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Wearable Motion Recognition System Based on Dynamic Time Warping

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Abstract. In order to monitor the rehabilitation training of stroke patients in unsupervised situation and provide rehabilitation advice for rehabilitation clinicians, a wearable wireless motion recognition system has been developed using 9-axis wearable sensors, to identify patients' typical upper limb movements, e.g. Bobath handshake, stretch elbow and press hand, shoulder joint horizontal outreach, elbow buckling contact, paraplegia hand touch the shoulder, sequine pressure rotary before supination. After the original data is collected and preprocessed, each rehabilitation training action is segmented. Dynamic Time Warping (DTW) algorithm is used to calculate the similarity between each motion segment and the standard template data, and the motion recognition is carried out according to the calculated results. To verify the performance of the system, 20 stroke patients were recruited as volunteers. Each patient wore a 9-axis wearable sensor on his upper limb and performed six rehabilitation training exercises. After motion segmentation, 1400 motion fragments were obtained and used as samples to test the system. It has been found that the recognition accuracy of the system for the six rehabilitation training exercises is over 90%. This result provides a well reference for further development of an automated system for stroke patient rehabilitation motion recognition.

1. Introduction

Nowadays, with the improvement of people's living standard and the rapid aging of population in many countries, stroke has become a leading cause of death and ongoing disability in the world. According to an incomplete statistics, there are about 1.5 million patients died from stroke each year in China, and there are more than 2 million new stroke patients each year [1]. On the other hand, there is no enough rehabilitation centers or other rehabilitation institutions for treating stroke patients. At the same time, the healthcare expenditure dedicated to stroke related diseases is becoming higher and higher which is out of the affordability of many families. Therefore, many current researches have been focused on developing unsupervised rehabilitation methods which enable the patients to perform scheduled rehabilitation training outside medical facilities[2].

During the rehabilitation process, recording patients' motion is one of the most difficult tasks. At present, the common human motion-capturing methods are visual based tracking systems which utilize optical sensors and visual markers to track the body movements. Visual based tracking systems provide higher standard accuracy in general. However, the systems using visual markers may experience occlusion problem which means these systems will have a problem capturing the movements that involves body overlapping and joint rotating while these movements can commonly be found in rehabilitation training exercises[3]. Visual based systems are also relatively heavy, costly, and difficult to set up or calibrate which make it not suitable for home-based application.



According to that, a wearable motion recognition system has been developed using high-precision 9-axis wearable sensors and Dynamic Time Warping (DTW) algorithm. The system is easy to wear, and due to its low-power design, the system can work continuously two hours per day for more than one week time, which make the system very suitable for the application of unsupervised home rehabilitation monitoring.

2. System Description

2.1 General Description

During the rehabilitation training progress, the training data is collected by three wearable wireless sensor nodes. Where node 1 and node 2 are 9-axis wearable sensors fixed in forearm and upper arm affected on thumb respectively. Then the data is sent to the receive module wirelessly, and then sent to PC via USB interface. On the PC, the raw data is stored on the hard disk and displayed on the screen. So the patients can then watch their real-time training motions of their fingers and wrist at the same time, which can enhance their training interest and confidence. After preprocessing, periodic segmentation, and similarity computing, a complex network was established to analyze the quality of the rehabilitation training motions. Finally, the rehabilitation assessment results were sent to rehabilitation information management, for rehabilitation guidance and basis. The schematic diagram of wearable rehabilitation assessment system is shown in Fig. 1.

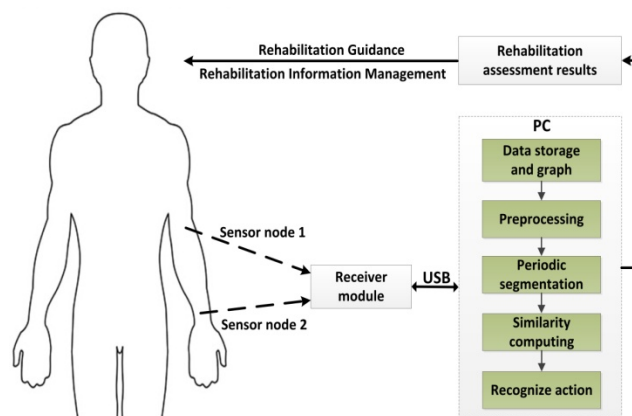


Figure 1: The schematic diagram of wearable rehabilitation assessment system

2.2 Hardware

The hardware system consists of two 9-axis wearable sensor nodes, a hand motion tracking node and a receiver module connected to PC via an USB port. For each 9-axis wearable sensor node, there are 3-axis acceleration sensors, 3-axis angular velocity sensors, and 3-axis geomagnetic sensors and a low-power ZigBee MCU. With a 480mAh lithium battery and the total working cost of 28mA, each node can work continuously two hours a day for at least one week. Due to small size, low power consumption and low cost, the wearable system is very suitable for the application of rehabilitation monitoring and data collection.

When the system is operating, the MCU of the receiver module sends out an address command every 5ms for node selection. Each node compares the address with its addresses. Only the node whose address is in agreement with the address sent from the receiver sends its data to the ZigBee receiver. So for each sensor, the total data acquisition time is 10ms, i.e., in every second it sends 100 packets of data to PC through the receiver module. This data transmission rate is enough for rehabilitation training purpose[4].

The 9-axis wearable sensor nodes and tracking node are attached to the patient's sick upper arm, low arm and hand respectively, as shown in Fig. 2.



Figure 2: Fixed position of the 9-axis wearable sensor nodes

2.3 Motion Recognition Process

Because stroke patients have varying degrees of limb dyskinesia, the quality of their movements will be lower than the normal subjects, so there is a phenomenon of irregular movements, which is mainly manifested in the low similarity with the standard template. The operation of rehabilitation training was identified by calculating the similarity measure distance D between the training action and the standard template in different periods of rehabilitation training. The recognition process of rehabilitation training is shown in Fig. 3.

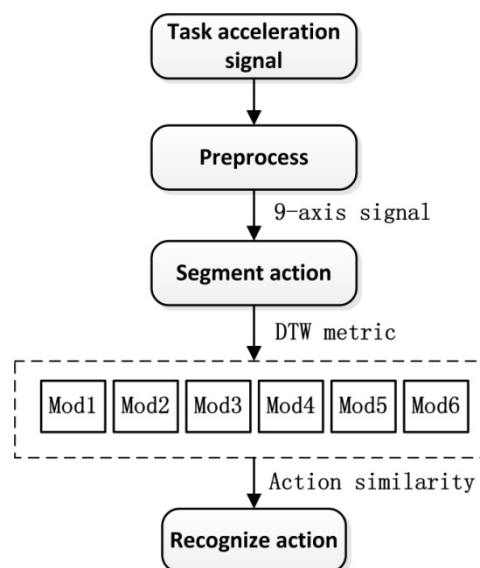


Figure 3: Recognition process of rehabilitation training for stroke patients

2.4 DTW Model

At present, dynamic time warping (DTW) is the most widely used method to measure signal similarity. It is an optimization algorithm that can compress or stretch the signal adaptively to establish a mapping between two time series, as shown in Fig. 4. Using the distance of the normalized path to evaluate the similarity between sequences can overcome the problem that the sequences can not match because of the different signal lengths[5]. The rehabilitation motions of stroke patients are not standardized because of limb dyskinesia. Therefore, DTW is very suitable for the recognition of rehabilitation training motions.

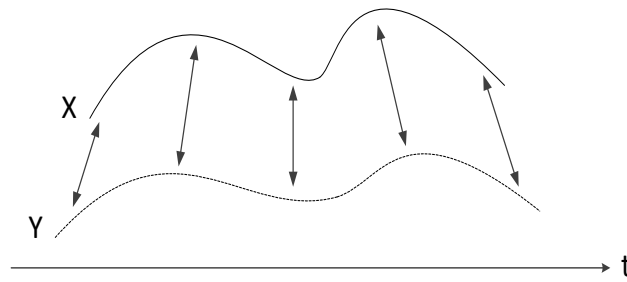


Figure 4: Schematic diagram of DTW algorithm

For two time sequences X and Y , whose lengths are $|X|$ and $|Y|$, their warp path can be expressed as $W = w_1, w_2, \dots, w_K$, where $\max(|X|, |Y|) \leq K \leq |X| + |Y|$, w_k is a set of coordinates (i, j) , here, i represents the i th value in sequence X and j represents the j th value in sequence Y . The selection of warp paths should satisfy the following conditions, the first is the boundary conditions, i.e., the starting and ending points of W are $w_1 = (1, 1)$, $w_K = (|X|, |Y|)$, so as to ensure that W contains every coordinate in sequence X and Y . Then the selection of warp paths should satisfy continuity, that is, points and points can not be cross point matching, and can only match the points that are adjacent to the current point. second, it is necessary to satisfy the monotone increase of i and j in W , that is:

$$\begin{aligned} w_k &= (i, j), w_{k+1} = (i', j') \\ i &\leq i' \leq i+1, j \leq j' \leq j+1 \end{aligned} \quad (1)$$

Finally, the warp path distance is obtained according to the warp path, as shown in formula (2):

$$Dist(W) = \sum_{k=1}^{K-1} Dist(w_k, w_{k+1}) \quad (2)$$

When DTW algorithm is used to realize dynamic path planning, $D(i, j)$ is used to represent the distance between two time sequences, as shown in formula (3):

$$D(i, j) = Dist(i, j) + \min[D(i-1, j), D(i, j-1), D(i-1, j-1)] \quad (3)$$

$D(|X|, |Y|)$ is the distance between the two time sequences, which represents the similarity.

3. Experiments

3.1 Data Sampling and Preprocessing

In order to examine the performance of the proposed system, an experiment involved in 20 stroke patients was carried out. Several typical rehabilitation training motions, such as Bobath handshake, labeled "a", stretch elbow and press hand, labeled "b", shoulder joint horizontal outreach, labeled "c", elbow buckling contact, labeled "d", paraplegia hand touch the shoulder, labeled "e", sequine pressure rotary before supination, labeled "f". These rehabilitation training motions were used in the experiment.

The experiment was carried out in Suzhou Xiangcheng People's Hospital, which was certified by the Hospital Ethics Committee and approved by the subjects and their families. The subjects included 20 middle-aged and elderly stroke patients, including 11 males and 9 females, with an average age of (65.1 ± 13.4) years. There were 12 right-sided patients with Brunnstrom score of 2-4, 8 left-sided patients with Brunnstrom score of 2-3.

The patients were asked to repetitively perform these common upper limb exercises with 9-axis wearable sensors attached to their arms. The exercises were sampled under relatively loose supervision, which means the movements recorded were performed at various speed and completeness, in order to simulate the real practice situation. During the whole data acquisition process, all the training

exercises of the patients were guided by a rehabilitation doctor. Therefore, the raw data were accord with the real practice situations.

The original signal collected will have burrs and spikes due to the patient's motion jitter, noise and other reasons. Band pass filtering and median filtering are used to preprocess the original signal. Fig. 5 shows the original acceleration signal, band-pass filtered signal and median filtered signal. It can be seen that the peak and burr of acceleration signal are basically filtered out after band-pass filtering and median filtering.

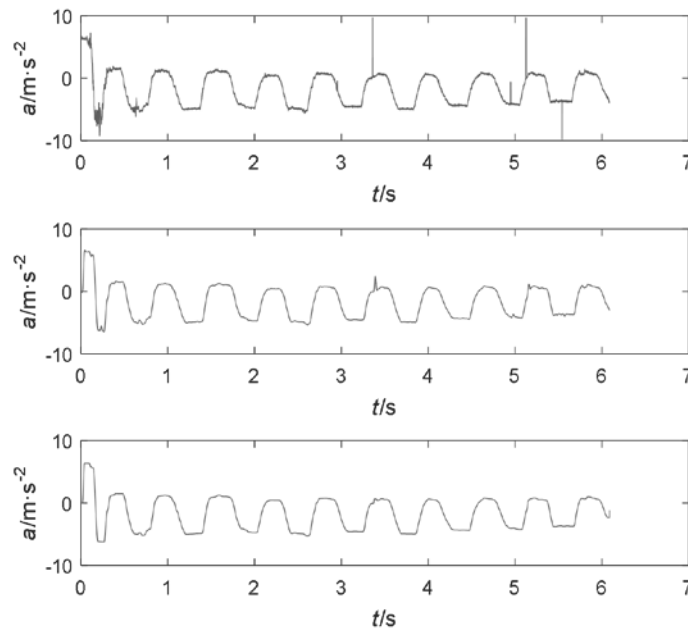


Figure 5: The original acceleration signal, band-pass filtered signal and median filtered signal

3.2 Motion Segmentation

Before using similarity measure to recognize and evaluate the effect of rehabilitation training, it is necessary to segment each action into different motion segments in acceleration signals. In order to eliminate the influence of different axes on the result, the X-axis signal is uniformly selected for all actions.

First, differential processing of preprocessed X-axis acceleration signal $ax(t)$ is carried out, as shown in formula (4). If the length of original signal is m , then a differential signal $y(t)$ with a length of $m-1$ is returned. Fig. 6 shows the X-axis acceleration signal and its differential signal under the Bobath handshake. It can be seen that the region where the differential signal is approximately zero corresponds to the peak and trough of the acceleration signal. The position of the trough can be obtained from the negative to positive position of the differential signal. The signal between the two adjacent troughs is defined as a single action.

$$y(t) = [ax(2) - ax(1), ax(3) - ax(2), \dots, ax(m) - ax(m-1)] \quad (4)$$

The differential signal will fluctuate around zero, which will affect the judgment of the peak value of the acceleration signal, resulting in multiple judgments or misjudgments[6]. Therefore, the original differential signal is moved as a whole according to the fixed value to get a new differential signal, and then judged one by one. If at a certain time, the signal $y(i) < 0$ and $y(i+1) \geq 0$, then the i will be carved as the action point. Finally, the signal between the two adjacent action points is defined as a single action signal. Fig. 7 shows the segmentation results for rehabilitation training motions of Bobath handshake and sequine pressure rotary before supination, the signal between two adjacent vertical lines is the acceleration signal of a single action.

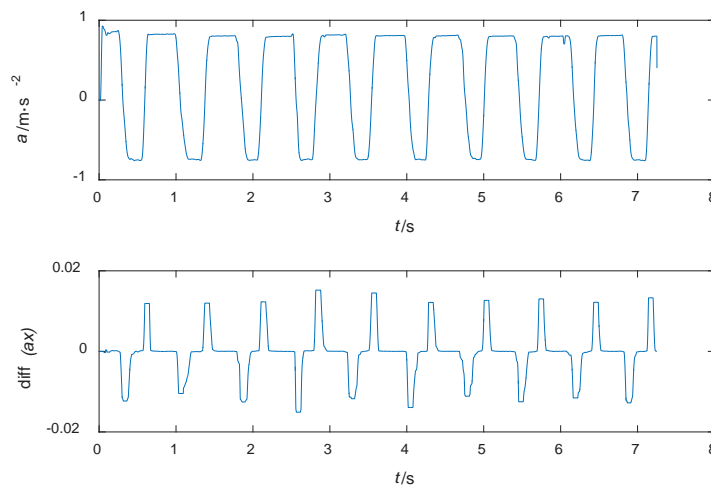


Figure 6: Acceleration signal and differential signal of Bobath handshake action

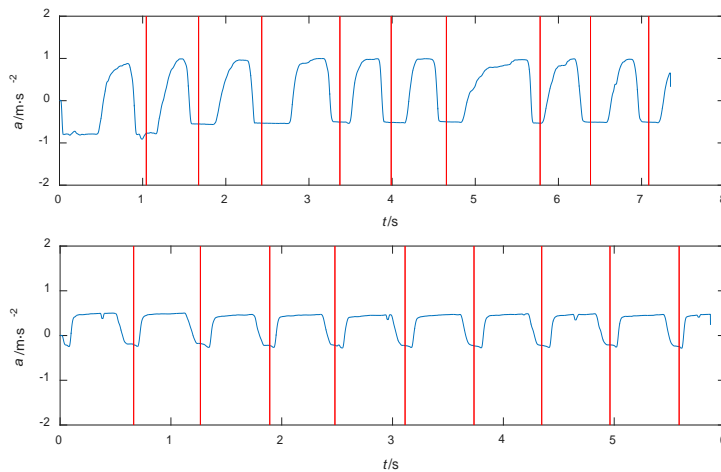


Figure 7: Segmentation results of different actions

3.3 Motion Recognition Model based on DTW

In order to recognize the action type of a certain signal, it is necessary to select the standard template for each training action, and then calculate the path distance D between the action signal and each template to compare the similarity between them, and take the template corresponding to the minimum distance (that is, the maximum similarity) as the type of the current action. Data collected from the same training operation for six different rehabilitation training motions were used as standard templates.

4. Results And Discussion

4.1 Experiments Results

The training data of 20 subjects including six different rehabilitation training motions were divided into 1400 motion segments. Compare the training data with the standard templates of six movements, and the actions were identified based on DTW similarity measure, the result is shown in Table 1. It can be seen that except for paraplegia hand touch the shoulder, labeled "e", the recognition accuracy is over 99%. Among them, the recognition accuracy of stretch elbow and press hand, labeled "b", shoulder joint horizontal outreach, labeled "c", sequine pressure rotary before supination, labeled "f" reached 100%, and the average recognition accuracy of all rehabilitation training motions was 98.3%.

Table 1: Recognition Results of Training Actions

Actual actions	a	b	c	d	e	f
Recognition Results						
a	274	0	0	0	0	0
b	0	200	0	0	1	0
c	0	0	216	0	3	0
d	1	0	0	235	5	0
e	0	0	0	1	209	0
f	0	0	0	0	14	241
Recognition Accuracy (%)	99.6	100	100	99.6	90.1	100

4.2 Discussion and the Future Work

From the above results, six typical upper limb rehabilitation training motions can be identified accurately with 9-axis wearable sensors and DTW algorithm. However, The accuracy of action recognition can't reach 100%. So it is necessary to find a better signal processing method to further improve the accuracy of rehabilitation training motions recognition.

Additionally, due to the limitation of experimental conditions, the number of samples and types of action are relatively small. Therefore more rehabilitation training motions and more stroke patients will be further studied and applied in the future.

5. Conclusion

In order to monitor the rehabilitation training of stroke patients in unsupervised situation, a wearable wireless measurement system for upper limb motion recognition has been developed using 9-axis wearable sensors, with motion recognition model based on DTW. The experiment results indicate that the recognition accuracy of the system for six typical rehabilitation training motions is over 90%, which provides a well reference for further development of an fully automated and real-time system for stroke patient rehabilitation training motion recognition.

6. References

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