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Intelligent Shoulder Joint Home-Based Self-Rehabilitation Monitoring System

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Abstract

Shoulder joint rehabilitation exercises are considered one of the most effective treatments for reducing shoulder pain and improving the range of motion. In addition to regular supervision from professional rehabilitation staff, participation in home-based self-practice can enhance the effectiveness of treatment. Therefore, this study proposes an intelligent monitoring system for home-based self-rehabilitation. In this system, smart phones serve as the platform for integrating an accelerometer-based sensor network for monitoring the performance of rehabilitation exercises by patients with shoulder injuries. The developed sensor network comprises 2 accelerometer sensors and the built-in smart phone accelerometer that communicate using Bluetooth protocols. The following 5 monitoring exercises were included in this study: touch ear, use fingers to climb wall both facing and sideways to the wall, clockwise and counterclockwise pendulum circles, active-assisted front and side stretches, and raises hand from back. Shoulder rehabilitation activities are recognized by the Support Vector Machine algorithms and recorded on the smart phone. These records can be used by patients as a reference of their activity. The records can also be uploaded to the hospital server to assist physicians in monitoring the effectiveness of exercises. The proposed approach is low cost and can be extended to various monitoring targets by simply installing a new Android app.

Keywords: *home-based self-rehabilitation, sensor network, shoulder joint injuries, smart phone, support vector machine (SVM)*

1. Introduction

The shoulder joint is the only joint in the human body that can be rotated 360°. However, the shoulder joint is easily injured by various bone and muscle damage, dislocation, and degradation caused by aging. Therefore, people of all ages are likely to experience shoulder pain and a limited range of motion. The problems of shoulder pain and limited range of motion have several causes, and are extremely complex. The differential diagnoses of shoulder injuries are traumatic and non-traumatic. Traumatic injury includes sports injuries or accidents (fractures, dislocations, or muscle tears) and repetitive movement. Non-traumatic injury includes impingement syndrome, adhesive capsulitis (frozen shoulder), joint degeneration (arthritis), and cervical nerve compression.

Upper limb rehabilitation exercise therapy can reduce spasms and pain, effectively improve shoulder joint activity, and prevent the occurrence of lymphedema. However, the effectiveness of rehabilitation often cannot be determined [1]. The main reason for the limited effectiveness of rehabilitation is that patients do not adhere to the exercise program prescribed for home-based rehabilitation. The primary goal of rehabilitation is to maintain shoulder

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mobility. Patients are liable to cease therapy if they doubt the effectiveness of the rehabilitation.

Because of the popularity of smart phone devices, related applications have been extensively developed. Establishment of the intelligent mobile phone as the calculation core, combined with the accelerometer-based motion detectors can ensure the efficacy of many home care activities [1, 2]. This study presents a wearable sensor network that integrates triaxial accelerometers and smart phone sensors to form an upper limb rehabilitation exercise monitoring system. Data of rehabilitation activity are collected using wearable sensors and built-in smart phone accelerometers, and recognized using a support vector machine (SVM) algorithm.

In this study, the following five types of exercises were monitored: 1) touch ear (external rotation), 2) use fingers to climb wall both facing and sideways to the wall, 3) clockwise and counterclockwise pendulum circles, 4) active-assisted front (flexion) and side (abduction) stretches, and 5) back hand raises (internal rotation) .

The remainder of this paper is organized as follows: Section 2 presents a summary of the results of related research; Section 3 introduces the architecture of the proposed home-based self-rehabilitation exercise monitoring system; Section 4 details the experiment results; and Section 5 provides the research conclusion and suggestions for future research.

2. Related Research

Upper limb rehabilitation requires a high repeatability and long-term continuous treatment, using a rehabilitation robot to replace the manual treatment can enable patients to continuously receive accurate guidance from a physiatrist-like [3, 4]. However, rehabilitation robots are high cost, difficult to maintain, and unsuitable for general home-based self-rehabilitation.

A typical approach for monitoring rehabilitation exercises involves using cameras to capture and recognize activities [5, 6]. However, this method has several disadvantages; for examples, rehabilitation locations are restricted, subtle movements are difficult to detect, and certain actions are performed out of the camera range.

Because of the rapid development of micro-electromechanical systems (MEMS) technology, sensors based on accelerometers and gyroscopes are widely employed for assessing and recognizing activities [1, 7-11]. Culhane *et al.*, [8] used an accelerometer monitoring device to analyze elderly people's gait, balance, and performance of daily activities. They investigated how elderly people can safely perform rehabilitation exercises at home when alone. Patel and Hughes *et al.*, [1] adopted an accelerometer to collect data of stroke patients who had completed actions according to the functional ability scale, and compared the calculation results with the total scale provided by medical staff. They confirmed that low-cost accelerometers can also achieve an acceptable accuracy level. Raso *et al.*, [10] developed a monitoring system, named m-Physio, for patients with insufficient time to visit a hospital, or who resided far from the hospital, to assist them with performing rehabilitation exercises. This system combines a smart phone with network applications to form a cycle monitoring system that enables therapists to understand the condition of patients immediately. Muscillo *et al.*, [11] proposed a real-time activity recognition method for detecting eight rehabilitation actions referenced from the Wolf Motor Function Test. Improved real-time dynamic time warping (RT-DTW) is used to recognize the actions in real time. The experiment results indicate that 60% of the actions can be identified before the end of the exercise.

Compared with robot and vision-based approaches, micro sensors have the advantages of low cost, minimal size and weight, comparatively lower susceptibility to environmental constraints, and high portability. Thus, micro sensors can serve as the key technology of home-based self-rehabilitation exercise monitoring systems.

3. Architecture of a Home-based Self-rehabilitation Exercise Monitoring System

The architecture of the proposed home-based self-rehabilitation exercise monitoring system is shown in Figure 1.

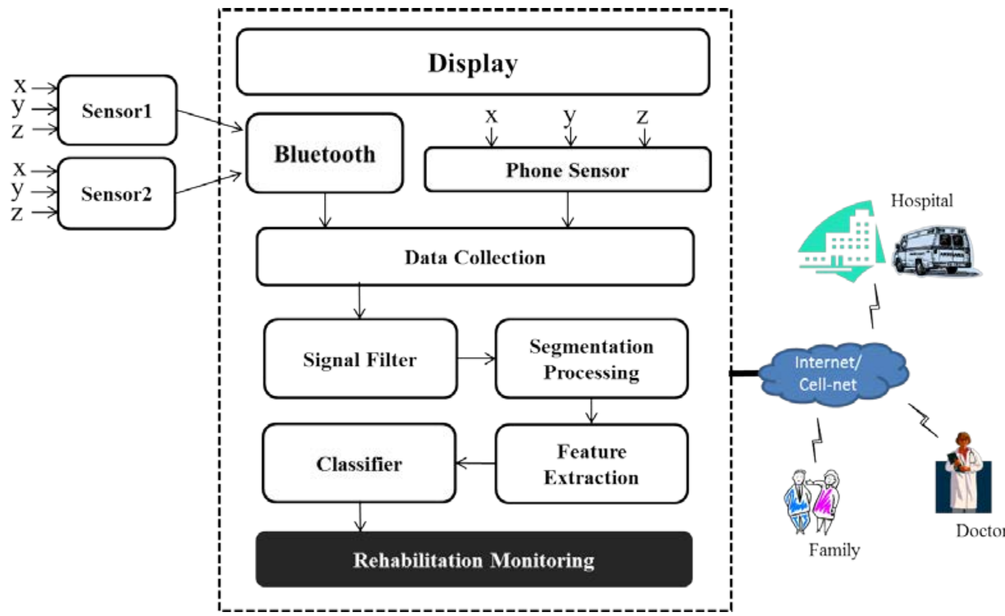


Figure 1. The Proposed System Architecture

The hardware of the proposed system comprises two accelerometer-based sensors and an Android-based smart phone. The sensors are responsible for collecting body movement data, and the smart phone serves as the main calculation platform. The primary components of the system are introduced in the following section.

A. Accelerometer-based Sensor

An accelerometer-based sensor was designed to capture body acceleration data. The sensor comprises the following components: 1) a LIS3LV02DQ triaxial acceleration sensing unit, 2) a MSP430F169 microcontroller processing unit, 3) a BTM-112 Bluetooth module wireless transmission unit, and (4) a lightweight rechargeable lithium battery as the power supply unit. The sensor dimensions are 40 mm * 28 mm * 18 mm (Figure 2). The sampling frequency was set as 32 Hz.

When the system is activated, the smart phone prompts the sensor processing unit through a Bluetooth protocol to capture movement information. The triaxial acceleration sensing unit senses arm acceleration data, which it transfers to the processing unit. After receiving the acceleration data, the processing unit transfers the data to the smart phone via the Bluetooth module. The analysis and recording tasks are executed by the smart phone.

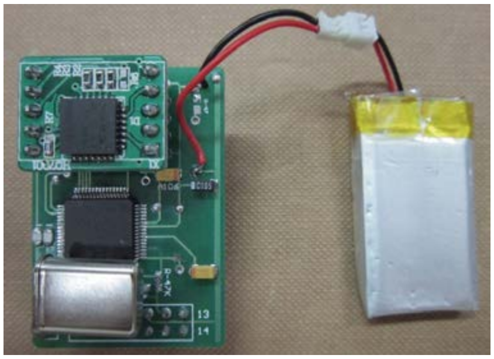


Figure 2. The Accelerometer-based Sensor

B. Signal Filter

To eliminate noise from the hardware circuit, a nonlinear median signal filter was adopted to pre-process the acceleration signal. The filtering window size was set as 7. After applying the median filter, a low-pass (moving average) filter was used to smooth the acceleration signal. The window size was set as 30. Figure 3 shows an example of data obtained from a wrist sensor when performing the touch ear exercise. The left image shows the original acceleration signal, and the right image shows the results of filtering using median and low-pass filters.

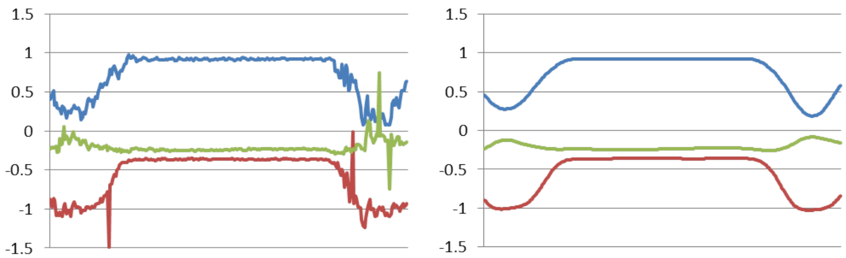
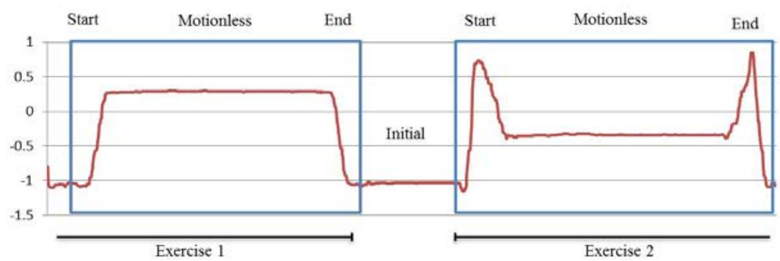


Figure 3. An Example of Signal Filtering that using Median and Low-pass Filter. The Left Hand Side Shows the Original Signal and the Right Hand Side Shows the Filtered Result

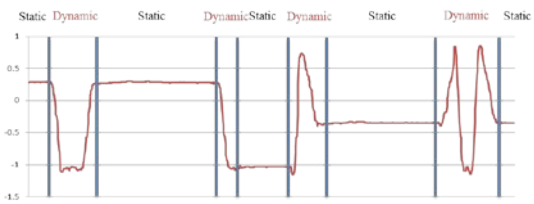
C. Segmentation

Accelerometer data were digitally filtered with a median filter to remove high-frequency noise and then segmented to isolate the movement actions. Patients were instructed to press the start button when beginning the periodic exercises and to press the end button after completing every exercise. Each exercise may involve one or more actions. The patients were allowed a 3-s interval to rest between actions. Segmentation was performed to distinguish the count for each action, which was conducted by the patient (Figure 4(a)). To improve the rehabilitation effects, the patients were instructed to remain stationary for at least 5 s when their action reached the highest range of motion (ROM) (for stopover action). This is beneficial for patient recovery.

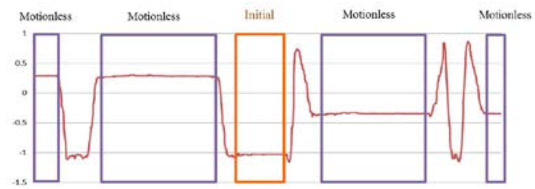
The raw data, including that collected when stationary (static) and in a state of motion (dynamic), were segmented using a hybrid segmentation algorithm to identify separate activity. The segmentation algorithm comprised the following five stages: 1) calculate the first difference between stationary and in motion states (Figure 4(b)); 2) for the stationary state and initial action, perform dynamic time warping (DTW) [8] to distinguish various actions between segments (Figure 4(c)); 3) delete unnecessary signals from the beginning and end of each action; 4) using a Haar wavelet transform function [12], remove the start and end of each action (Figure 4(d)); and 5) segment detailed actions from continuous data of rehabilitation exercises (Figure 4(e)).



(a) Segmenting the Static and Dynamic States

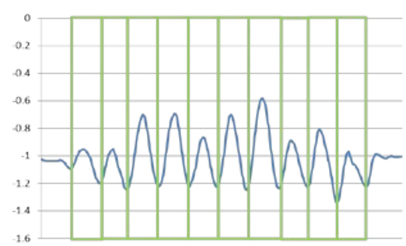


(b) Segmenting the static and dynamic states



(c) Segmenting the different actions

(d) Segmenting the start and end



(e) Segmenting the detailed actions

Figure 4. The Five Steps in Acceleration Signal Segmentation Process

D. Feature Extraction

Features were extracted from the accelerometer data to capture various aspects of the activities, such as the speed, smoothness, and coordination. Specifically, the following five features were estimated:

1) Mean value of the accelerometer time series

$$Mean = \frac{\sum_{i=1}^{n} x_i}{n} \qquad (1)$$

2) Root mean square value of the accelerometer time series

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} x_i}{n}} \tag{2}$$

3) Maximum value of the velocity time series

$$Max = \max(x_1, x_2, ..., x_n) \tag{3}$$

4) Minimum value of the velocity time series

$$Min = \min(x_1, x_2, ..., x_n) \tag{4}$$

5) Entropy of the accelerometer time series

$$Entropy = -\sum_{i=1}^{n} p(xi) \log_{10} p(x_i) \quad \text{where} \quad p(xi) = \frac{x_i^{\,2}}{\sum_{j=1}^{n} x_j^{\,2}} \tag{5}$$

E. Classifier

In this study, the SVM [13] algorithm was adopted as the core classification algorithm. SVM classification is widely employed for binary data classification and regression. Regarding categories, to identify the largest category edge interval (hyperplane), classification errors must be minimized. Because various rehabilitation activity data are input into the system, SVM processing follows a one-versus-all method, that is, the problem is divided into N classification categories (six types of exercises are included in this study). During the training phase, the collected training data are used to construct a support hyperplane. According to the identified features, data points are tagged with 1 when approaching one category; otherwise, if they approach other categories, they are tagged with -1. Thus, one piece of input data is tested using the N support hyperplane and subsequently allocated to the most appropriate category

4. Results

The sensor and smart phone device can be worn as shown in Figure 5. The smart phone was attached to the wrist for easy operation of the monitoring system.

A prototype of the intelligent rehabilitation monitoring system was produced. The experiment was conducted in a laboratory with 10 healthy and young adults and 14 patients[1]. The healthy young adults comprised three men and seven women aged between 20 and 25 years. The patients included five men and nine women aged between 44 and 67 years. To simulate the various situations that patients may encounter, each participant was required to perform the five rehabilitation exercises several times (Table 1). Every healthy young adult participant completed the exercises, using both their right and left shoulders, whereas the patients only performed the exercises using their injured shoulder. The data for two participants were incomplete and thus were excluded from this experiment. The captured data of the 10 healthy participants and seven randomly selected patients were analyzed using cross-validation. Data of the remaining five patients were extracted to serve as the validation data set.

[1] This experiment was approved by the institutional review board of the Buddhist Tzu-Chi General Hospital, Taiwan (IRB102-58).

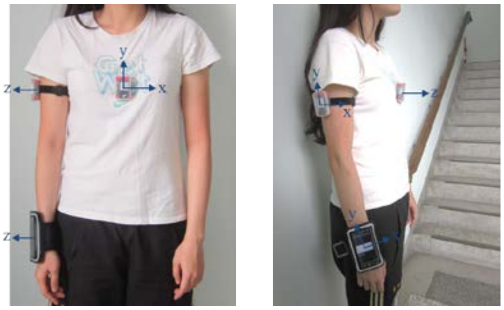
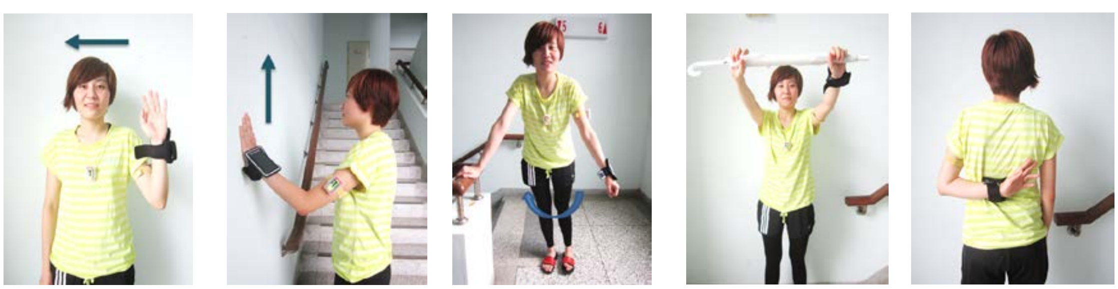


Figure 5. One Sensor and Smartphone is placed on the Affected Shoulder, and the other Sensor is placed on the Chest

Table 1. Exercise Types and Action Numbers of Training, Testing, and Validation

Exercise types	Total activities	Training	Testing	Validation
Touch ear(Fig.6(a))	160	108	27	25
use fingers to climb wall both facing and sideways to the wall (Fig.6(b))	320	216	54	50
Pendulum (Fig.6(c)) clockwise and counter clockwise	640	432	108	100
Active-assisted stretch (Fig.6(d)) fore and side	640	432	108	100
raises hand from back (Fig. 6(e))	160	108	27	25



(a)Touch ear

(b) Use fingers to climb wall (facing the wall)

(c) Pendulum counter clockwise

(d) Active-assisted stretch

(e) Raises hand from back

Figure 6. The Monitored Target Activities of Rehabilitation Exercise

A five-fold cross evaluation approach was adopted to identify the optimal classification model. Training and testing data for each exercise type were randomly divided into five subsets. The results of the proposed classification model are shown in Table 2.

Table 2. The Testing Results of Classification Model

			Segmenting error	Classified results					
				Touch ear	Raises hand from back	Use fingers to climb wall	Pendulum	Active-assisted stretch	Accuracy
Real	Touch ear	27	-2	25	0	0	0	0	92.6%
	Raises hand from back	27	-1	0	26	0	0	0	96.3%
	Use fingers to climb wall	54	+1	0	0	55	0	0	98.1%
	Pendulum	108	-6	0	0	0	102	0	94.4%
	Active-assisted stretch	108	-1	0	0	0	0	107	99.1%

The data of five independent participants (patients) were used to further validate the effectiveness of the classification model. The overall average correctness reached 100%, with a standard deviation of 0.02 (Table 3).

Table 3. Using Independent Validation Subjects to Validate the Experiment Results

Validation Subjects						
S1	S2	S3	S4	S5	Average correctness	Standard deviation
96.6%	96.6%	97.2%	96.9%	97.8%	96.85%	0.005

The experiment results indicate that errors primarily resulted from incorrect segmentation caused by the participants performing free and continuous activity. The segmenting correctness rate was 92.5% for the touching ear exercise (152/160), 98.1% for the back hand raise exercise (157/160), 97.2% for the finger wall climb exercise (1-9/320), 95.2% for the pendulum clockwise exercise (609/640), and 99.7% for the active-assisted stretch exercise (638/640).

5. Conclusion and Future Research

This study presented a low-cost expandable approach to monitoring home-based shoulder joint rehabilitation. Two accelerometer-based sensors and a built-in smart phone accelerometer captured the rehabilitation exercise data, which were then recognized by the SVM classification algorithm implemented in the smart phone. The proposed home-based self-rehabilitation exercise monitoring system provides the following three main benefits: 1) visibility: physiatrists can monitor adherence to the prescribed exercise program, that is, the actual daily rehabilitation duration, by referencing the exercise records stored on the smart phone; 2) portability: the system is not limited to a specific location, which allows rehabilitation exercises to be performed at any time and place; and (3) extendibility: the functions of the software installed on the smart phone can be extended or updated through the standard app update procedure, without hardware modifications.

In the future, such situations can be recognized immediately to ensure an appropriate response and avoid causing secondary damage during home-based self-rehabilitation. Furthermore, an automatic ROM measurement algorithm that serves as the basic function of the proposed rehabilitation monitoring system is set for development.

Acknowledgments

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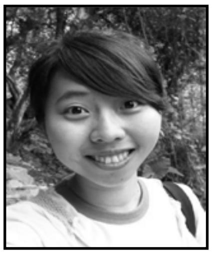

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