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A Kinematic Data Based Lower Limb Motor Function Evaluation Method for Post-Stroke Rehabilitation

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***Abstract*— Recent studies have demonstrated that home-based rehabilitation for stroke patients has excellent potential in reducing the cost and enhancing rehabilitation efficiency. Nonetheless, a timely and accurate rehabilitation assessment is required to attain efficacy and provide feedback to both clinicians and patients. In this paper, a lower limb motor function assessment approach based on limb kinematic data has been presented. The kinematic characteristics of lower limbs were quantified into specific evaluation parameters, which were calculated during a set of selected rehabilitation exercises. A body area network composed of two triaxial accelerometers was used to acquire the limb kinematic data of twenty stroke patients and six healthy subjects. While a referenced template was developed using the data from healthy subjects, an empirical score was obtained to evaluate the lower-limb motor function of stroke patients from the calculated parameters. The results have demonstrated that the scoring has a statistically significant strong correlation with the Brunnstrom stage classification, which provides a practical quantitative evaluation approach for home-based rehabilitation for lower limbs of stroke patients.**

***Clinical Relevance*— The proposed quality assessment method provides practical technical support for performing early support discharge rehabilitation.**

I. Introduction

Recently, stroke has become the second most common cause of death and the leading cause of ongoing disabilities worldwide [1, 2]. According to the report provided by the Ministry of Health of the People's Republic of China [3-5], 3 million new stroke incidents and 1.5 million stroke-related deaths are taking place every year, and the total number of survivors has exceeded 8 million. Due to the ongoing population aging and the shift in lifestyle, these numbers are increasing rapidly [6].

Although the brain damage caused by stroke incidents, especially cerebral hemorrhage, is often irreversible. However, with appropriate rehabilitation programs, the patients can still partially regain their body functionality due to neuroplasticity – the 'rewiring' ability of the human brain [7-9]. A paramount factor of post-stroke rehabilitation, the classification of impairment levels, is a compulsory procedure throughout the training program to track patient's recovery progress. The Brunnstrom classification is a well-known approach to classify post-stroke rehabilitation recovery progress into six Brunnstrom recovery stages. These stages begin from the stage of flaccidity to the stage characterized by the complete disappearance of spasticity. The recovery progress continues in line with the increase of Brunnstrom stages [10]. However, conventionally, the Brunnstrom stage classification is performed by experienced physicians, so subjective errors are sometimes inevitable.

Post-stroke rehabilitation is a long-term process. Early support discharge (ESD) is an innovative home-based rehabilitation method provided by a mobile rehabilitation team, which can reduce the massive need for health service resources [6]. However, an auxiliary mechanism is required to help patients and their families to effectively carry out rehabilitation at home [7]. A pivotal part of this mechanism is to evaluate the quality of rehabilitation training. With this evaluation, the home-based rehabilitation training programs can be monitored effectively [8].

Recently, a few studies have been carried out on remote guidance and monitoring of home rehabilitation for stroke patients using a body sensor network composed of multiple sensor nodes [9, 11]. In [12], researchers used two wireless inertial measurement units (IMU) and one wireless sEMG sensor to measure the acceleration of specified lower extremity movements and related muscle EMG signals of stroke patients. In their research, the support vector machine (SVM) classifier was used to classify patients' lower extremities impairment into Brunnstrom stages, and an accuracy rate of 95.2% was achieved. However, only one rehabilitation motion was considered in their research. In [13], a Brunnstrom evaluation system was developed for in-home upper-limb stroke rehabilitation with a triaxial acceleration sensor. This system used the PCA algorithm and fuzzy inference algorithm to classify into Brunnstrom stages automatically. Although this system achieved an 87.5% classification accuracy, the study on the quality evaluation of lower limb rehabilitation was limited.

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TABLE I. FOUR LOWER LIMB RECOVERY MOVEMENTS

Name of rehabilitation exercises	Related motor muscle	Objective of rehabilitation exercises
Bridge motion	Gluteus maximus, quadriceps femoris, gluteus medius, iliopsoas.	Increased pelvic control and improved selective leg muscle extension
Sitting and Standing Training	Iliopsoas, gluteus maximus	Increased control of lower limbs
Hip extension and knee extension	Gluteus maximus, biceps femoris, iliopsoas	Inhibit lower limb spasm
Alternating weight-bearing on both legs	Iliopsoas, quadriceps femoris, gluteus medius, gluteus maximus, triceps calf, tibialis anterior	Experience alternating weight-bearing on upper and lower limbs to prepare for walking

This paper proposed a novel kinematic data-based assessment method for quantitative evaluation of lower limb mobility for home-based poststroke rehabilitation. A wearable body acceleration sensor network, comprising two IMU acceleration sensors, has been used for acquiring kinematic data, which were used to calculate the specific evaluation parameters. A systemic scoring formula based on the calculated parameters was developed to quantitatively assess the lower-limb mobility of stroke patients. In the following sections, the experiment methodologies will be explained first, followed by the data analysis, and finally, the study is summarized, including the future work.

II. EXPERIMENT DESIGN AND DATA COLLECTION

Based on the daily activity needs of stroke patients at home and the recommendations from experienced rehabilitation therapists, four rehabilitation training movements were selected, as shown in Table I.

Patients' lower-limb motions were tracked using two inertial measurement units (IMU) based body sensor network for kinematic analysis. The hardware circuit of the accelerometer mainly included two sensor modules: the control module and the receiver module. The sensor module used an ADXL345 (Analog Devices, Inc., USA) accelerometer with a sampling frequency of 40 Hz. The control module used the wireless microcontroller CC2530 (Texas Instruments, USA). Two IMU units were worn on the designated parts of a patient's lower limbs to obtain the motion signals from the specified parts of rehabilitation training. For Bridge motion, two IMU sensors were worn on the middle thigh and lower abdomen, respectively, as shown in Fig. 1. For the other three rehabilitation motions, two IMU sensors were worn on the middle thigh and middle calf, respectively, as shown in Fig 2.

Twenty stroke patients at different Brunnstrom stages participated in this experiment. The patients were recruited from Jiaxing 2nd hospital, China and Longhu Hospital, China. Six healthy participants from the Department of Biomedical Engineering of Shantou University also participated. This experiment was approved by the Ethics Committee of the Jiaxing 2nd Hospital and the Ethics Committee of the Longhu Hospital affiliated with Shantou University.

TABLE II. QUALITY EVALUATION FORM OF LOWER LIMB REHABILITATION EXERCISE

Rehabilitation exercises	Evaluation parameters and labels	Weight	Score	Gross Score
Bridge motion	1. Range of motion of hip joint	2		
	2. Period of motion	1		
	3. Time difference between hip extension and flexion	1		
	4. Standard deviation of planar trembling of limbs during vertical motion	1		

Figure 1. A participant wearing IMU sensors during bridge motion rehabilitation exercise.

Figure 2. A participant wearing IMU sensors during other rehabilitation exercises.

III. LOWER LIMB REHABILITATION EVALUATION METHOD DESCRIPTION

The captured IMU data were pre-processed with a 5-point median filter and outlier remover. The pre-processed data were used to calculate evaluation parameters and quality scoring, as shown in Fig. 3. Before data collection, patients were trained on the four selected rehabilitation motions, as shown in Table I. The data collected using the two IMU sensors were transmitted to the PC via a ZigBee for further analysis.

A. Selection & Calculation of Quality Evaluation Parameters

As reported by G. Wang *et al.* [14] and Wan *et al.* [15], the lower-limb motion of stroke patients has the following characteristics compared to healthy people: (1) the mean angular velocity of the extension and flexion for hip joint and knee joint is lower; (2) the extension range of hip joint is significantly limited; (3) the trembling of the limbs increases. Based on the characteristics established by the above studies, the following parameters were used for lower-limb evaluation: mobility, movement time, the time difference between the beginning of the movement and the turning point (the point at which the direction of limb movement changes between

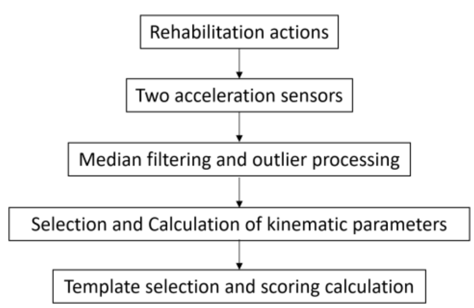

Figure 3. Evaluation flow chart.

flexion and extension), the time difference between the beginning of the movement and the end of the movement, and the planar trembling of limbs during vertical motion. A weightage was associated with each of these parameters as recommended by experienced rehabilitation therapists. The evaluation parameters and the corresponding weights for the bridge motion movement are shown in Table II.

According to a model proposed by Chen *et al.* [16], the limbs can be simplified into the model as shown in Fig. 4. Using the geometry of Fig. 4, the calculation of the range of motion (ROM) of the joints is given by (1) and (2).

$$\theta_i = \tan^{-1}\left(\frac{A_{xi}}{\sqrt{A_{yi}^2+A_{zi}^2}}\right) \tag{1}$$

$$\theta = |\theta_s - \theta_h| \tag{2}$$

where θ_i is the angle value of a point i (goes from 1 to the end of data sequence) on x-axis relative to the natural coordinate system at a certain point in the sequence, A_{xi}, A_{yi} and A_{zi} are the corresponding values of x, y and z-axis sequences, θ_s is the angle value at the beginning of the rehabilitation movement, θ_h is the angle value at the turning point of the movement, and θ is the ROM of the hip or knee joint during a rehabilitation movement.

The time duration of the movement in one period and the time difference between the extension and flexion of joints are given in (3) and (4), respectively.

$$T = \frac{N}{f} \tag{3}$$

$$T_{diff} = \left|\frac{N_{start}-N_{end}}{f}\right| \tag{4}$$

where N is the number of sample points, f is the sampling frequency, N_{start} is the number of sample points from the start to the end of a rehabilitation exercise, N_{end} is the number of sample points from the turning point to the end of a rehabilitation exercise, and T_{diff} is the time difference between joint extension and flexion.

The mean squared error of planar trembling of limbs during vertical motion along the y-axis can reflect the ability of stroke patients to control the limb muscles, which can be calculated using (5).

$$STD(y) = \sqrt{\frac{\sum(\bar{y}-y_i)^2}{N}} \tag{5}$$

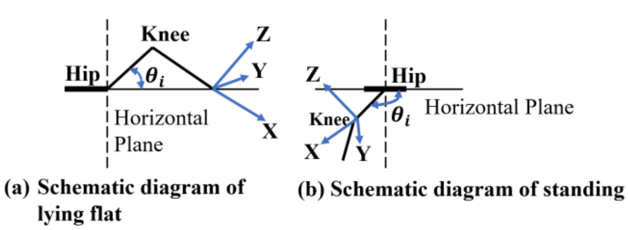

Figure 4. Simplified sketch of human joints.

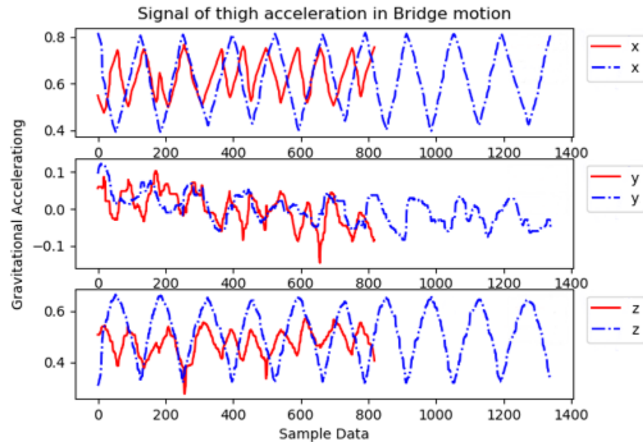

Figure 5. The waveform of the bridge motion rehabilitation exercise of a Brunnstrom stage V patient (red) and a healthy participant (blue), recorded using the IMU sensors. The horizontal axis represents the sampling data points (sampling time multiplied by sampling frequency). The vertical axis represents the acceleration recorded for the motion relative to the gravitational acceleration g (the sign indicates the direction).

where *STD*(y) represents the mean squared deviation of shaking in the vertical motion plane of the impaired leg, $\bar{y}$ represents the mean of the Y-axis sequence, y_i represents the value of a point i (goes from 1 to the end of the data sequence) on the Y-axis, and N represents the number of sampling points of the sequence.

B. Template Selection and Scoring Example

Fig. 5 shows the waveform of the bridge motion rehabilitation exercise of a Brunnstrom stage V patient and a healthy participant, recorded using the IMU sensors. It can be observed that healthy participant's movement data has better uniformity and periodicity. The calculation shows that the evaluation parameters of the healthy participants have the minimum variability and fluctuation. The difference in evaluation parameters between patients and healthy participants is in line with that of exercise mobility. Therefore, the mean values of the evaluation parameters of the six healthy participants' rehabilitation training exercises, were taken as the template for further analysis. The scoring formula is given by:

$$\text{Score} = \sum \frac{\alpha_i}{\alpha_{si}} \times 100\% + \sum \frac{\beta_i}{\beta_{si}} \times 100\% \tag{6}$$

TABLE III. MEAN AND STANDARD DEVIATION OF SCORES OF EACH OF THE REHABILITATION MOTION OF PATIENTS OF BRUNNSTROM STAGE III, IV AND V. STATISTICALLY SIGNIFICANT CORRELATION BETWEEN THE SCORES AND THE BRUNNSTROM STAGES HAVE BEEN OBSERVED USING SPEARMAN'S RANK-ORDER CORRELATION.

Rehabilitation exercises	Brunnstrom III	Brunnstrom IV	Brunnstrom V	Spearman's rank-order correlation
Bridge motion	59.7 ± 1.8	65.7 ± 6.0	81.2 ± 6.2	$r_s(18) = 0.847$, $p < 0.001$
Sitting and Standing Training	63.8 ± 5.4	69.6 ± 3.0	78.4 ± 5.1	$r_s(18) = 0.837$, $p < 0.001$
Hip extension and knee extension	56.7 ± 4.2	67.2 ± 3.0	70.5 ± 4.6	$r_s(18) = 0.746$, $p < 0.001$
Alternating weight-bearing on both legs	69.0 ± 4.5	74.2 ± 5.2	80.4 ± 8.1	$r_s(18) = 0.558$, $p = 0.011$

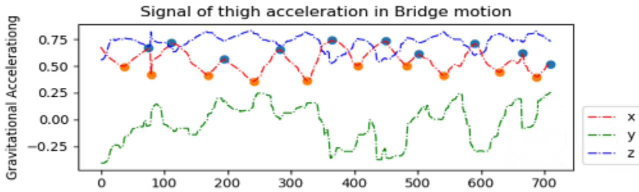

Figure 6. The waveform of the bridge motion rehabilitation exercise of a Brunnstrom stage III patient, recorded using an IMU sensor placed on the thigh. The red point is the turning point of the motion, and the blue point is the starting point or the ending point of the motion.

where "Score" is the final score of a rehabilitation motion, which essentially shows the motor capability of the limb, α_i is a positive correlation evaluation parameter (the subscript indicates the type), α_{si} is a template corresponding to α_i (derived from the healthy participant). β_i is a negative correlation evaluation parameter, β_{si} is a template corresponding to β_i. A positive/negative correlation evaluation parameter indicates a positive/negative correlation between the parameter value and the rehabilitation quality. For example, the range of motion of a joint denoted as θ is considered as a type of α_i since it is positively correlated with rehabilitation quality.

Fig. 6 shows the bridge motion rehabilitation exercise waveform for a Brunnstrom stage III patient recorded using the IMU sensor on the thigh. The average acceleration of starting point and turning point as well as the length of sample points during the motion can be extracted from the waveform, which is used to calculate the parameters required in the scoring formula. The same method is applied to other motions.

IV. Result and Discussion

Table III shows the mean and standard deviation of each rehabilitation exercise score for patients at different Brunnstrom stages, calculated using the proposed evaluation method. Statistically significant strong correlations have been observed between the scores and the Brunnstrom stage classification using Spearman's rank-order correlation. The scores of hip extension and knee extension are lower than those of the other three motions, whereas, for healthy participants, the scores remain the same as those of other motions. The possible reason is that in daily home life, patients have more opportunities to sit, stand, walk, and turn over than to extend hip and knee. In conclusion, in contrast to patients with lower Brunnstrom stage, patients with higher Brunnstrom stage have higher scores and can better complete the in-home rehabilitation for lower limbs.

V. Conclusion

In this study, a two-node wearable device was utilized to record the acceleration signals of four popularly used lower-limb rehabilitation exercises. An evaluation method using kinematic-data-based parameters was proposed to quantitatively assess stroke patients' lower-limb motor-impairment levels. The scoring of this method was proven to have a strong correlation with the classification of Brunnstrom stages under statistical analysis. The proposed model was designed to be practical to perform with minimal financial and computational cost, which provides feasible technical support for the implementation of ESD rehabilitation. In the future study, it is expected that the assessment method will be further extended to a highly automatic and integrated home-based rehabilitation system by introducing advanced machine learning technology for motion recognition and classification.

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