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應用加速度器與曲率檢知器於評估肩關節功能之復健

Evaluation of Shoulder Functionality Based on Accelerometer and Bending Sensor

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Abstract

Persistent rehabilitation can help post-operation patients maintain functionality of shoulder motion. It prevents body from more severe symptoms such as lymphedema and keeps well capability of doing activities of daily life. However, lots of patients always ignore the importance of persistent rehabilitation due to the deficiency of self-awareness about body status. It makes patients do not spontaneously continue rehabilitation for at least one year. Therefore, it is necessary to provide a mechanism that makes patients gain much incentive to motivate them to do rehabilitation more frequently.

Based on the signals from accelerometer and bending sensor, this thesis adopts the supervised learning technique to implement the shoulder functionality evaluation system with linear regression model. The system identifies the most stable shoulder range of motion according to the six shoulder evaluation exercises performed by patients. It also shows the assessment for capability of activities of daily life in order to instantly boost self-awareness about shoulder health status. Not only the feasibility study shows that the mean square error in prediction angle of shoulder range of motion is below $12°$, but also the system obtains the positive affirmation from real-world patients and physical therapist after they try out the system.

Keywords: Accelerometer, Bending Senser, Posture Recognition, Linear Regression

摘要

乳癌患者在手術完畢後，必須進行一系列復健運動以維持正常肩關節的活動度。此舉不僅可避免諸多的術後併發症，同時也能保有維持日常生活的肩關節功能。然而，復健伴隨而來的不舒適感以及無立即成效的特性，讓病患漠視它的必要性而導致長期復健運動處方的成效不彰。因此，迫切需要一個機制能夠評估身體復原的狀況，提升病患自身健康狀態的認知，進而鼓勵其積極地持續復健運動。

本研究以加速度器與曲率檢知器的訊號爲基礎，利用線性迴歸模型與監督式學習方法實作出肩關節功能性評估系統。系統依據病患做出的六種臨床上評估肩關節功能性的運動，偵測出最穩定的肩關節活動度，並以此爲基準評估日常生活行爲的功能性。目的在反映病患身體復原的程度，提升病患對自我身體健康狀態的認知。在系統效能評估上，對於肩關節活動度的判斷均方誤差角度在六類評估動作中皆小於12度。爾後，透過“乳癌防治基金會”的協助，實際請求病患嘗試此系統，獲得病患與物理治療師一致的正面肯定，證實了此系統在眞實世界的可行性。

關鍵字: 加速度器、曲率檢知器、姿態辨識、線性迴歸

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Chapter 1

Introduction

1.1 Motivation

It is very important to do rehabilitation in order to reduce the incidence of complications after operation. In general, breast cancer patients probably suffer from some post-operative complications such as change in appearance, decrease in muscle strength, and deterioration of shoulder range of motion. In order to avoid these complications, patients are educated to do rehabilitation exercises periodically after surgery during at least one year. Persistent rehabilitation can help patients keep normal circulation of lymph and maintain functionality of shoulder motion so that they can prevent body from more severe symptoms such as Lymphedema.

However, lots of patients always ignore the importance of persistent rehabilitation and do not spontaneously continue it for at least one year. The reasons why they are not motivated to persist on rehabilitation is that rehabilitation is tedious and uncomfortable, and that the benefit from rehabilitation is not instantly and obviously reflected on the advancement of patients' body status. As a result, when patients notice that they can scarcely doing activity of daily life as usual, they are always infected with severe lymphedema. It will have two main harmful influences on both physical and psychological aspects. First of all, it causes shoulder range of motion to deteriorate. The poor functionality of shoulder motion actually makes people not perform activity of daily life well and have low quality of life. Thus, they need more time and efforts to recover their health. Secondly, it makes patients' appearances unattractive so that they are not interested in public activities due to less confidence in their appearances. This negative impact on their mental health will make patients gradually lose their social ability.

Consequently, it is worth designing and implementing the mechanism that makes post-operation survivors more aware of their body status and gain incentive to encourage themselves doing rehabilitation more frequently. Moreover, it can track patients' rehabilitation progress and show the records to patients' relatives, friends, or physical therapists so as to give patients instant advises and encouragement.

1.2 Background

In order to design the mechanism mentioned above, we have to get involved in some preliminaries. In this section, we will describe the background about how to design and implement the mechanism in terms of clinical medicine preliminaries and wearable computer technology.

1.2.1 Clinical Medicine Preliminaries

The robust functionality of shoulder motion is necessary for people to perform activities of daily life well. In clinical research, the achievement in [20] presents that the capability of shoulder motion is highly relative to the stable ability of performing activities of daily life. Another achievement in [11] verifies that shoulder motion is massively involved in the private activities, including combing hair, wearing underwear, going to toilet, and so on. In other words, the poor functionality of shoulder motion makes people not perform activities of daily life well.

Generally speaking, there is a typical metric for evaluation in shoulder functionality, called **range of motion (ROM)**. Matsen just uses this metric to define the required shoulder range of motion for each primary activity of daily life in [11], which is shown in Table 1.1. In practice, patients are asked to finish each exercise of shoulder evaluation as possible as they can and keep the last posture for seconds. Physical therapists will observe patients for the whole time and regard the most stable posture as the index of current shoulder functionality. The evaluation exercises are six exercises for evaluation of shoulder range of motion such as flexion, abduction, extension, internal rotation, external rotation, and horizontal abduction. The detailed definition of each exercise is defined in Appendix A and diagrams of each exercise are described in Appendix B.

To sum up, if we want to implement a mechanism to help patients be much aware of their healthy status, it is necessary to accurately recognize what is the most stable posture performed by patients when they do a specific evaluation exercise.

Table 1.1: Relation between ADLs and shoulder ROM

ADLs	Exercise	Required ROM
Comb hair	Abduction External rotation	$0° \sim 100°$ $0° \sim 90°$
Wear underwear Tielet	Extension horizontal abduction Internal rotation	$38° \sim 56°$ $0° \sim 69°$ $0° \sim 90°$
Take something high	flexion	$0° \sim 148°$
Eat and drink	flexion	$36° \sim 52°$

1.2.2 Wearable Computing Technology

The recent achievements of WearIT@work project proposes the feasibility of wearable application in the field of healthcare, industry production, maintenance, and emergency response [16]. The most obvious characteristic is highly portable; thus, its significant result demonstrates that wearable computing solutions are successful not only in plausible scenarios but also in real-world application. It inspires us to design the mechanism for tracking shoulder motion functionality using wearable sensor.

Also, according to the clinical observation, we discover some characteristics when patients practice exercises of shoulder evaluation. One is that patients do exercises slowly, and the other is that each evaluation exercise can be simplified as the motions along sagittal plane, coronal plane, or transverse plane 1.1. When patients are deployed an accelerometer on the external side of lower arm to do exercises, it can capture the motion change along sagittal plane and coronal plane by the effect of gravity. Besides, a bending sensor can capture the motion along transverse plane when patients are equipped with bending sensor between an upper arm and a shoulder joint by sensor curvature.

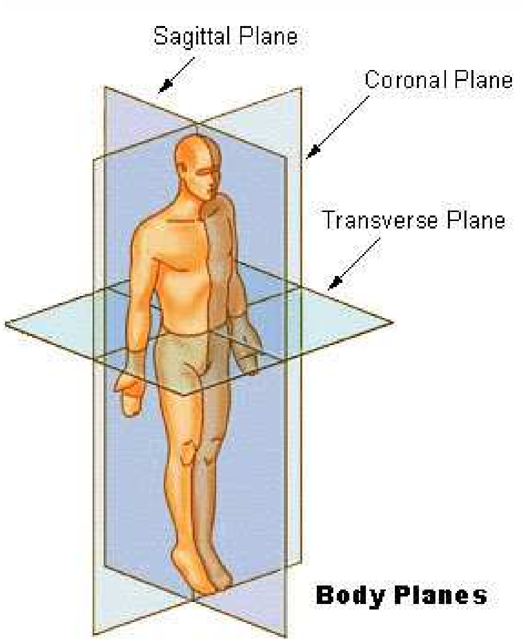


Figure 1.1: Body Planes

Consequently, when patients do the exercise, postures performed by them can be recognized by the accelerometer and the bending sensor under the some deployment constraints.

1.3 Objectives

According to what mentioned in previous sections, the objectives of this thesis is to implement a wearable computing system with a accelerometer and a bending sensor. It will evaluate functionality of shoulder in terms of range of motion, and then based on the information in Table 1.1 to analyze these ranges of motion and assess the capability of primary activities of daily life. The system overview is showed in Figure 1.2.

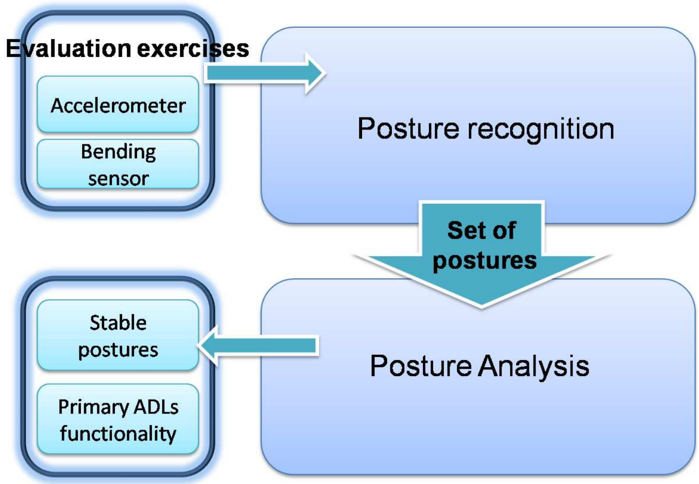


Figure 1.2: System overview

Furthermore, we not only verify the feasibility of the system by evaluating the performance with physical therapists but also survey users' acceptance by user studies.

1.4 Thesis Structure

The remainder of this thesis is organized as follow. In Chapter 2, we explore other research fields related to our thesis. In Chapter 3, we explain problem definition, proposed solution, and what the system is. In Chapter 4, we describe how to implement this system including hardware and software. In Chapter 5, we evaluation our system performance and survey the comments from domain expert and real-world patients. Finally, Chapter 6 is the conclusion and future work.

Chapter 2

Related Work

In 2007, Pan [17] adopts activity recognition technique to identify patients' rehabilitation exercises. This information can help doctors monitor which exercises performed by patients. However, it is difficult to recognize the quality and quantity of rehabilitation exercises. This information deficiency makes the evaluation of shoulder functionality unreachable. Instead, the thesis provides the mechanism to detect shoulder range of motion for evaluation in shoulder functionality.

According to the proposed system outline in previous chapter, there are three main components to support whole system, which are accelerometer, bending sensor, and posture recognition technique. In this chapter, I explore the state-of-the-art about wearable computing system in views of these three relevant sections. At beginning, I will introduce several wearable computing systems and ideas, which make use of accelerometer to help people solve real problems. In addition, I will present some creative projects, which implement interesting system with bending sensor to improve our quality of life. Finally, I will provide some research achievement about the feasibility of posture recognition based on wearable computing system.

2.1 Accelerometer Application

Accelerometer is a prevalent and popular tool in wearable computing system as a result of its reduced size and light weight. Undoubtedly, it is widely applied to wearable computing system in order to detect or recognize human activity and body movement for various purposes, which include physical exercise recognition, gesture recognition, and activity of daily life(ADL) recognition. I will describe the recent works one after another in the following sections.

2.1.1 Physical Activity Recognition

The advance of physical activity recognition might improve the feasibility of intelligent health assessment that help people become aware of whether their energy consumption is balanced so as to make human stay physically fit and health. In 2007, Chang *et al.* [8] were well aware that no mechanism is used for tracking of free weight exercise. They incorporated two three-axis accelerometers to automatically recognize which type of exercise people do and how many repetitions the specific exercise performed. One of the accelerometer was embedded into workout glove to track hand motion and another one was equipped on waist to catch the body posture information. In their designed experiment, they define nine free weight exercises as target classes and use Naïve Bayes and Hidden Markov Model(HMM) as classifiers to recognize what people perform; moreover, they develop peak detection algorithm based on accelerometer signal strength and apply Viterbi algorithm with a Hidden Markov Model to count repetitions of exercise. The result shows the recognition accuracy is almost 90% and roughly 5% miscount rate for counting repetitions.

Similarly, Tapia *et al.* [19] deployed five three-axis wireless accelerometers and one heart rate monitor on certain human body parts, which are upper arm, lower arm, waist, thigh, and leg, to track human physical exercises. However, their achievement not only recognize the physical the exercise performed but also detected the intensity of exercise during a period of time. In their experiment, they regarded thirty physical gymnasium activities as target classes and use Naïve Bayes and Decision Tree as classifiers to separately process subject-dependent and subject-independent analyses. The result shows that recognition accuracy performance of 94.6% for subject-dependent and 56.3% for subject-independent. It indicates that body characteristics has high diversity between individual subjects so finding a dominant approach to perform well in cross subjects scenario is hard for wearable computing system.

2.1.2 Hand Gesture Recognition

Contemporary innovative human-computer interface design and implementation is based on the development of gesture recognition. Obviously, the accelerometer is the proper solution on wearable computing system to capture finger movement and wrist orientation. In 2007, Chen [3] used accelerometers to realize multi-degree-of-freedom interface based on surface electromyography (sEMG) signals system. Although EMG-based interface systems performed well on recognition of moving fingers on a small scale and clenching a fist by analyzing muscle activities, they have difficulties extracting gesture withdrawal and hand rotation information from sEMG. Thus, they deployed accelerometers on one wrist and one back of hand to capture what EMG-based systems can hardly fetch. The experiment collected twenty four kinds of hand gestures and the result showed that a accelerometer improved the recognition accuracy of 5-10% compared with the experiment used EMG sensor solely.

2.1.3 ADL Recognition

ADL recognition technique is indispensable for constructing ubiquitous context-aware computer system applications that are the components in intelligent space. In 2004, Bao *et al.* [1] explored this problem by using five biaxial wireless accelerometers placed on different body parts, which include arm, wrist, waist, thigh and leg. They adopted several machine learning approaches to recognize twenty common ADLs such as reading, watching TV, brushing teeth, and so on. The result demonstrated the best performance recognizing these defined activities with accuracy of 84%. Moreover, the result also suggested that suitable places to deploy accelerometers are thighs and the dominant wrist, which are determinant body position in view of ADL recognition.

In 2007, Jeong *et al.* [9] prototyped a real-time system with a single small-size accelerometer on waist in order to monitor activity volume and recognize emergency situation such as falling during daily life. They adopted simple signal processing techniques instead of machine learning technique to reach their goal. They defined five activities, walk, run, fall, stand, and lie, and then got the recognition accuracy of above 98% based on their designed experiment.

2.2 Bending Sensor Application

back problem is attributed to A bad seating posture and there is no means to properly avoid this harmful habit. Therefore, Dunne *et al.* [4] employed a garment-integrated bending sensor to develop the seated spinal posture monitoring system for long-term computer users in working environment. It can observe users' seated posture and respond real-time feedbacks on computer screen to make users aware of poor seating posture.

Furthermore, Simone *et al.* [18] believed that results from measurement in the clinic setting do not exactly reflect the hand functionality when people participate social activities, which affects the quality of exercise prescription for rehabilitation treatment. They designed a wearable sensor glove with bending sensor to evaluate hand functional capability according to fingers bending capability. Their future vision is that wearable device can evaluate people's range of motion in their daily activities.

2.3 Posture Recognition Technology

Posture recognition problem can be solved by two approaches: vision-based approach and wearable-based approach. There is no dominant technique because of pros and cons among these two techniques. From the aspect of vision-based approach , although it provides high recognition performance, it costs high computation power and low portability [2]; in contrast, wearable-based approach has less computation cost and high portability, but it may bring lower recognition accuracy. In this section, I will depict a series of works in wearable-based approach to do posture recognition task.

Giorgino *et al.* in [7] use conductive elastomers as strain senors attaching on upper limbs and defines seven postures, which are four postures consisting of one exercise movement and three error postures for rehabilitation process. They developed a tight-fitting garment attached with several conductive elastomers on upper limbs and evaluate whether it is general enough to recognize postures after the sensor is taken off and put back on. However, they only calls for one subject to do that experiment. In order to make it more significant, they call for more people to collect the data set under the same methodology and deployment. In [6], researchers collect data from multiple subjects instead of a single subject. They verify that the classification model is general enough not only for a single subject but multiple subjects after sensor is taken off and put back on. Each sample in this data set is almostly classified into correct class label.

In addition, C. Mattmann verifies the feasibility of calculating the upper body posture with elongation sensors integrated into a tight-fitting clothing [14]. First of all, C. Mattamann utilized an optical motion tracking system to observe the different elongation pattern in tight-fitting cloth with respect to these four predefined postures, which are bending forward, bending backward, moving the arms forward, and lifting the shoulder. He found that it is easy to discriminate these patterns by human eyes. Furthermore, In [15], they deploy strain sensitive fibers to the undershirt and verify that different postures are recognized by measuring distinguishable elongation patterns of five postures, which are lifting shoulder, twisting(left/right), bending sideward(left/right), bending forward, bending strongly forward, and moving shoulder forward. They observed that it is obvious to extract elongation patterns in tight-fitting cloth from the data value of strain sensor with respect to different postures. Moreover, They request eight participants wearing the garment described in [13] and performing 27 upper body postures in [12]. They invited eight male subjects and each of them wear this garment and performed 27 predefined upper body postures. They use Naïve Bayes as a classifier with 5-fold cross validation procedure to evaluate their experiment. The classification rate of 84% was achieved for all-user classification and 65% for an independent user.

Chapter 3

Shoulder Functionality Evaluation System

3.1 System overview

Figure 3.1 shows the architecture and flow chart of the system. It has to detect user shoulder healthy status in terms of range of motion and functionality of activities of daily life. The *Posture recognition module* takes charge of recognizing postures performed by user, and then the *Posture analysis module* determines the most stable posture among the postures performed and assess the capability about activities of daily life. In this section, we will describe hardware deployment, system input and output, and the solution we proposed in the following sections. Moreover, The detailed descriptions about each components in the system are presented in Chapter 4.

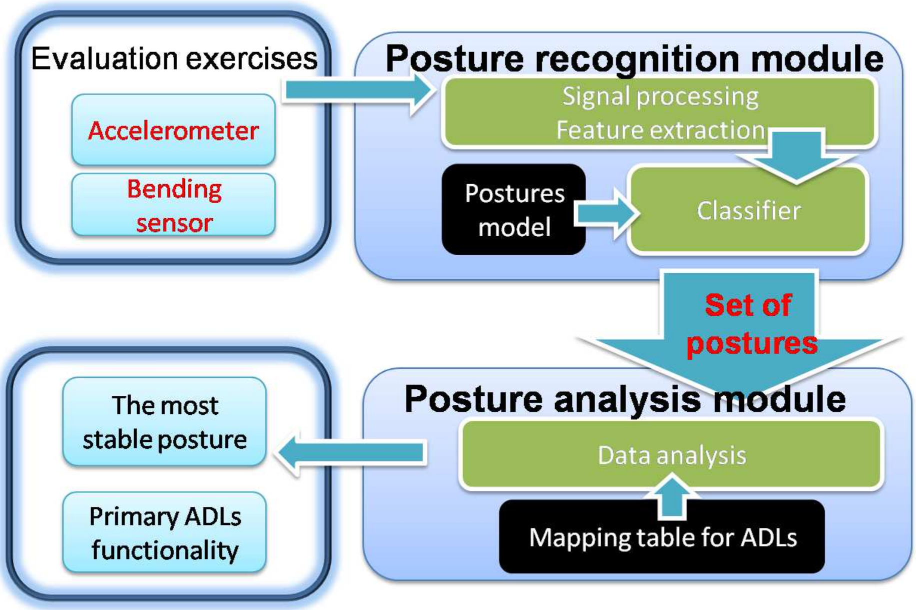
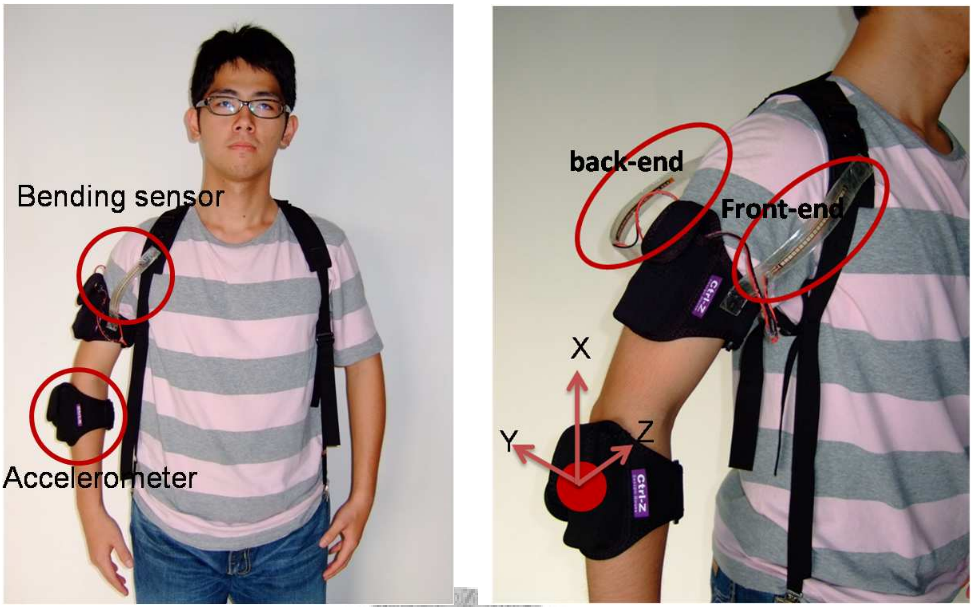


Figure 3.1: System Architecture

3.2 Hardware Deployment

We instrument a three-axis accelerometer onto the outside of lower arm and let the positive x-axis direction forward to the sky. In addition, we deploy two bending sensors on the shoulder sling and let users wear the sling. There are two bending sensors in the trunk front-end and back-end. The diagrams of hardware deployment are shown in Figure 3.2. Figure 3.2(a) illustrates the appearance of deploying sensors on body, and Figure 3.2(b) depicts the positive direction for each axis of accelerometer and where the two bending sensors are deployed.



(a) Front view (b) Side View

Figure 3.2: Sensor Deployment

3.3 Problem Definition

3.3.1 Input

Users wear an accelerometer and two bending sensors on their upper limbs to do six evaluation exercises. The order of exercise is flexion, abduction, extension, external rotation, internal rotation, and horizontal abduction. For each exercise, users have to follow two steps described as follow. The first step is called *calibration mode* and the second one is called *operation mode*.

1. Hold the starting posture for a period of time.

2. Hold the extreme posture after the starting posture for longer period of time.

Before describing the input, I have to define some notations.

Definition 3.1 *I regard t_1 as flexion, t_2 as abduction, t_3 as extension, t_4 as internal rotation, t_5 as external rotation, and t_6 as horizontal abduction.*

Then, I denote C_{t_i} is a set of sensor data collected at first step and E_{t_i} is a set of sensor data collected at second step when users do exercise t_i. The inputs are described as follow:

$$Input_1 = (C_{t_1}, C_{t_2}, C_{t_3}, C_{t_4}, C_{t_5}, C_{t_6})$$

$$Input_2 = (E_{t_1}, E_{t_2}, E_{t_3}, E_{t_4}, E_{t_5}, E_{t_6})$$

3.3.2 Output

The system will generate two kinds of outputs. One is a set of the most stable postures for each evaluation exercise, and the other is the capability of activities of daily life based on the result of the most stable postures set. Also, I have to define some notations before describing the output.

Definition 3.2 *According to the observation from Table 1.1, we discover that "combing hair", "wearing underwear" ,and "fetching something from high place" are required the best shoulder functionality to perform them. Thus, choose them as targets we want to evaluate. Here, we denote ADL_1 as "combing hair", ADL_2 as "wearing underwear" , and ADL_3 as "fetching something from high place".*

Definition 3.3 *We define $p_{t_i,s}$ as the starting posture. $p_{t_i,j}$ is the posture relative to the $p_{t_i,s}$, and j degree is the shoulder angle of motion relative to the starting posture for*

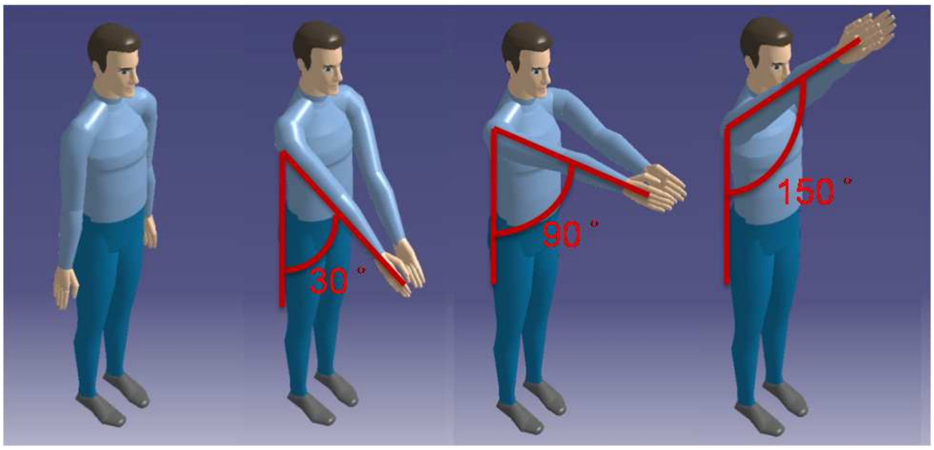


Figure 3.3: Diagram of Posture definition for flexion

each exercise type t_i. we define posture set $\mathcal{P}$ as following.

$$
\begin{aligned}
Let \quad F &= \{p_{t_i,j} | i = 1\ ,\ 0 \leq j \leq 180, j \in N\} \\
Let \quad G &= \{p_{t_i,j} | i = 3\ ,\ 0 \leq j \leq 60, j \in N\} \\
Let \quad H &= \{p_{t_i,j} | i \in \{2, 4, 5, 6\}\ ,\ 0 \leq j \leq 90, j \in N\} \\
\mathcal{P} &= F \cup G \cup H
\end{aligned}
$$

We take flexion for example to present what $p_{t_i,s}$ and $p_{t_i,j}$ mean in Figure 3.3. The diagrams from left to right are $p_{t_1,s}$, $p_{t_1,30}$, $p_{t_1,90}$, and $p_{t_1,150}$. To sum up, I denote P_{t_i} as the most stable posture for each exercise type t_i and S_{ADL_i} as the capability of activity of daily life ADL_i. The outputs are described as follow:

$$
\begin{aligned}
Output_1 &= (P_{t_1}, P_{t_2}, P_{t_3}, P_{t_4}, P_{t_5}, P_{t_6})\ ,\ \forall P_{t_i} \in \mathcal{P} \\
Output_2 &= (s_{ADL_1}, S_{ADL_2}, S_{ADL_3})\ ,\ \forall S_{ADL_i} \in N
\end{aligned}
$$

3.4 Proposed Solution

3.4.1 Posture recognition module

The main task of this module is using a sequence of postures to represent what users performs when they do the specific exercise. Thus, the most important function in this module is to accurately recognize the postures performed by users. Generally speaking, we can regard this task as supervised learning problem and make use of machine learning method to solve it.

Usually, there are several steps when using machine learning method on this problem. The first step is to collect lots of sensor data by requesting users hold different postures. Then, the second step is to transfer sensor data into features that represent the characteristics of original data to construct the "Postures model". Figure 3.4 shows the diagram of model training stage. Finally, when users wear the sensors to do evaluation exercises, the "Posture classifier" will recognize what users perform based on the "Postures model".

3.4.2 Posture analysis module

This module takes charge of two tasks. One of them is to decide the most stable posture from the posture set generated by "Posture recognition module". The other is to determine the functionality of three primary activities of daily life based on the relation between these activities and shoulder range of motion in Table 1.1. In other words, I try to use statistical method to extract both meaningful and readable information from

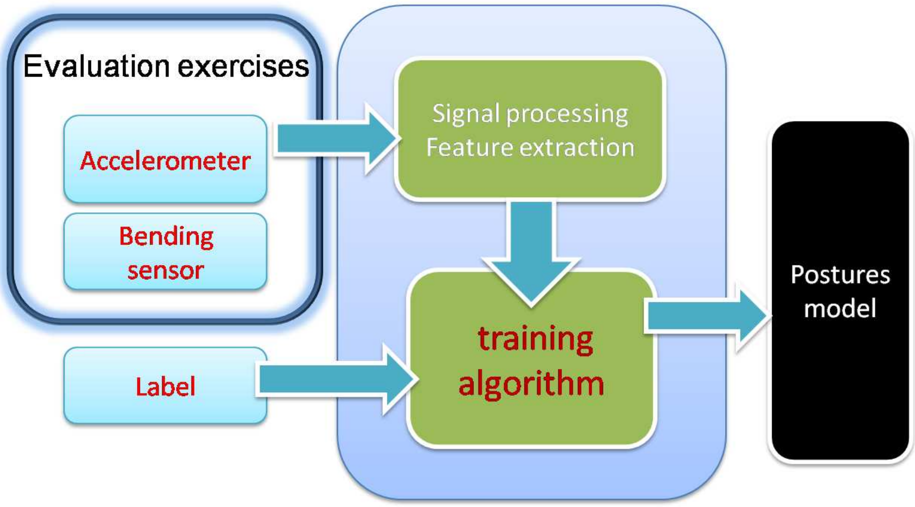


Figure 3.4: Diagram of Training Postire Model

postures.

Chapter 4

Implementation

4.1 Hardware

The accelerometer used in the system is *ADXL330* single-chip produced by Texas Instrument[1]. It is a 3-axis accelerometer with measurement range of ±3g and sensitivity of 20 mg. Also, the bending sensor used in the system is piezo-resistive sensor. This type of sensor is more reliable and portable than other types mentioned in the survey produced by Dunne[5].

In order to sample accelerometer and bending sensor signals, I use Taroko as sensor board to design and implement an wireless sensor tool kit. It is controlled by *MSP430F1611* and embedded a single-chip *CC2420* that is 2.4GHz IEEE 802.15.4 compliant radio frequency transceiver.

The tool kit is composed of sender and receiver. For a sender, analog signals from

[1] http://www.ti.com

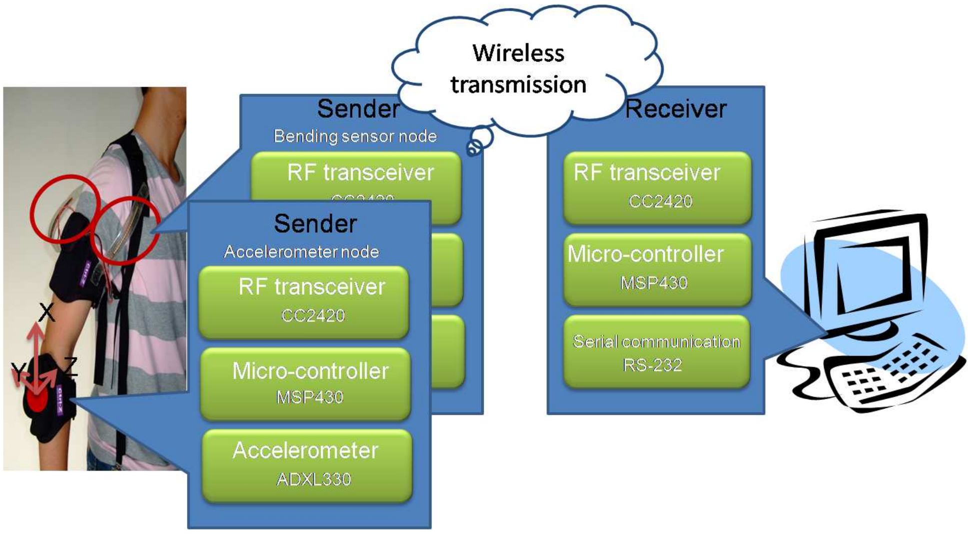
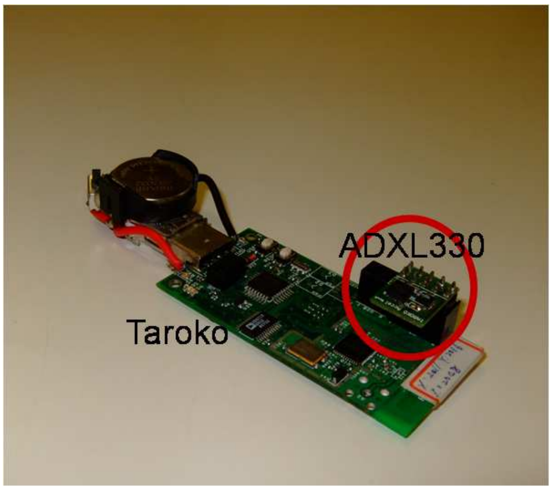
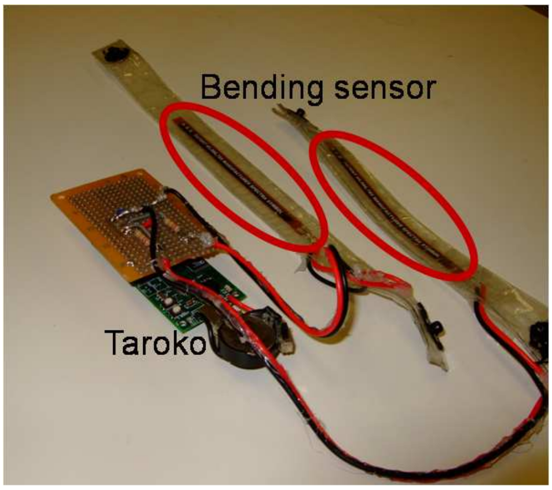


Figure 4.1: Schematic of Sensor work flow

accelerometer and bending sensor are sampled at the rate of 10 Hz and converted by ADC, an Analog-to-digital converter, module into digital signals. In addition, signals have to go through a low-pass filter in order to remove the noise caused by circuit. Finally, signals are transmitted via 2.4G bandwidth for wireless communication to receiver. For a receiver, it is connected to the host PC and waits for any packages sent by remote senders. When receiving the data, it passes them through RS-232 communication to the host computer. Figure 4.1 shows the schematic diagram of the sensor work flow and the realization of sensor toolkit is shown in Figure 4.2.



(a) Accelerometer node



(b) Bending sensor node

Figure 4.2: Sensor Components

4.2 Posture Recognition

4.2.1 Simple Signal Processing

After I observe each evaluation exercise in detail, I discover that each exercise is a limb movement in which we regard the specific joint as pivot and rotate the limb along one of the body planes. For example, internal rotation and external rotation are the movements in which we regard the elbow as pivot and rotate the lower arm along coronal plane. From the aspect of the accelerometer instrumented on the external side of lower arm, only the x-axis and z-axis change the signal values dramatically according to the gravity effect. Besides, horizontal abduction is the movement in which we regard the shoulder joint as pivot and shift arm outward along transverse plane. Only the bending sensors change the signal values tremendously according to bended curve.

Therefore, I can choose the dominant signal sources to do basic signal processing and extract the features for each exercise type. The detail settings are described as follow.

- **Flexion:** x-axis and y-axis of accelerometer.
- **Abduction:** x-axis and z-axis of accelerometer.
- **Extension:** x-axis and y-axis of accelerometer.
- **Internal rotation:** x-axis and z-axis of accelerometer.
- **External rotation:** x-axis and z-axis of accelerometer.
- **Horizontal abduction:** front-end and back-end bending sensors.

For each exercise t_i, the signal processing is composed of two steps. First, all signals in E_{t_i} separately subtract ones in C_{t_i} to form a new set of calibrated signals CS_{t_i} representing the difference between the posture performed and the starting posture.

The equation 4.1 is the implementation.

$$CS_{t_i} = E_{t_i} - C_{t_i} \quad , \quad \forall i \in \{1,2,3,4,5,6\} \tag{4.1}$$

Second, extract signals from dominant axes of calibrated signals CS_{t_i}, and then combine them into a single sequence of signal ds_{t_i}. For each CS_{t_i}, there are five signals including three axes (x-axis, y-axis , z-axis) of accelerometer, one signal from front-end bending sensor, and one signal from back-end bending sensor. The accelerometer manual shows that each signal changes values linearly to the the incline difference with regard to gravity direction, and the bending sensor manual depicts that the signal changes values linearly to the bending curvature. I take advantage of the property to combine dominant signals from CS_{t_i} into a sequence of signal ds_{t_i}. In order to explain how to select dominant signals and combine them, I define some notations in Definition 4.1 and show the implementation in equation 4.2.

Definition 4.1 *I denote x, y, z as the three axes of accelerometer, f as the first channel of bending sensor deployed in front-end body ,and b as the second channel of one deployed in back-end body. Therefore, $cs_{t_i}^{channel}$ as a sequence of signal from the $channel$ when users perform exercise t_i, where $channel \in \{x,y,z,f,b\}$. In other words, $CS_{t_i} = \left(cs_{t_i}^{x}, cs_{t_i}^{y}, cs_{t_i}^{z}, cs_{t_i}^{f}, cs_{t_i}^{b}\right)$.*

$$ds_{t_i} = \begin{cases} cs_{t_i}^{x} & \text{if } i = 1 \\ cs_{t_i}^{x} + cs_{t_i}^{z} & \text{if } i = 2,5 \\ cs_{t_i}^{y} - cs_{t_i}^{z} & \text{if } i = 3 \\ cs_{t_i}^{z} - cs_{t_i}^{x} & \text{if } i = 4 \\ cs_{t_i}^{f} - cs_{t_i}^{b} & \text{if } i = 6 \end{cases} \tag{4.2}$$

4.2.2 Feature Extraction

The calibrated value of bending sensor actually reflects the motion change along transverse plane. It changes the value based on the bended curvature. Also, for accelerometer, the DC component of calibrated signals can capture the motion change along sagittal plane and coronal plane. It changes value according to the incline difference with respect to gravity direction. Thus, the value of bending sensor and the DC component of accelerometer represent the characteristics of any postures based on the hardware deployment.

Consequently, I set the window and let it slide with overlapped half of size to extract feature for each exercise t_i. The feature extracted from bending sensor is **mean** value over the window. The DC component of the accelerometer signal among the window is mean according to the analytic result in [10]. So, the feature from accelerometer is also **mean** value over the window. I denote w_j as the j-th window, $size$ as window size, s_j as the starting index of w_j, and ds_{t_i} is a sequence of values $(v_1, v_2, ..., v_k, ..., v_n)$. Equation 4.3 shows how to transfer the values over the window w_j into a single feature value f_j.

$$f_j = \frac{1}{size} \sum_{k=s_j}^{s_j+size} (v_k) \tag{4.3}$$

According to the equation aboved, I configure $size$ as 5 samples and transfer a sequence of values ds_{t_i} into a set of features point $F_{t_i} = (f_1, f_2, ..., f_j, ..., f_m)$, where m is the number of windows.

4.2.3 Posture Classifier

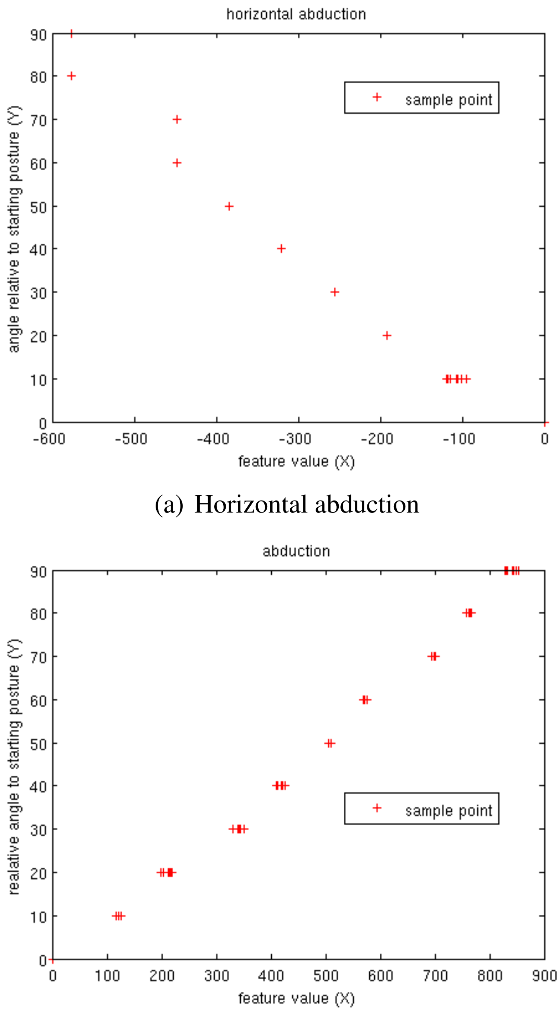
Posture classifier is the most important component in this system. it has to recognize the postures performed by users. Before deciding how to implement the posture classifier, I do some preliminary to observe the relationship between features and posture. I request a subject to wear the sensors mentioned previously to do abduction and horizontal abduction. The subject holds ten postures $p_{t_5,j}$ for internal rotation and ten postures $P_{t_6,j}$ for horizontal abduction, where $j \in \{0, 10, 20, ..., 90\}$. In Figure 4.3, the y axis means the shoulder angle of motion relative to starting posture and the x axis means feature values. I discover that there is approximately linearity between feature and posture. In other words, the posture is the approximately linear function of feature values.

Consequently, I use linear regression to model this relationship. The "Posture model" is a set of parameters of linear function. For each exercise t_i, there are two parameters A_{t_i} and B_{t_i} for linear function. The "posture classifier" uses two parameters to generate the predicted value, and then determine what is the posture performed by users. Equation 4.4 shows how to infer range of motion angle.

$$angle \quad = \quad A_{t_i} \times f_{t_i} + B_{t_i} \tag{4.4}$$

The posture representing this range of motion angle is $p_{t_i,angle}$. The set of features will be transformed to a set of postures by "Posture classifier", and pass them to "Posture analysis" for next step processing.

Moreover, how to decide the parameters for each exercise is the most important stage for constructing the posture recognition module. In the following section, I will



(a) Horizontal abduction

(b) Abduction

Figure 4.3: Relation between features and posture

narrate how to decide the parameters with machine learning method, and the performance of posture classifier is evaluated in section 5.1. It is a necessary step to verify the feasibility of designed system.

Posture Model Trainning

A set of labeled data $(y_1, x_2), (y_2, x_2), ..., (y_i, x_i), ..., (y_n, x_n)$ are necessary for training linear regression model. I regard y_i as angle value and x as the feature value to train model with least square method. In this section, I suppose the two parameters are m and b. The linear regression function is

$$y = f(x) = mx + b$$

Let Y_i is the value of $f(x_i)$, which means Y_i is the best predicted value of linear regression model. I have to minimize the following equation based on the least square method.

$$E = \sum_{i=1}^{n} [y_i - Y_i]^2 = \sum_{i=1}^{n} [y_i - (mx_i + b)]^2$$

In order to minimize E, m and b have to satisfy the following equation.

$$\begin{aligned} m &= \frac{n \sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i - \sum_{i=1}^{n} y_i)}{n \sum_{i=1}^{n} x_i^2 - \sum_{i=1}^{n} x_i} \\ b &= \frac{1}{n}(\sum_{i=1}^{n} y_i - m \sum_{i=1}^{n} x_i) \end{aligned}$$

4.3 Posture Analysis

A set of postures performed is the input for this module.

First of all, this module constructs a histogram to show what proportion of postures performed falling into each of several posture categories. In the histogram, the x-axis is split to non-overlapping intervals. Each interval represents a certain range of angle. The y-axis is the frequency of postures in the given input posture set. Then, the posture

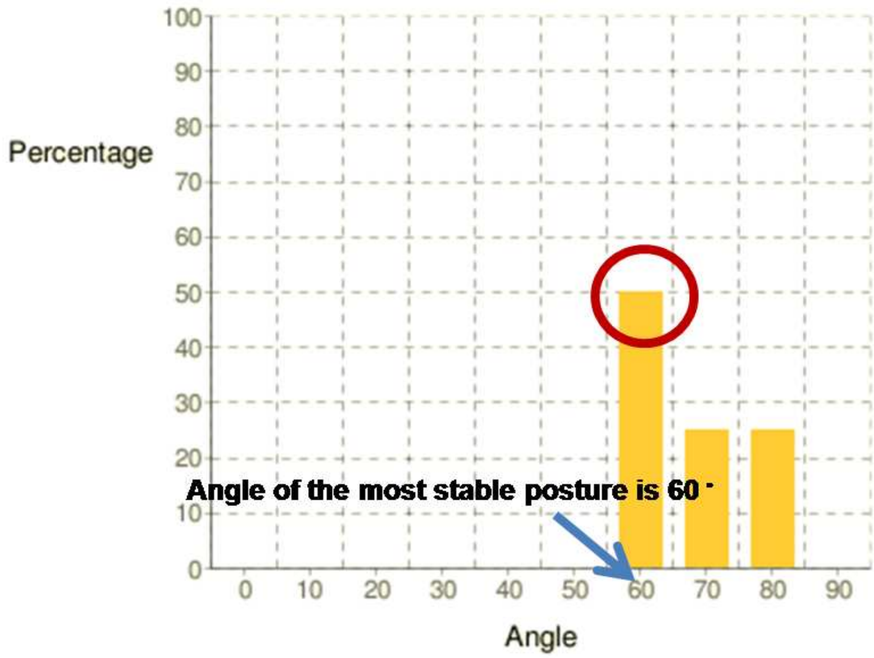


Figure 4.4: Diagram of histogram

that has the most high frequency is the most stable posture. Figure 4.4 shows the diagram of histogram among postures performed.

Secondly, this module generates the score to represent the capability of three activities of daily life according to the most stable posture among total exercise and Table 1.1. I denote $angle_{t_j}$ is the range of motion from the most stable posture performed for exercise t_j, and $bound_{ADL_i,t_j}$ is the most extreme range of motion with exercise t_j according to activity category ADL_i. Equation 4.5 shows the implementation about posture analysis.

$$
\begin{aligned}
T_{ADL_i} &= \begin{cases} \{2,5\} & \text{if } i=1 \\ \{3,4,6\} & \text{if } i=2 \\ \{1\} & \text{if } i=3 \end{cases} \\
S_{ADL_i} &= \frac{1}{N(T_{ADL_i})} \sum_{j \in T_{ADL_i}} \frac{angle_{type_j}}{bound_{ADL_i,type_j}}
\end{aligned}
\tag{4.5}
$$

Chapter 5

Evaluation

In this section, I design some experiments to evaluate the system performance in two aspects. One is that whether the wearable sensors have the enough capability of accurately recognizing posture performed by user. It is the fundamental performance of proposed system. The other is that whether target users are willing to use this system, and whether they are exactly motivated to do rehabilitation frequently.

5.1 Feasibility Study

5.1.1 Data Collection

Each subject has to wear sensors as Figure 3.2 and hold these 69 different postures to collect labeled data. The 69 posture are $p_{t_1,j}$, where $j \in \{0, 10, 20, ..., 180\}$, and $p_{t_2,j}$, $p_{t_3,j}$, ..., $p_{t_6,j}$, where $j \in \{0, 10, 20, ..., 90\}$. In practical, I call for 13 subjects wearing accelerometer and bending sensor to hold the 69 postures for 3 seconds.

5.1.2 Methodology

Because I use linear regression to be the model for posture classifier, the prevailing evaluation metric is root mean squared error and the standard deviation of root mean squared error. After collecting a set of labeled data, I do some signal processing steps as described in section 4.2.1 and extract features with the method mentioned in section 4.2.2 to form a feature set. Therefore, there are 12 samples for each posture after feature extraction and totally 10764 samples among 69 postures performed by 13 subjects.

For each exercise, I regard the features from the same subject as one fold, and create a 13-fold partition of the collected data to process 13-folds cross validation for estimation of system performance. In other words, I use subject-based cross validation to evaluate the performance of classifier.

5.1.3 Result

The result of performance evaluation is shown in Figure 5.1. The x-axis is six evaluation exercises and the y-axis is the error angle degree with respect to the ground truth. The **Mean** bar represents average of mean squared error, and the **SD** illustrates standard deviation of mean squared error.

General speaking, the overall mean squared errors angle from each of exercise type is less than $12°$. Besides, taking standard deviation of mean square error into consideration, the max error angle is also under $15°$. According to the opinions from physical therapist, The error angle must be less than $20°$ so that the system has the

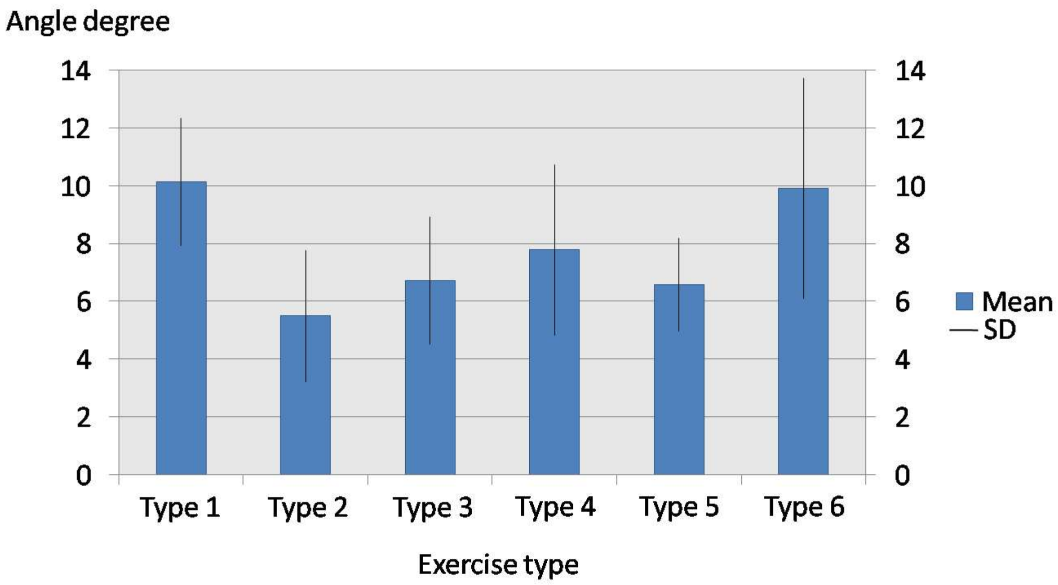


Figure 5.1: Result of Feasibility Study

enough feasibility to deployed in real-world situation. Therefore, the result of this feasibility study shows that the solution we proposed is feasible in aspect of system performance.

However, flexion (t_1) and horizontal abduction (t_6) are two exercises that give higher error rate than others. For flexion, only x-axis of accelerometer can be extracted feature as a result of the characteristics of exercise. Because accelerometer changes values less near +1G and -1G, the feature samples collected when subjects hold $p_{t_1,0}$ and $p_{t_1,10}$ are not clearly discriminated. For the same reason, the samples collected from $p_{t_1,170}$ and $p_{t_1,180}$ are hardly distinguished. In Figure 5.2, the fact is shown clearly. For horizontal abduction, the deployment of bending sensor is much complicated than accelerometer. Large diversity about bending sensor deployment causes much noise among labeled data.

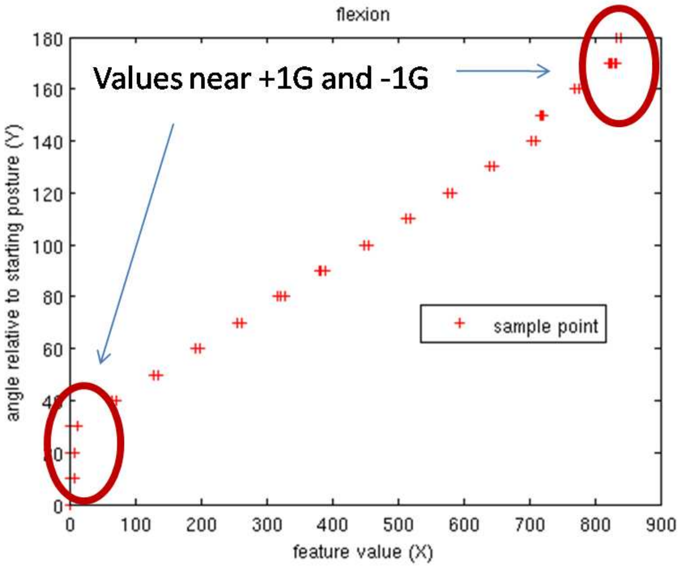


Figure 5.2: Relation between features and posture for flexion

5.2 Field test

5.2.1 Methodology

I implement two user interfaces for users. One is used for shoulder evaluation, and the other is used for checking result of evaluation. First of all, user interface used for shoulder evaluation is composed of remote controller (Figure 5.3(a)) and software application (Figure 5.3(b)). The remote controller is used for users to decide when the system starting the evaluation process. The software application displays the information about which exercise type users performed in current state. For each exercise type, the software interface consists of calibration mode and operation mode. The calibration mode asks the users to record their starting posture. Following calibration, the software enters operation mode and users can freely start the evaluation process.

Secondly, becasue all data are stored in the remote website, I implement a web-based page (Figure 5.3(c)) for users to examine their functionality in shoulder range of motion and to assess the capability about activities of daily life. Users can check posture histogram to be aware their functionality and survey the score bar for three primary activities of daily life via browser.

Moreover, I go to the *Foundation of Breast Cancer Prevention and Treatment*[1] for calling for real-world patients trying the system based on the supervision of physical therapist. The system recognizes the most stable posture performed by real-world patients in real time and instantly illustrates the shoulder functionality as the feedback. After that, I make an interview with them after trying out the system in order to get some suggestions.

5.2.2 Result

There are two main comments from physical therapist. One is that the performance of recognizing what postures performed by users is accurate enough to let this system be realized in real world. She gives the recognition performance a quantitative score 80 based on the full score 100, and declares that she is willing to recommend the system to the target users. The other is that the appearance of sensor and complication of deployment are needed to be improved so as to enhance user acceptance.

After three patients make an initiative to try out the system, all of them affirm that the system makes them more aware of their body status. Also, they declare that the system will provide patients incentive to motivate themselves to do rehabilitation.

[1]http://www.breastcf.org.tw/

However, all of them agree with the statement that the complications of deployment are needed to be improved. It is the main obstacles for them to accept the system. Furthermore, they expect the system can display much abundant and various information. If the system can recommend them what rehabilitation exercise suitable for current body state to improve themselves, it will provide much incentive and novelty for patients.

(a) Remote controller

(b) Software application

(c) Web-base page

Figure 5.3: User Interface

Chapter 6

Conclusion

This thesis presents a pioneering study on the feasibility: whether the wearable computing system is practical for detecting shoulder range of motion performed by post-operation patients. The proposed system is aims to visualize the shoulder healthy status as incentives to motivate the patients to do exercises spontaneously. This chapter provides the summary of the key contributions of the system and gives attention to the future work to overcome the current limitations.

6.1 Summary of Work

We take the most stable upper limb posture to represent capability of shoulder range of motion. Then, detection for shoulder range of motion is transferred to the recognition of upper limb posture. Thus, we regard this recognition task as a supervised learning problem and use machine learning method to solve it. In the first step, we design wireless devices of an accelerometer and two bending sensors to sense the shoulder motion along human planes. In the second step, we call for 13 subjects wearing sensors to collects lots of training data by requesting them to hold each of pre-defined postures. Finally, we use subject-based cross validation to evaluate the system performance of recognition accuracy.

Furthermore, we conduct the simple field test on the help of *Foundation of Breast Cancer Prevention and Treatment* to get some comments and suggestions about the proposed system.

6.2 Summary of Contributions

This thesis verifies that the accelerometer and the bending sensor have adequate sensing ability to capture the change among shoulder motion. Meanwhile, It also proves that it is feasible to take advantage of linear regression model for upper limbs posture recognition with supervised learning techniques.

The experiment result shows that the root mean squared error angle is below 12° for six evaluation exercises by means of subject-based 13 folds cross validation. The performance of accuracy satisfies the requirements from physical therapist. Besides, the result of simple field test demonstrates that the real-world patients affirm that the system actually provide them incentive to promote self-awareness about shoulder healthy status and motivate them to do exercises.

6.3 Future Work

The current achievements just take the initial step toward this issue. There are several key points to be modified for polishing the system. First of all, the accelerometer and bending sensor are featured with low computation cost and low energy consumption. It suggests that this mechanism can be implemented on mobile computing device to improve the portability . Second, the patients and physical therapist also proclaim that the way of deploying sensors is complex and the appearance of sensors is not attractive. The sensor decoration and the way of hardware deployment may be ameliorated to improve the user acceptance and practicality. Third, the system may take domain knowledge into consideration to generate much meaningful and abundant information such as rehabilitation program recommendation. Finally, the system may be conducted much formal user study from large target users in order to gain the much reliability and validity.

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Appendix A

Evaluation Exercises Definition

- **Flexion**

  Starting posture Stand, palms inward, thumbs forward, arm at sides.

  Movement Raise arms with straight elbow along sagittal plane until almost overhead .

- **Extension**

  Starting posture Stand, palms inward, thumbs forward, arm at sides.

  Movement Raise arms with straight elbow along the sagittal plane with opposite direction of flexion.

- **Abduction**

  Starting posture Stand, palms inward, thumbs forward, arm at sides.

Movement Raise arms with straight elbow along coronal plane until on the same height of shoulder.

- **Internal rotation**

Starting posture Stand, elbow bended with angle 90 degree between upper and lower arm, and arm parallel with coronal plane on the same height of shoulder.

Movement Regard elbow as pivot and lower arm rotate upward along sagittal plane until parallel with coronal plane.

- **External rotation**

Starting posture Stand, elbow bended with angle 90 degree between upper and lower arm, and arm parallel with coronal plane on the same height of shoulder.

Movement Regard elbow as pivot and lower arm rotate downward along sagittal plane until parallel with coronal plane.

- **Horizontal abduction**

Starting posture Stand, palms inward, arm parallel with sagittal plane with the same height of shoulder.

Movement Shift arm outward along transverse plane until parallel with coronal plane.

Appendix B

Evaluation Exercise Diagrams

The following diagrams are depicted the six evaluation exercise. The order from left to right in each diagram shows a series of postures derived from processing specific evaluation exercises along time sequence.

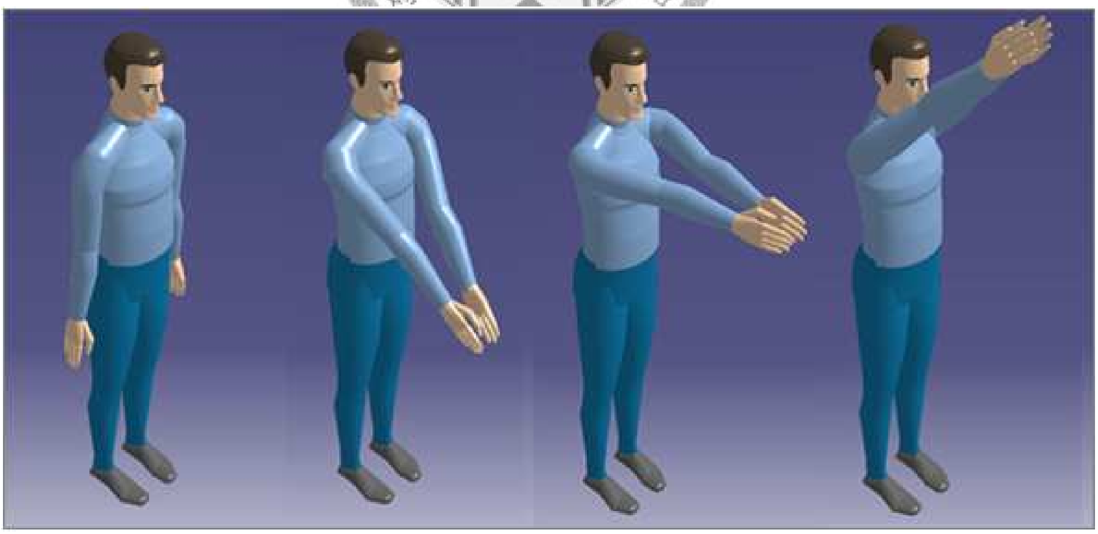

Figure B.1: Shoulder flexion

Figure B.2: Shoulder extension

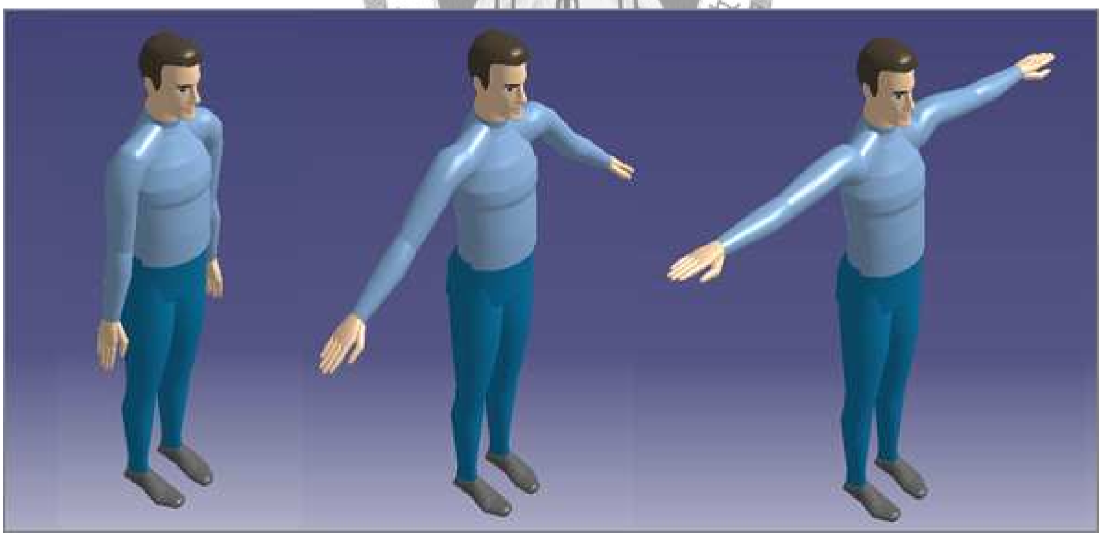

Figure B.3: shoulder abduction

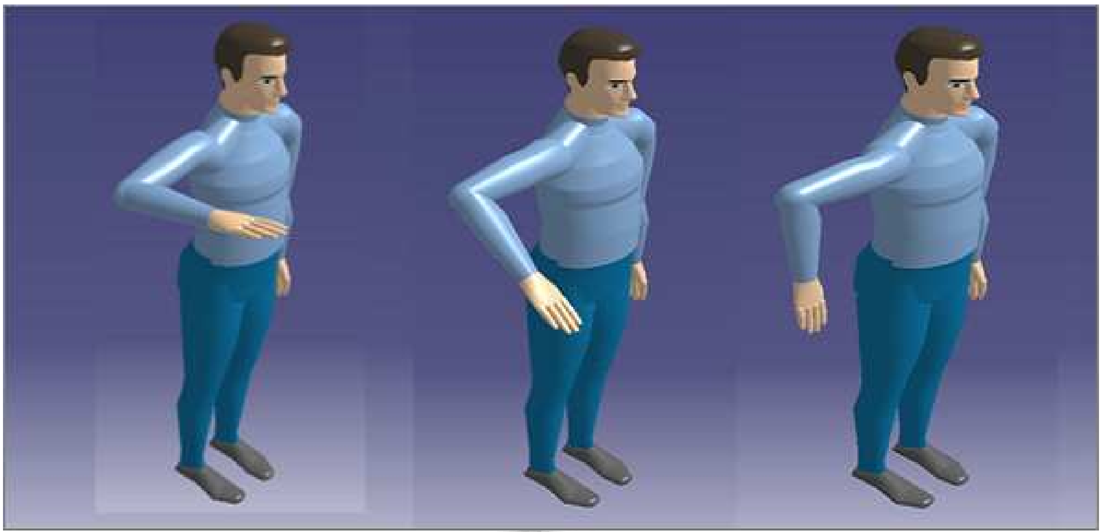

Figure B.4: Shoulder internal rotation

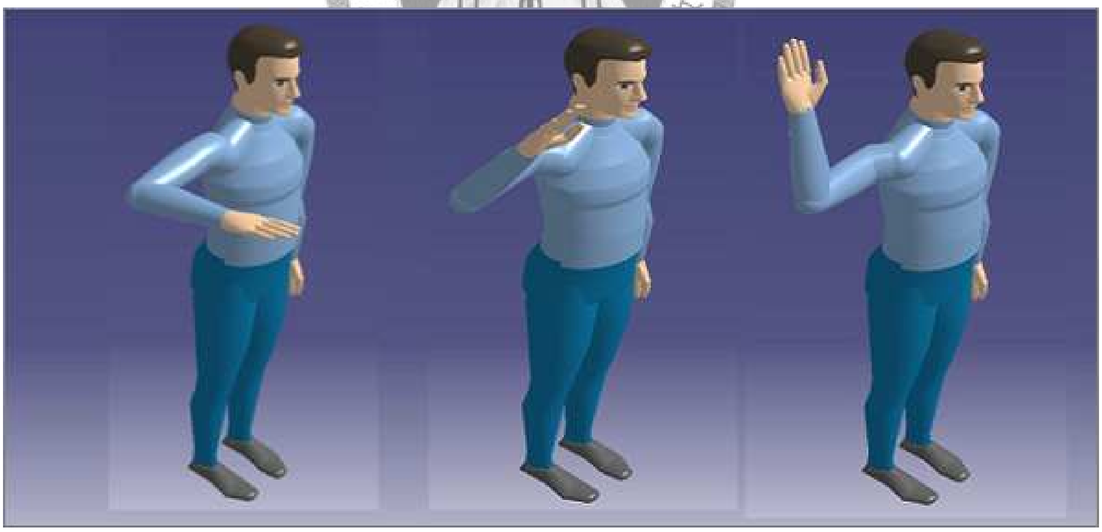

Figure B.5: Shoulder external rotation

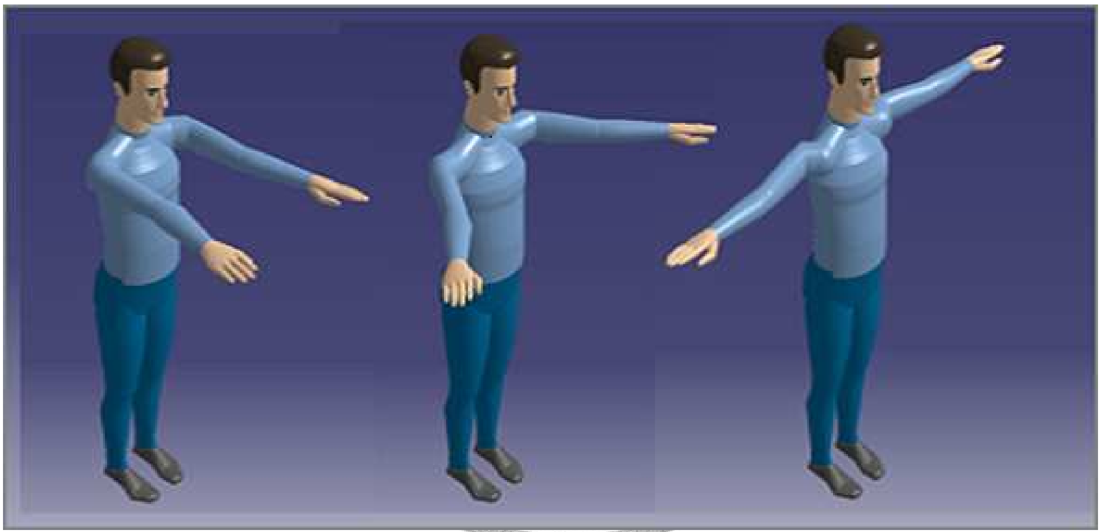

Figure B.6: Shoulder external rotation