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Upper Limb Rehabilitation System for Stroke Survivors Based on Multi-Modal Sensors and Machine Learning

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ABSTRACT Nowadays, rehabilitation training for stroke survivors is mainly completed under the guidance of the physician. There are various treatment ways, however, most of them are affected by various factors such as experience of physician and training intensity. The treatment effect cannot be fed back in time, and objective evaluation data is lacking. In addition, the treatment method is complicated, costly, and highly dependent on physicians. Moreover, stroke survivors' compliance is poor, which leads to various limitations. This paper combines the Internet-of-Things, machine learning, and intelligence system technologies to design a smartphone-based intelligence system to help stroke survivors to improve upper limb rehabilitation. With the built-in multi-modal sensors of the smart phone, training action data of users can be obtained, and then transfer to the server through the Internet. This research presents a DTW-KNN joint algorithm to recognize accuracy of rehabilitation actions and classify to multiple training completion levels. The experimental results show that the DTW-KNN algorithm can evaluate the rehabilitation actions, the accuracy rates of the classification in excellent, good, and normal are 85.7%, 66.7%, and 80% respectively. The intelligence system presented in this paper can help stroke survivors to proceed rehabilitation training independently and remotely, which reduces medical costs and psychological burden.

INDEX TERMS Machine learning, multi-modal sensor, Internet-of-Things, upper limb rehabilitation, intelligent system.

I. INTRODUCTION

Stroke, which has the characteristics of high incidence and disability, is a serious, common, and disabling global health-care problem in current years [1]. It is usually caused by a blood clot that blocks the blood vessels in the brain. In addition, stroke can also be caused by a blood vessel rupture, causing blood to leak into the surrounding area [2]. Stroke is a common neurological disease and a leading cause of chronic disability worldwide [3]. The main symptom after stroke is hemiplegia, which is accompanied by a variety of complications, including movement, perception and cognition, paresthesias, language and visual disorders [4]. Stroke seriously affects stroke survivors' quality of daily life [5]. According to the World Health Organization report, 80% of stroke survivors have varying degrees of limb dysfunction, and more than 60% of them still have upper limb dysfunction after entering the chronic phase [6]. Rehabilitation of the lower limbs of stroke survivors is mainly carried out in the hospital, while after discharging from the hospital, stroke survivors usually need long-term rehabilitation training to restore and maintain upper limb movement ability. Studies have shown that regular high-intensity repetitive rehabilitation training is essential for stroke recovery. However, only a small number of stroke survivors actually follow the physician's recommendations for the recommended training [7].

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Rehabilitation treatment is an effective way to reduce the disability rate of stroke. Therefore, the rehabilitation of upper limb function is particularly important for stroke survivors.

Modern rehabilitation therapy techniques and methods are effective in restoring and improving the physical abilities of the physically disabled community [8]. Mudied *et al.* have proposed a bilateral upper limb training therapy [9]. Giovanni *et al.* have attempted to use the properties of mirror neurons to train stroke survivors with upper limb paralysis to restore neurological control and coordination of their movements [10], as well as myoelectric biofeedback [11] and neuromuscular electrical stimulation [12]. Floriana *et al.* have studied the use of motor imagination exercises during the recovery period of stroke survivors based on the brain-computer interface [13]. In recent years, virtual reality technology is often used in upper limb rehabilitation after stroke. But Laver K E *et al.* have found evidence that using virtual reality and interactive video games is not more beneficial than traditional therapies in improving upper limb function [14].

The above methods all rely on medical venues and equipment, and can't meet the long-term rehabilitation needs of stroke survivors. Traditional rehabilitation training is inefficient, and the quality of the rehabilitation training program completed by stroke survivors who discharged from the hospital is not satisfactory. There is also a lack of a comprehensive rehabilitation training evaluation system, and it is difficult for physicians to optimize training to obtain the best treatment plan for stroke survivors [15]. In addition, a large number of stroke survivors and a limited number of physicians lead to a heavy workload for physicians and lack of comprehensive rehabilitation guidance for stroke survivors.

Through the analysis of the above research status, it can be seen that there are still the following problems in the upper limb rehabilitation research for the stroke group: The existing stroke rehabilitation treatment technology is expensive and not conducive to use at home. The number of stroke survivors is large, the medical resources are limited, and the traditional rehabilitation training is difficult to guarantee training intensity and efficiency. There is a lack of objective data to evaluate the training parameters and rehabilitation effects. Stroke survivors still need to undergo long-term rehabilitation training after discharging from the hospital. Due to the lack of subjective enthusiasm, only a few stroke survivors may complete the rehabilitation plan, and the rehabilitation data could not be fed back to the rehabilitation physicians in time, resulting in the physicians being unable to track the health status of those discharged stroke survivors. Furthermore, the COVID-19 aggravates the difficulties of rehabilitation tracking and increase the medical risks during the training sessions in rehabilitation facilities. Some researchers have focused on developing COVID-19 related intelligent systems to improve healthcare services [16], [17].

Considering these issues, an IoT and machine learning based intelligent system for stroke survivors to improve upper limb rehabilitation is designed and presented in this paper, which applies the built-in sensors of the mobile device to collect data on stroke survivors' rehabilitation actions, transfers the data to the remote server, and uses Dynamic Time Warping (DTW) and K-Nearest Neighbor (K-Nearest Neighbor, KNN) to complete the classification and evaluation of action accuracy, so as to realize an end-to-end upper limb functional rehabilitation system.

II. RELATED WORKS

With the development of technologies such as the Internet-of-Things and artificial intelligence, a large number of new methodologies have been widely used in the field of healthcare, disease diagnosis, and rehabilitation [18]. Some researchers have utilized sensor technology to acquire and aggregate health information for multiple applications [19]– [21]. Moreover, data mining, multiple data fusion, and human-machine collaboration have been utilized to analyze and evaluate the rehabilitation of stroke survivors, which will effectively improve the quality of health service, assist stroke survivors in rehabilitation and improve the quality of life. The number of people who need to recover after a stroke is increasing rapidly, and the cost and pressure of medical budgets are also increasing [22].

Research in traditional therapy and motor learning theory demonstrates that the intensity of practice and feedback on tasks is important [23]–[26]. And there are studies showing that multiple repetitions of intensive exercise training can improve the acute and long-term treatment effects after a stroke [27], [28]. This recognition has promoted the development of new therapies, such as robotic therapy, which provides opportunities for repetitive exercise training [29]. Due to the high cost of such high-intensity training and the need for a lot of effort, a robotic rehabilitation system has been proposed to help physicians provide consistent and repeatable training [30]– [32]. Stanford University has developed a robotic upper limb rehabilitation system based on the PUMA 500 and 600 industrial robots, which can assist stroke survivors in performing mirror movements of the affected and healthy sides of the upper limb [33], [34]. Some universities in Europe have also designed and developed various upper limb rehabilitation robot systems [35]– [38]. However, studies have shown that some upper limb robots are not capable of performing wrist flexion and extension training, and these robots are expensive [39].

The key to upper limb rehabilitation training for stroke survivors is to efficiently and accurately identify and acquire stroke survivors' movements data. Zhang X *et al.* have proposed a gesture recognition framework based on the information fusion of a three-axis accelerometer and a multi-channel EMG sensor [40]. Kinect is a somatosensory peripheral of the home video game console XBOX360 developed by Microsoft [41]. It has functions of dynamic capture and image recognition. Aşkın A *et al.* have studied that the use of Kinect-based VR training may help improve the motor function of stroke survivors with chronic stroke [42].However, the Kinect device has high requirements in the field,

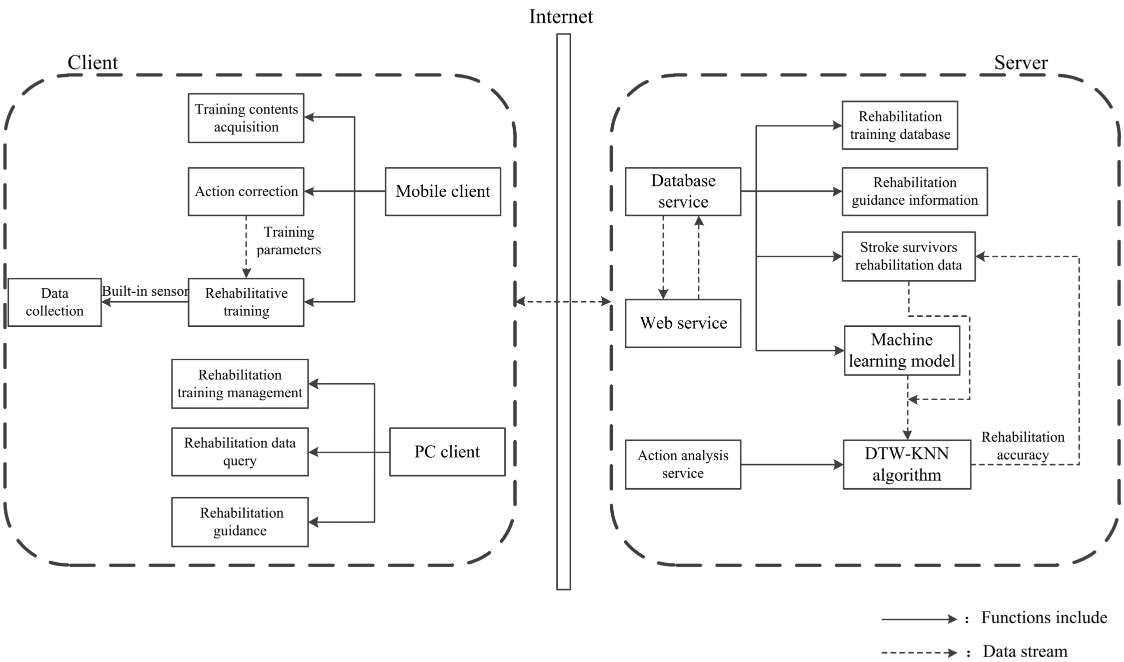


FIGURE 1. Structure diagram of upper limb functional rehabilitation system.

there must be no obstacles and there is a distance constraint between stroke survivors and equipment. In contrast, mobile devices can be easily carried anywhere and do not require complicated installation and configuration procedures [43]. Although only 37% of the population over 55 in developed countries had a smartphone in 2013, it is expected to exceed 80% by 2020 [44]. In addition, researchers have applied machine learning in the field of rehabilitation system [45]. At the same time, Some researchers have also used machine learning-based methods to identify the activities of daily living (ADL) dependence of stroke survivors [46]. These references all show that machine learning methods can be effectively applied to the area of human rehabilitation.

III. SYSTEM ARCHITECTURE

With the spread of smartphones, the variety of sensors built into mobile phones has diversified, and smartphones have become portable mobile electronic devices with comprehensive functions. The built-in gyroscope and device orientation sensor of the smartphone can make good measurements of rotation and deflection. With the accelerometer, it can measure and reconstruct a complete three-dimensional movement. Therefore, the combination of above three sensors can accurately analyze and judge the actual situation of the user. The system realizes the acquisition of rehabilitation movement data of stroke survivors through the built-in multi-sensor of the smartphone, and uses the Internet, artificial intelligence and other technologies to make the upper limb functional rehabilitation system intelligent operation. Stroke survivors perform rehabilitation training according to the training contents bound by the physicians through the mobile phone, and then the rehabilitation action data is sent to the server through the Internet for classifying and evaluating action accuracy. Based on this end-to-end upper limb function rehabilitation system, the physicians can remotely know stroke survivors' rehabilitation situation in time, and they can better formulate the next stage of rehabilitation training for stroke survivors and deliver it to stroke survivors remotely.

The upper limb functional rehabilitation system consists of two main parts, the client side and the server side. The structure of the upper limb rehabilitation system is shown in Figure 1. The client includes mobile client and PC client. Mobile client is implemented through an intelligent mobile platform, which aims to help stroke survivors with rehabilitation training. Stroke survivors are able to take the mobile phone for rehabilitation according to the training contents added by the physician, and the rehabilitation movement data is sent to the server through the Internet for accurate classification and evaluation. Physicians can view stroke survivors' rehabilitation through the PC client, and they can manage stroke survivors' rehabilitation training and provide remote rehabilitation guidance. The server includes database service and action analysis service. Database service is used to manage the database and provide data storage function. Action analysis service is designed to process and analyze the rehabilitation data from mobile client and perform accuracy classification judgments. In the following chapters, this article will introduce the four modules of the two parts of the upper limb functional rehabilitation system in detail.

A. MOBILE CLIENT

Mobile client is implemented through a smart mobile platform and supports multiple operating systems, such as Android and iOS. Mobile client and the server use the B/S mode for network communication through the HTTP protocol based on the TCP/IP protocol. Mobile client is mainly used to server stroke survivors, which includes functions such as training contents acquisition, movement correction, and rehabilitation training.

Stroke survivors can obtain training contents from the server through the Internet, since the need for feedback during rehabilitation training varies from different stroke survivors, and the upper limb function is expected to recover gradually with rehabilitation training. Therefore, it's necessary to perform action correction for each stroke survivors, that is, set the training parameters of the action. There is no doubt that uncorrected training movements can't be trained. The phone will provide vibration and audible feedback to stroke survivors when stroke survivors' training reaches the training parameters of the action. When stroke survivors perform a certain training action correction, mobile client will prompt stroke survivors to do the action three times as hard as possible. After calculating and comparing the maximum resultant acceleration of the three actions, multiply it by the proportional coefficient to obtain the training parameters of the action for stroke survivors. The resultant acceleration value is the sum of the square of the three-axis acceleration of the mobile device, and the proportional coefficient is set by the physicians.

The rehabilitation training function utilizes a smartphone's built-in accelerometer, gyroscope and directional sensors. The three-axis direction of the mobile device is shown in Figure 2. As the displacement and angle of the mobile phone varies, the value of its built-in multi-sensor is constantly changing. According to the rehabilitation actions performed by stroke survivors, mobile client performs data sampling of the accelerometer, gyroscope, and device direction. Since the rehabilitation training is an upper limb movement, stroke survivors' overall movement is slower, smoother and there will be no major mutations in a short time. The sensor data will not fluctuate greatly, so the sampling frequency is set to 16Hz, and the collected data meet the data requirements of the system. Mobile client can adapt to a variety of operating systems of mobile devices, and has good compatibility with user devices and high operational efficiency. Figure 3 is a screenshot of mobile client interface. There are two types of rehabilitation training, fast training and custom training respectively. The content of fast training is added by the physicians through the PC client for stroke survivors. The content of custom training includes all the rehabilitation actions in the rehabilitation training action database, and stroke survivors can choose any training action to add for training, as shown in Figure 3(a). When stroke survivors start training, relevant training instructions and action diagrams will be shown to them, and mobile phone built-in sensor data will be displayed in real time, as shown in Figure 3(b). In addition, stroke survivors can view the completion of the day's training in the training history, as show in Figure 3(c).

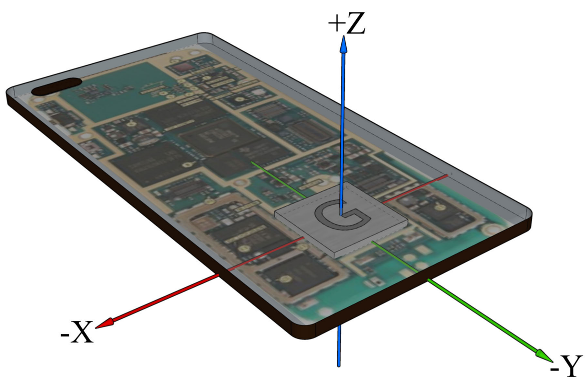


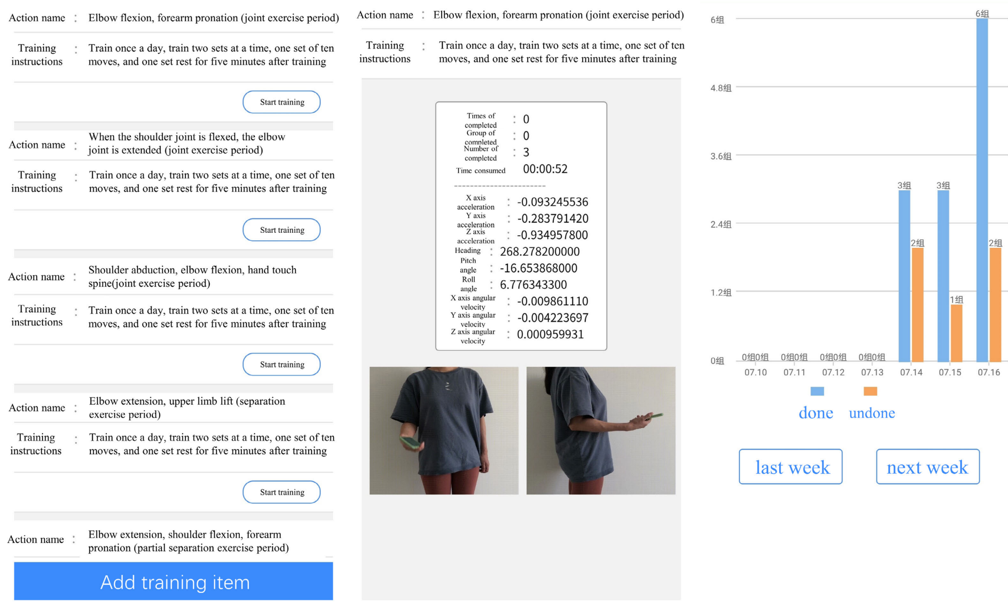
FIGURE 2. Three-axis pointing diagram of mobile equipment.

B. PC CLIENT

PC client can carry out data interaction with mobile client. It includes some functions such as managing rehabilitation training, querying stroke survivors rehabilitation data and providing remote rehabilitation guidance. Physicians can manage the rehabilitation training of stroke survivors, that is, access the rehabilitation training database through PC client, upload the rehabilitation training content and set the proportion coefficient of the training action for stroke survivors on mobile client, and can provide corresponding rehabilitation guidance information. Physicians are able to query all stroke survivors' rehabilitation data and the completion of their rehabilitation training from mobile client, but they can only manage their own stroke survivors. In addition, physicians can provide stroke survivors with remote rehabilitation guidance and adjust rehabilitation training plans through PC client according to stroke survivors' rehabilitation progress, so that stroke survivors can complete rehabilitation training in an efficient and convenient way. Stroke survivors can also use PC client to view their personal information and training status.

C. DATABASE SERVICE

Database service coordinates the requests sent by mobile client and PC client, performs corresponding data storage, and manages the database. This study uses a lightweight MySQL database, HTTP protocol is used for communication between database service and clients. Database service mainly includes rehabilitation training database, rehabilitation guidance information, stroke survivors rehabilitation database and machine learning models, etc. The rehabilitation training database and rehabilitation guidance information store various rehabilitation training content and rehabilitation guidance information of the physician, respectively, and the rehabilitation data and records from mobile client



(a) (b) (c)

FIGURE 3. Mobile client interface.

are stored in stroke survivors rehabilitation database. The machine learning model is built for stroke survivors rehabilitation data and aims to process stroke survivors rehabilitation data.

D. ACTION ANALYSIS SERVICE

Stroke survivors' rehabilitation movement data acquired through the built-in sensors of the mobile device can be regarded as an movement sequence, including nine attributes: three-axis acceleration values a_x, a_y, a_z measured by the accelerometer, angular velocity value ω_x, ω_y, ω_z of mobile phone rotating around three-axis measured by gyroscope, and the pitch angle β, heading angle α and roll angle γ of the mobile phone measured by the device direction sensor. The action analysis service uses DTW-KNN algorithm to analyze stroke survivors' rehabilitation action data and judge the accuracy of the rehabilitation action.

1) DYNAMIC TIME WARPING ALGORITHM (DTW)

Dynamic Time Warping algorithm(DTW) is a dynamic planning algorithm that calculates the similarity of two time series, especially series of different lengths. It can flexibly realize template matching and solve many discrete time series matching problems. Since the speed and amplitude of rehabilitation actions performed by stroke survivors in different stages of rehabilitation will be quite different, there must be a difference between stroke survivors' rehabilitation actions and standard actions, and DTW algorithm can measure the similarity of two non-equal length sequences, which is suitable for processing sequence data collected in this study. Figure 4 shows a comparison of the x-axis acceleration between two rehabilitation movements.

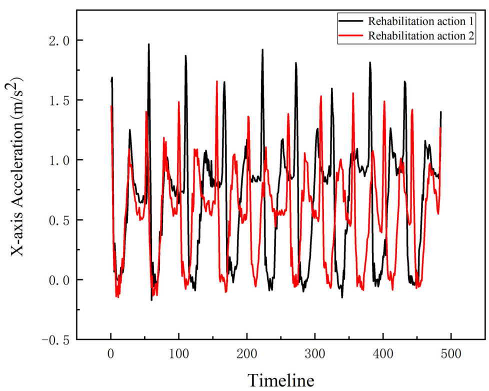


FIGURE 4. Comparison of acceleration in the x-axis direction between two rehabilitation actions.

Suppose there is a sample sequence and a test sequence, and there is a point-to-point distance function in the sequence:

$$d(i, j) = f(x_i, y_j) \geq 0 \tag{1}$$

DTW first obtains a sequence distance matrix M according to the distance between the sequence points, and then generates a loss matrix M_c according to the distance matrix. The core of DTW is to solve the distortion curve, that is the correspondence between points, which can be expressed as:

$$\phi(k) = (\phi_x(k), \phi_y(k)) \tag{2}$$

The possible value of $\phi_x(k)$ is $1, 2, \ldots, N$, and the value of $\phi_y(k)$ may be $1, 2, \ldots, M$, $k = 1, 2, \ldots, T$. That is to find out T correspondences from the midpoint of the X sequence to the midpoint of the Y sequence. In a given situation, the cumulative distance of the two sequences can be solved:

$$d_\phi(X, Y) = \sum_{k=1}^{T} d(\phi_x(k), \phi_y(k)) \tag{3}$$

The final output of DTW is to find the most suitable distortion curve to minimize the cumulative distance, that is, the value of the last row and last column of the loss matrix:

$$DTW(X, Y) = \min_{\phi} d_\phi(X, Y) \tag{4}$$

This output value is used to measure the similarity between stroke survivors' movements and the standard movements, and the output standardized distance can be further input to the KNN classifier.

2) K-NEAREST NEIGHBOR ALGORITHM (KNN)

K-Nearest Neighbor method is one of the most intuitive and effective methods in data mining classification technology. The core idea is that if most of the K nearest training samples in the feature space of a test sample belong to a certain category, then the samples also fall into this category. KNN finds the K training samples closest to the test sample in the training sample based on a certain distance metric, and the selected training samples have been correctly classified. We consider that this is a voting mechanism. For multi-classification problems, in order to avoid the same number of votes for the two categories, the K value of K-Nearest Neighbors is generally an odd number. In order to ensure the accuracy of the classification algorithm and voting efficiency, the K value in this research is 11.

3) JUDGMENT METHOD OF REHABILITATION ACTIONS BASED ON DTW-KNN MODEL

In this study, we have collected several template actions in advance through mobile client and invited physicians to classify them. DTW is used to calculate the distance for 9 attributes between the test action and each template action, and the cumulative sum of the distances between the 9 attributes is used as the distance between two actions, then the data is normalized for several distances, and the distance data is imported into the KNN algorithm classifier. In this study, the completion of rehabilitation actions of stroke survivors is divided into three categories, namely A (excellent), B (good), and C (general). The KNN classification algorithm votes based on the selected K value to obtain the category to which the test action belongs, that is, the completion status, so as to realize the classification and judgment of the accuracy of stroke survivors' rehabilitation action. The flowchart of the rehabilitation action evaluation method based on the DTW-KNN model is shown in Figure 5.

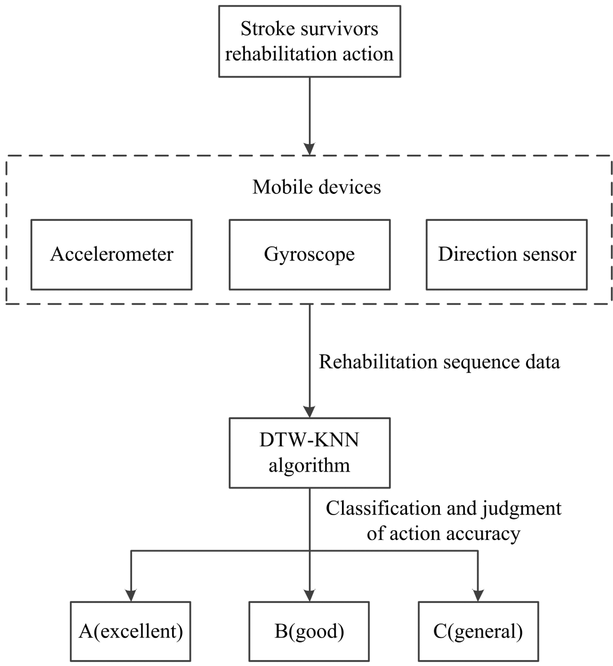


FIGURE 5. Judgment method of rehabilitation actions based on DTW-KNN model.

IV. EXPERIMENTAL RESULTS

This study intends to verify the design experiment of the research results of the upper limb functional rehabilitation system, and use the DTW-KNN model to classify and judge the completion of rehabilitation actions. In this experiment, a number of stroke survivors with Brunnstrom staging as the joint exercise phase(III) are used as examples to verify, and choose elbow flexion as an example of rehabilitation action. This experiment collects stroke survivors training data through mobile client, obtains a total of 150 sets of data as template actions, and invites physicians to classify the accuracy of the actions completed in three categories, A(excellent), B(good), C(general). There are 50 groups of each type of action, and each group contains 10 actions.

In the experiment, a number of joint exercise phase stroke survivors are selected to train for a number of test actions(elbow flexion). The actual situation of the test actions are judged and classified by the physician through observation on the spot, from excellent, good to general, in order of A, B, and C. There are 18 groups of test actions. After the physicians' observation and judgment, there are 6 groups of A,B, and C test actions. Figure 6 is a comparison diagram of some attributes of a test action and a type A action. The solid line is the test action, the dashed line is the type A template action. Figure 6 (a), (b), (c), (d) are the x-axis acceleration comparison, the x-axis angular velocity comparison, the z-axis angular velocity comparison and the heading angle comparison between the two actions in sequence.

The output of the experimental results is Type A 5, Type B 3, Type C 3, that is, the 11 template actions closest to the test action include 5 type A actions, 3 type B actions, and 3 type C actions, so DTW-KNN model judges that the completion of the test action is a type A action, that is, the completion is excellent, and the actual situation of the test

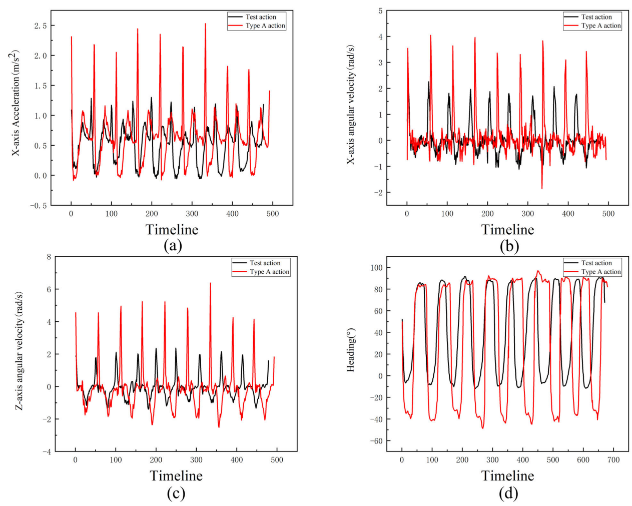


FIGURE 6. **Comparison of some attributes between test action and A-type template action.**

action observed by the physicians is also A. Subsequently, the remaining 17 sets of test action data were put into the DTW-KNN model for classification and evaluation, and the actual situation and the classification confusion matrix determined by the model were obtained, as shown in Table 1.

TABLE 1. **Classification confusion matrix.**

Actual situation	*A*			*B*			*C*		
Model decision	*A*	*B*	*C*	*A*	*B*	*C*	*A*	*B*	*C*
Number of groups	6	0	0	1	4	1	0	2	4

Through the confusion matrix, the following conclusions can be drawn: the accuracy of the classification model is 77.8%, and the relevant indicators of the three types of test actions of A, B, and C are shown in Table 2.

TABLE 2. **Detailed indicators of ABC three types of test actions.**

Indicators	*A test action*	*B test action*	*C test action*
Accuracy	85.7%	66.7%	80%
Recall	100%	66.7%	66.7%
Specificity	91.7%	83.3%	91.7%

In Table 2, the A,B,C test actions are the completion of the test actions(elbow flexion) performed by the stroke survivors tested in the experiment, A test action represents excellent completion, B test action represents good completion, and C test action represents general completion. It can be seen from Table 2 that the overall classification accuracy of the classification model is good, the accuracy of class A and C test action prediction classification is well, and the accuracy of class B test action prediction classification is good. In the later period, this research will be promoted to expand the data volume of the test samples, and improve by introducing other algorithms combined with DTW-KNN comparison, so as to obtain the optimal algorithm to classify and judge stroke survivors' rehabilitation actions.

V. CONCLUSION

This research aims at the upper limb functional rehabilitation stroke survivors group, combined with the Internet and artificial intelligence and other technologies to design a remote rehabilitation intelligent system based on multi-mode sensors. Stroke survivors hold mobile devices for rehabilitation training, and use the built-in multi-sensor of the smartphone to capture stroke survivors' upper limb rehabilitation action. Then the rehabilitation movement data is sent to the remote server through the Internet, and the DTW-KNN algorithm is used on the server to realize the analysis and accuracy classification of stroke survivors' rehabilitation movement, thereby realizing an end-to-end upper limb rehabilitation system. Compared with traditional rehabilitation training, this method is not limited by time and space, and stroke survivors are suitable for self-rehabilitation training at home. Physicians can manage their own stroke survivors through the PC client, and can know stroke survivors' rehabilitation progress in time, so that they can better formulate the next stage of rehabilitation training plan for stroke survivors.

Since the output value of the built-in accelerometer of the mobile device is referenced to the mobile phone coordinate system, it is difficult to truly reflect the actual action state of stroke survivors under the inertial coordinate system, which results in a certain error in the rehabilitation action. In the KNN classification algorithm, since various template actions have to be traversed each time, a larger amount of calculation and a larger storage resource will be generated. In addition, the accuracy of class B actions needs to be improved. Since this research is still in the initial stage, the later stage will be through the introduction of related mathematical methods for spatial coordinate conversion, and the acceleration data will be mapped from the mobile phone coordinate system to the inertial coordinate system, so as to ensure that the data can accurately reflect the actual stroke survivors' actual situation under any position of the mobile phone. In addition, relevant improved algorithms or neural network methods will be introduced to improve the efficiency and accuracy of classification and evaluation of the accuracy of rehabilitation actions.

In addition, this rehabilitation system can be used not only for stroke rehabilitation, but also for physical rehabilitation in other situations, such as limb dysfunction caused by rheumatoid arthritis, cervical spondylosis and lumbar disc herniation etc.

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