. 34, no. 4, pp. 349–356, 2011, doi: 10.1097/mrr.0b013e32834d330a.

[8] S. Fasoli et al., "Assessing the motor status score: A scale for the evaluation of upper limb motor outcomes in patients after stroke," *Neurorehabilitation Neural Repair*, vol. 16, no. 3, pp. 283–289, Sep. 2002, doi: 10.1177/154596802401105216.

[9] C.-L. Chen et al., "Responsiveness and minimal clinically important difference of modified Ashworth scale in patients with stroke," *Eur. J. Phys. Rehabil. Med.*, vol. 55, no. 6, pp. 754–760, Jan. 2020, doi: 10.23736/S1973-9087.19.05545-X.

[10] R. C. Lyle, "A performance test for assessment of upper limb function in physical rehabilitation treatment and research," *Int. J. Rehabil. Res.*, vol. 4, no. 4, pp. 483–492, Dec. 1981.

[11] S. N. Min et al., "Review on evaluation methods to pre-detect the stroke using wearable devices," in *Proc. Int. Conf. Phys. Ergonom. Hum. Factors*, 2016, pp. 783–789.

[12] T. Yoshikawa et al., "Physiatrist and registered therapist operating acute rehabilitation (PROr) in stroke," *Ann. Phys. Rehabil. Med.*, vol. 61, p. e181, Jul. 2018, doi: 10.1016/j.rehab.2018.05.413.

[13] A. Pandey and A. Jain, "Comparative analysis of KNN algorithm using various normalization techniques," *Int. J. Comput. Netw. Inf. Secur.*, vol. 9, no. 11, pp. 36–42, Nov. 2017.

[14] C. Wang, L. Peng, Z.-G. Hou, J. Li, T. Zhang, and J. Zhao, "Quantitative assessment of upper-limb motor function for post-stroke rehabilitation based on motor synergy analysis and multi-modality fusion," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 943–952, Apr. 2020, doi: 10.1109/TNSRE.2020.2978273.

[15] C. Yang, X. Xi, S. Chen, S. M. Miran, X. Hua, and Z. Luo, "SEMG-based multifeatures and predictive model for knee-joint-angle estimation," *AIP Adv.*, vol. 9, no. 9, Sep. 2019, Art. no. 095042, doi: 10.1063/1.5120470.

[16] K. Kumar, A. Joshua, R. Kedambadi, and P. Mithra, "Eclectic/mixed model method for upper extremity functional recovery in stroke rehabilitation: A pilot study," *J. Natural Sci., Biol. Med.*, vol. 8, no. 1, p. 75, 2017.

[17] A. L. Shestakov and A. V. Keller, "Optimal dynamic measurement method using digital moving average filter," *J. Phys., Conf. Ser.*, vol. 1864, no. 1, May 2021, Art. no. 012073, doi: 10.1088/1742-6596/1864/1/012073.

[18] D. O. McInerney and M. Nieuwenhuis, "A comparative analysis of kNN and decision tree methods for the Irish national forest inventory," *Int. J. Remote Sens.*, vol. 30, no. 19, pp. 4937–4955, Sep. 2009, doi: 10.1080/01431160903022936.

[19] T. Kikuchi et al., "Development of a 6-DOF rehabilitation robot and its software for clinical evaluation based on virtual reality," in *Proc. IEEE/ICME Int. Conf. Complex Med. Eng.*, May 2007, pp. 1285–1288.

[20] Y. Fan and Y. Yin, "Active and progressive exoskeleton rehabilitation using multisource information fusion from EMG and force-position EPP," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 12, pp. 3314–3321, Dec. 2013, doi: 10.1109/TBME.2013.2267741.

[21] D. B. R. S. E. Humbert, "Novel Kinect-based method to assess 3D reachable workspace in musculoskeletal shoulder dysfunctions: Case reports," *Int. J. Phys. Med. Rehabil.*, vol. 3, no. 3, p. 1000274, 2015, doi: 10.4172/2329-9096.1000274.

[22] J.-Y. Kim, G. Park, S.-A. Lee, and Y. Nam, "Analysis of machine learning-based assessment for elbow spasticity using inertial sensors," *Sensors*, vol. 20, no. 6, p. 1622, Mar. 2020, doi: 10.3390/s20061622.

[23] M. Zhang et al., "Quantitative evaluation system of upper limb motor function of stroke patients based on desktop rehabilitation robot," *Sensors*, vol. 22, no. 3, p. 1170, Feb. 2022, doi: 10.3390/s22031170.

[24] L. A. Ingram, V. K. Carroll, A. A. Butler, M. A. Brodie, S. C. Gandevia, and S. R. Lord, "Quantifying upper limb motor impairment in people with Parkinson's disease: A physiological profiling approach," *PeerJ*, vol. 9, Feb. 2021, Art. no. e10735, doi: 10.7717/peerj.10735.

[25] J.-B. Yang, J. Liu, J. Wang, H.-S. Sii, and H.-W. Wang, "Belief rule-base inference methodology using the evidential reasoning approach-RIMER," *IEEE Trans. Syst., Man, Cybern., A, Syst. Hum.*, vol. 36, no. 2, pp. 266–285, Mar. 2006.

[26] L. G. Macedo and D. J. Magee, "Differences in range of motion between dominant and nondominant sides of upper and lower extremities," *J. Manipulative Physiolog. Therapeutics*, vol. 31, no. 8, pp. 577–582, Oct. 2008, doi: 10.1016/j.jmpt.2008.09.003.

[27] H. Li, G. Zhao, Y. Zhou, X. Chen, Z. Ji, and L. Wang, "Relationship of EMG/SMG features and muscle strength level: An exploratory study on tibialis anterior muscles during plantar-flexion among hemiplegia patients," *Biomed. Eng. OnLine*, vol. 13, no. 1, pp. 1–15, Dec. 2014, doi: 10.1186/1475-925X-13-5.

[28] I. Saad, N. H. Bais, C. Bun Seng, H. M. Zuhir, and N. Bolong, "Electromyogram (EMG) signal processing analysis for clinical rehabilitation application," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Dec. 2015, pp. 105–110.

[29] M. G. De Giorgi and M. Quarta, "Data regarding dynamic performance predictions of an aeroengine," *Data Brief*, vol. 31, Aug. 2020, Art. no. 105977, doi: 10.1016/j.dib.2020.105977.

[30] P. Xie et al., "Analysis of correlation between surface electromyography and spasticity after stroke," *J. Biomed. Eng.*, vol. 32, no. 4, p. 795, 2015, doi: 10.7507/1001-5515.20150144.

[31] R. W. Bohannon and M. B. Smith, "Interrater reliability of a modified Ashworth scale of muscle spasticity," *Phys. Therapy*, vol. 67, no. 2, pp. 206–207, Feb. 1987, doi: 10.1093/ptj/67.2.206.