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Objective Evaluation of Hand ROM and Motion Quality based on Motion Capture and Brunnstrom Scale *

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***Abstract*— Evaluation of hand performance based on the collected data can be used to objectively and accurately assess the characteristics of hand motion quality for stroke patients. Current hand motion assessment is usually done by clinicians, which is heavily dependent on the therapist's experience and subjective judgment, the quality of motion is not quantifiable and intuitional. This paper proposes an objective evaluation method of the hand motion quality using the optical motion capture system combined with Brunnstrom criteria which is assessment a scale commonly used in clinics. The motion capture system is used to detect the maximum range of motion (ROM) of ten finger joints during the hand motion. A K-Nearest Neighbor algorithm is adapted to classify the hand movement quality levels of Brunnstrom evaluation criteria. Computer recognition of rehabilitation assessment of medical scale is realized, and it can intuitively and accurately reflect the user's hand movement state. Experiments were designed by taking into account the motion characteristics of Brunnstrom assessment, and the ROM of five common hand movements, including common flexion, co-extension, thumb flexion, thumb-pinch, and spherical grasp were measured. A comparative study was conducted between the proposed method and the Brunnstrom scale, and the results verified this method's capability in evaluating the human hand motion quality, which has potential for rehabilitation evaluation of the hand motion of stroke patients and to provide the basis for the formulation of rehabilitation training programs.**

I. INTRODUCTION

With the aggravation of the aging of society, the number of people with dyskinesia caused by strokes and other causes is growing rapidly. In particular, the lack of motor function in the upper limbs and hands seriously affects the daily life of patients. Studies have shown that the motor function of the upper limbs accounts for 60% of the total motor function, while the motor function of the hand accounts for 90% of the upper limb motor function[1], about 65% of stroke patients still have hand dysfunction after 6 months of rehabilitation[2]. Mainly manifested as abnormal increase of muscle tension in flexor muscles, contracture of muscles and soft tissues, swelling of hands, stiffness, pain, sensory disturbances, decreased range of finger joints, and coordination of fingers and dysfunction. In clinic, the rehabilitation evaluation of the patients' notion is carried out first, and according to the evaluation results, appropriate intervention measures were taken to help patients with rehabilitation. Rehabilitation evaluation is essential for monitoring patients' rehabilitation status, verifying rehabilitation results and determining rehabilitation interventions.

At present, the rehabilitation stage of patients is evaluated by rehabilitation physicians clinically. The commonly used rehabilitation evaluation method is the medical stroke evaluation scale, the commonly used assessment scales are Brunnstrom assessment, fugl-meyer (FAM) assessment, simple upper limb function assessment (STEF), Lindmark motor function assessment, Barthel (BIA) forefinger, Ashworth spasm assessment method, posture assessment (PASS) scale, etc.[3, 4]. The rehabilitation evaluation of doctors dependent on personal experience and subjective consciousness heavily, so it is impossible to obtain objective and accurate quantitative evaluation results and visually display the information of patients' rehabilitation status. In view of this series of problems, many researchers have proposed the method of monitoring patients' rehabilitation status[5]. Hsu et al. developed an inertial-based wearable sensing device for measuring and evaluating the range of shoulder joint motion[6]. Jiang and others applied wearable sensor network and Internet of Things technology to the rehabilitation evaluation system to design a remote upper limb rehabilitation evaluation system[7]. Bonnechère and other serious games (SG) combined with Kinect sensors to collect wrist relative displacement data for upper limb rehabilitation training and evaluation[8], Chen et al. developed real-time leg motion tracking equipment to obtain ankle motion angle data for lower limb rehabilitation assessment[9], From the above, mentioned objective rehabilitation evaluation methods, there are many single joint applications in the upper limbs and lower limbs. There are 20 degrees of freedom in the hand, and collecting the data of hand movement is difficult. Li et al. used the Vicon optical motion capture system to obtain changes in the angular motion of the hand joints and visually displayed the exercise data[10], but did not combine with the clinical medical evaluation grade classification method.

This paper proposes a method of hand movement quality rehabilitation evaluation based on the ROM of hand joint. According to the classification criteria of the hand exercise rehabilitation level in the clinical medicine Brunnstrom rating scale, the range of joint motion of each level is quantified as a reference template, the range of motion (ROM) of 10 major joints of the hand was obtained through the three-dimensional

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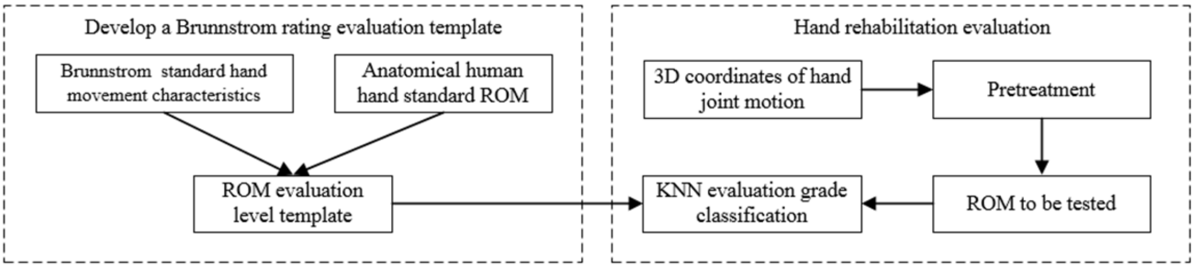

Figure 1. Rehabilitation evaluation process

motion capture system Qualisys. The K-Nearest Neighbor algorithm is used to classify the subjects' motion data to achieve the machine identification of the rehabilitation evaluation level of the Brunnstrom Medical Scale. The method not only intuitively displays the movement state of the patient's rehabilitation, but also reflects the difference between the current rehabilitation level of the patient and other grades. The evaluation result is rated by Brunnstrom and is convenient for clinical application. The motion capture system and experimental method used in the experiment will be described in detail in the second section of this paper. The third section will discuss the experimental results, and the fourth section will be a summary.

II. METHODS AND MATERIALS

The medical scale dyskinesia level assessment is a semi-quantitative assessment method. To achieve the rehabilitation assessment of a computer-integrated medical scale, it is necessary to quantify the medical scale and characterize the assessment level as a criterion for evaluation. Brunnstrom's assessment of the standard opponent's assessment is mainly the range of flexion and extension of the hand, the most direct response to this labeled parameter is the ROM of the main motor joint of the hand. The ROM evaluation standard is developed, and the ROM of hand joints is collected. After pre-processing, the KNN machine learning classification is performed to obtain the Brunnstrom evaluation result. The process is shown in Fig. 1.

A. *Hand range of motion (ROM)*

The hand is a multi-jointed human body consisting of 27 bones divided into the wrist, metacarpal and phalanx, the anatomy of the hand is shown in Fig. 2. The fine movements of the hand are mainly done by the metacarpal and phalanx[11]. Except for the thumb, which has only 2 phalanges, the other fingers have 3 phalanges, namely the proximal phalanx, the middle finger bone and the distal phalanx. The joint connecting the metacarpal and phalanx is called the metacarpophalangeal joint (MCP), and the metacarpophalangeal joint is close to the metacarpophalangeal joint. The proximal interphalangeal joint (DIP), followed by the distal interphalangeal joint (PIP).

Joint ROM directly reflects the level of residual motor function in hemiplegic patients. It is also commonly used in clinic, and is measured by protractor. According to the anatomical definition, the standard human joint mobility is shown in Tab. I . Studies have shown that, in order to bend the proximal interphalangeal joint to a certain angle, the distal interphalangeal joint must also follow a certain angle of bending. The movement of the two joints has the following linear constraint relationship $\mathrm{ROM}_{\mathrm{PIP}} = {}^{2}/_{3}\,\mathrm{ROM}_{\mathrm{DIP}}$ [12]. The main joints of the hand movement are the metacarpophalangeal joint and the proximal interphalangeal joint, after the patients' hand movement function is fully recovered, the maximum ROM of the hand joint can reach the following criteria.

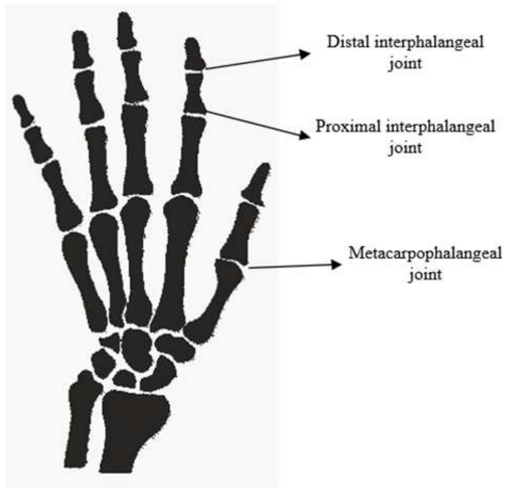

Figure 2.Hand joint diagram

TABLE I. Standard ROM of finger joint

Joint	Reference value (°)
Thumb metacarpophalangeal flexion	60
Four-finger metacarpophalangeal joint flexion	90
Thumb interphalangeal joint flexion	80
Four-finger interphalangeal joint flexion	Proximal 100, Distal 70

B. *Brunnstrom scale for hand motion quantification*

According to the six stages of the recovery process of hemiplegic motor function, Bruunstrom rehabilitation evaluation standard proposes exercise evaluation standards according to the characteristics of upper limbs, lower limbs and hand movements at each level. It is the evaluation standard for clinical use in many hospitals. There are many actions in the evaluation of upper limbs and hand function. Each action is divided into 5 functional levels (0 to 4 points). The function of the upper limbs and hands is represented by the score. The method of ranking is: 0 points: no joints motion. 1 point: The joint movement to be tested reaches 1/4 of the normal range of motion. 2 points: The joint movement to be tested reaches 1/2 of the normal range of motion. 3 points: The joint movement to be tested reaches 3/4 of the normal range of motion. 4 points : The joint movement is up to the full range of normal activities[13].

In terms of hand function assessment, it includes 6 function levels[14], i.e., I: sluggish, no movement; II: only slight finger flexion, passive movement sensation; III: finger buckling can be flexed, but not stretched Finger; IV: can grip and release the thumb on the side, the finger can be stretched in a small range at will; V: side pinch and release, finger and release, fingertips pinch and release, columnar grip and release; VI: Perform a variety of hand movements, but the speed and accuracy is slightly worse. According to the movement of the hand, the rehabilitation training and evaluation actions are divided into five: common flexion, co-extension, thumb flexion, thumb-pinch and spherical grasp[15, 16].

According to the Bruunstrom standard and the standard joint ROM of the knuckles, the maximum joint ROM of each joint flexion is measured. The joint motion range of the rehabilitation evaluation level is determined by the action completion degree $1/4$, $1/2$, $3/4$, 1 as the quantitative coefficient. Separately express the Bruunstrom grade I, III, IV, V, VI. Bruunstrom grade I and grade II dyskinesia patients have no active joint activity, so do not quantify the standard, the method proposed in this paper applies to rehabilitation evaluation of patients with active joint motion above grade III. The tolerance for each joint activity is ±5, so the activity of each joint in the template is 11 sets of data.

C. Hand motion data acquisition and preprocessing

Hand motion data acquisition uses the three-dimensional optical motion capture system Qualisys, which is one of the most advanced millimeter-level three-dimensional infrared marker motion tracking system. This experiment uses 8 infrared marker cameras and 1 video recording camera, as shown in Fig. 3.

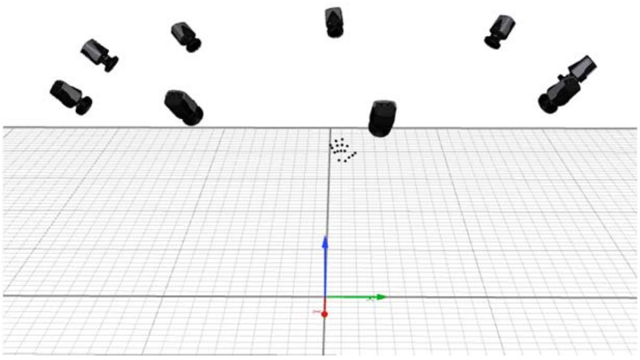

Figure 3. 3D motion capture system

Ten main joints of the hand motion data can be measured by 17 markers, as shown in Fig. 4.

Set the time to collect a set of data is 15 seconds, the sampling frequency is 100Hz, and the following five gestures are performed in sequence: common flexion, co-extension, thumb flexion, thumb-pinch, spherical grip. The motion capture system will record the three-dimensional coordinates of each point within 15s, thereby obtaining 1500 sets of original three-dimensional coordinate data. Next, the data will be preprocessed. The preprocessing is divided into the following two steps:

Figure 4. Locations of 17 markers for hand motion capture

(1) Calculation of the joint ROM

Obtaining the three-dimensional coordinates of each maker by motion capture system. The flexion angle of the joint motion is shown in Fig. 5, and the ROM of the joint to be measured can be calculated by by the three markers. For example $A(a_1, a_2, a_3)$, $B(b_1, b_2, b_3)$, $C(c_1, c_2, c_3)$ three markers can be used to calculate FPIP, the ROM of the interphalangeal joint of index finger by (1),(2),(3) and (4).

$$|AB| = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2} \quad (1)$$

$$|BC| = \sqrt{(b_1 - c_1)^2 + (b_2 - c_2)^2 + (b_3 - c_3)^2} \quad (2)$$

$$|AC| = \sqrt{(a_1 - c_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2} \quad (3)$$

$$\mathrm{FPIP} = 180 - \cos^{-1}\frac{|AB|^2 + |BC|^2 - |AC|^2}{2 \times |AB| \times |BC|} \quad (4)$$

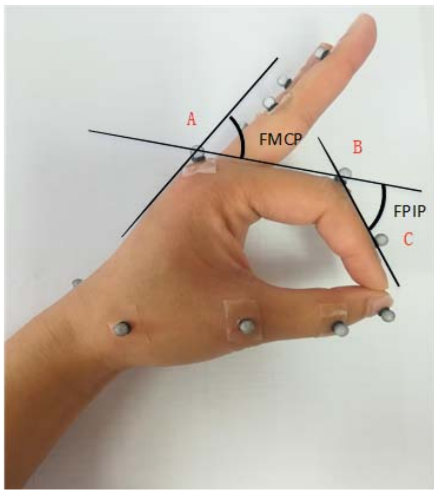

Figure 5. ROM of the hand joints

(2) Sorting

The movement angle data of each joint are arranged in descending order, and the highest activity of the joints during the exercise is arranged first, and the first 11 are extracted as the data to be tested.

D. *Motion quality level classification based on KNN algorithm*

After quantifying the Bruunstrom standard, the joint activity of each evaluation level is obtained. As a reference template for evaluation and judgment, these templates can also be samples that have been correctly classified. Therefore, this paper uses KNN algorithm to achieve the classification of rehabilitation evaluation.

The KNN(K-Nearest Neighbor) algorithm is a well-known pattern recognition statistical method. The core idea of the algorithm is that if the majority of the K most neighboring samples in a feature space belong to a certain category, the sample also belongs to this category has the characteristics of the sample on this category. We use the evaluation template as the sample data for the training. The classification steps are as follows [17-20]:

Step 1: Data initialization

Ten separate joints are used as the characteristics of the sample, and the sample data and the test data are respectively regarded as a matrix of 10×11.

Step2: Calculating distance

The training samples are traversed, and the Euclidean distance dist of the data to be tested and each sample data is calculated by (1).

$$dist(x, y) = \left[\sum_{j=1}^{d}(x_j - y_j)\right]^{\frac{1}{2}} = [(x - y)(x - y)^T]^{\frac{1}{2}} \quad (5)$$

Step3: Sorting

The training samples are sorted in ascending order according to the Euclidean distance, and the top K with the smallest Euclidean distance is selected as the K-maximum proximity distance maxdist.

Step 4: Comparison

Iterate through all the training sample data and compare the Euclidean distance dist and K-maximum zero close distance maxdist calculated in step 1 one by one. If dist is greater than or equal to maxdist, discard the sample and traverse the next sample. If dist is smaller than maxdist, it is used as K- nearest sample.

Step5: Resulting statistics

The frequency of occurrence of each category in the K-nearest neighbor sample is counted, and it is determined that the data to be tested belongs to the category with the highest frequency of occurrence.

The empirical rule is that K is generally lower than the square root of the number of training samples. If the k value is selected too small, the classification accuracy will be reduced and the interference of the noise data will be amplified; if the K value is selected too large, the noise will increase and the classification effect will be reduced. Therefore, after the data to be tested is classified, the error rate is calculated, and the different K values are continuously set to re-train, and finally the K value with the smallest error rate is taken. The number of training samples per experiment is 4, so take K = $\{k1, k2.\dots ki\}$, i is less than or equal to 16, conduct training, when K is equal to 11, the error rate is the smallest.

III. RESULTS AND DISCUSSION

In this experiment, data were collected from healthy limbs. For comparison and verification, the movement of the affected limb was also simulated according to the 6 motor function levels of Bruunstrom hand function evaluation, and the data of the simulated limb were collected. In this paper, experimental results were analyzed using two sets of experimental data. One group was the normal movement of the hand, and the other was the motion characteristics of the hand-measured of Bruunstrom III (fingers flexed in hook grip but not extended).

In Fig. 6, it shows the range of motion of the thumb metacarpophalangeal joint and interphalangeal joint, and the index finger metacarpophalangeal joint and proximal interphalangeal joint during 15s of normal hand movement.

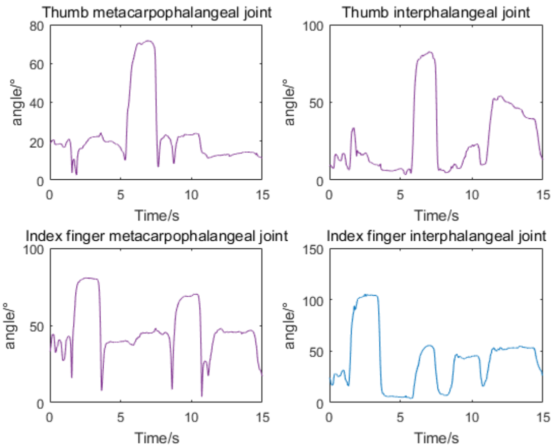

Figure 6. ROM of thumb metacarpophalangeal joint and interphalangeal joint, index finger metacarpophalangeal joint and proximal interphalangeal joint

As can be seen from the Fig. 6, the maximum ROM of the thumb metacarpophalangeal joint is close to the standard ROM of human thumb metacarpophalangeal joint at 60 °. The maximum ROM of thumb interphalangeal joint is close to the standard of human standard thumb metacarpophalangeal joint at 80 °. And the maximum ROM of the index finger metacarpophalangeal joint is close to the standard ROM of human index finger metacarpophalangeal joint at 90 °. Maximum ROM of the index finger interphalangeal is close to the standard ROM of human index finger interphalangeal at 100 °. After getting the data to be tested, obtaining rehabilitation evaluation results by KNN classifying. The results are shown in Fig. 7 and Fig. 8.

In Fig. 7, (a), (b), (c) and (d) are respectively the grade III, IV, V and VI assessment templates of Bruunstrom hand assessment criteria, allowable error of ± 5, so there are 11 sets of data for each level, representing the largest range of joint motion of ten fingers in each level. Fig. 7(e) shows the data to be measured in normal motion of the hand, and represents the ROM of the largest 11 groups with 10 joints in normal motion of the hand. Fig. 7(f) is the classification result of the data to be tested.The ROM to be tested nearly reaches the Brunnstrom VI level. Fig. 7(g) shows among the minimum K distances in the classification results, the frequency of the VI is the highest, so the evaluation result is Brunnstrom VI. The classification accuracy of Brunnstrom VI reference sample data is 1.

In Fig. 8, among the classification results, class III has the highest frequency of occurrence among the minimum K distances, and the evaluation result is Brunnstrom III level.

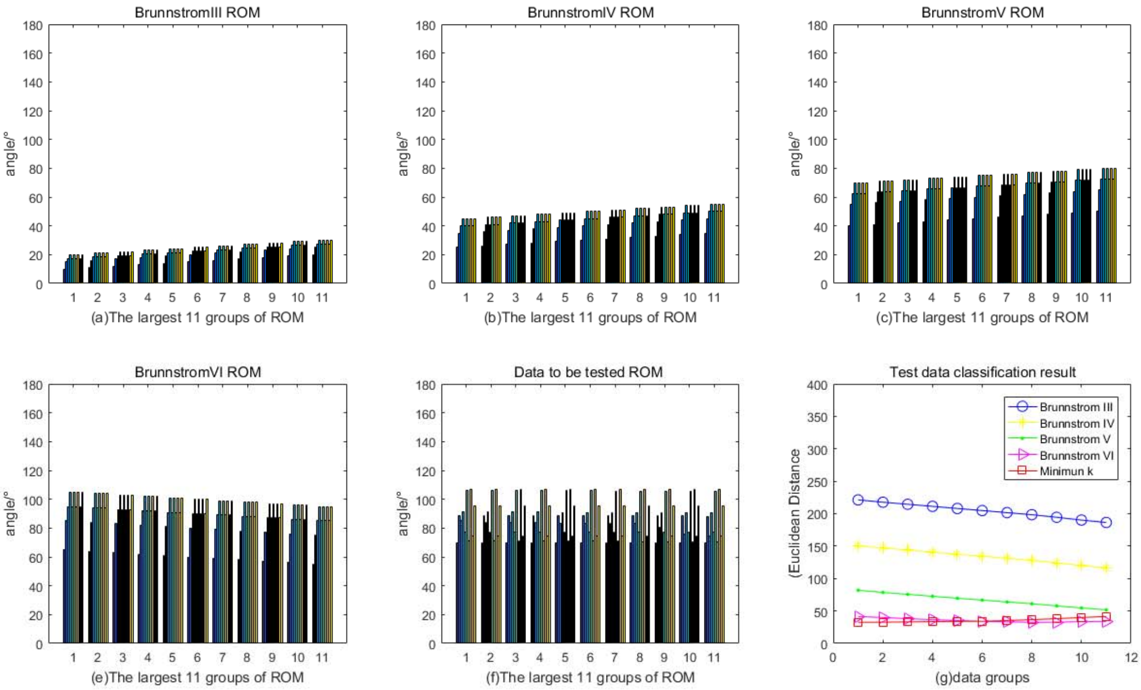

Figure 7. Results of normal limb movements

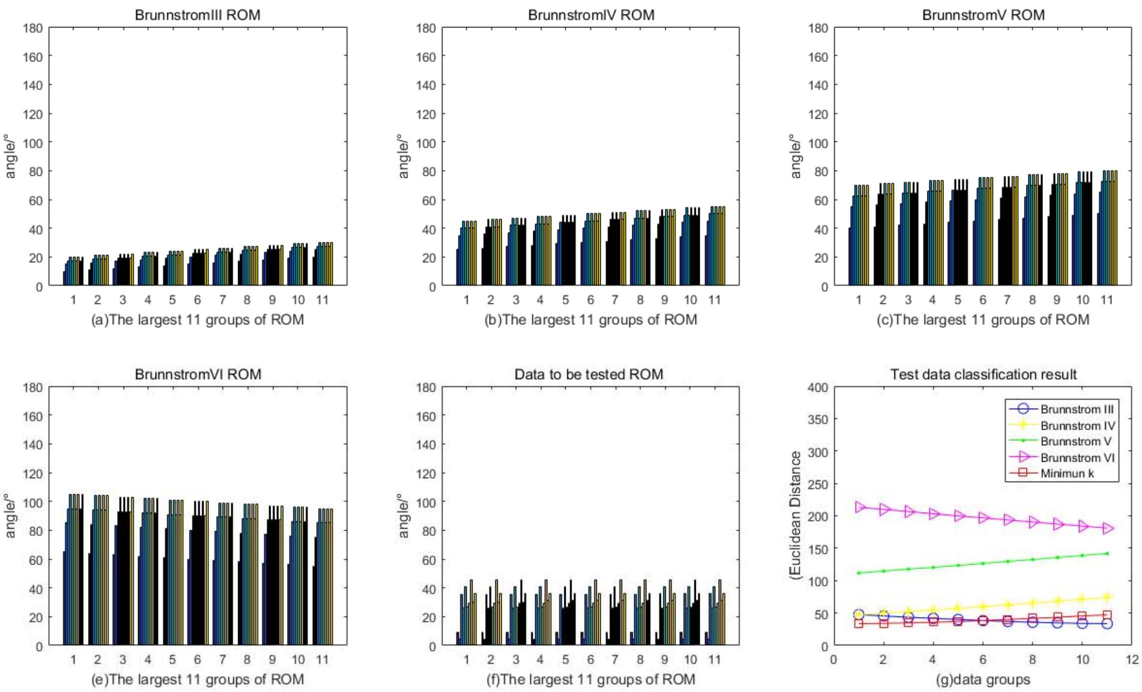

Figure 8. Results of Simulated limb movement

IV. CONCLUSION

This paper designs a rehabilitation evaluation method of the hand by combining the hand motor joint ROM with the stroke rehabilitation assessment Brunnstrom medical scale. The 3D optical motion capture system Qualisys was used to collect the hand motion coordinates, and the ROM was analyzed and processed, and the evaluation level was classified by the KNN algorithm. It implements an automated rehabilitation assessment method that combines machine learning with clinical medicine. Further research will be carried out to combine multimodal motion information with rehabilitation assessment, and to improve the assessment method so that the assessment training results can be automatically fed back into virtual reality or rehabilitation robot assisted training, which will become the basis for rehabilitation decision-making and realize an intelligent rehabilitation system.

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