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Remote Activity Monitoring of the Elderly Using a Two-Axis Accelerometer

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Abstract

This paper presents a design and experimental study of a remote posture monitoring system. The monitoring system aims for applications in activity analysis of the elderly. We propose a wearable sensor system, which consists of a two-axis accelerometer and RF wireless communication modules. The acquired body motion signals from accelerometers are transmitted to a host computer via RF link for feature extraction and pattern recognition. Wavelet transform techniques are adopted for feature extraction of human body postures. The signal is decomposed into five levels and low-frequency components are extracted to obtain useful features. Pattern recognition techniques are then applied to distinguish five basic postures: up stairs, down stairs, walking, standing, and sitting. Experimental results are presented to show the effectiveness of the proposed method.

Keywords: Posture estimation, activity analysis, wearable sensor, pattern recognition.

1. Introduction

Due to rapid progress in medical and medi-care technologies, human life has lengthened for the past decades. The population of elder people is thus increasing globally. Most developed countries including European countries and Japan are already so called society of silver-hairs. Homecare and home assistance of the elderly have become important issues of future society. Many researchers have been working on various assistant devices to allow the elderly still have an independent living standard for their aging life. Among many advanced healthcare technologies, a remote activity monitoring system facilitate assistance for safety warning and life-saving of the elderly.

Currently, human-behavior monitoring systems can be divided into two types. The first type of activity monitoring system consists of multiple sensors installed in a room for monitoring the body activities. Ogawa *et al*. [1] developed a remote monitoring system for elderly patients in their domestic house. Several sensors were installed, including infrared sensors to detect human movement, magnetic switches to detect the opening and closing of doors, wattmeters embedded in wall sockets to detect the use of household appliances, and a CO_2 sensor to detect the presence of a subject in a room. Noguchi *et al.* [2] also developed a system for detecting human behaviors in a room by several types of sensors embedded in the room.

In the second type of activity monitoring system, portable sensor modules are placed on human body to detect and record body posture signals. Noury [3] ultilized piezoelectric accelerometer, tilt switch and vibration sensors to construct a sensor system to detect whether the elderly fall down or not. The sensor signals were transmitted to a processor by using RF wireless communication. Najafi and Aminian[4] developed a kinematic sensor for detecting human body posture as well as the time of walking. Mathie *et al.* [5] monitored human posture using a tri-axial accelerometer. The acceleration signals are transmitted to a computer for processing via RF wireless communication. Sekine and Tamura [6][7] placed an accelerometer and a memory card on a belt for measuring and recording the body motion. Five postures were recognized using a wavelet transform design. Lee and Mase[8] designed a portable sensor module, which is composed of accelerometer and a gyroscope for recognize sitting, standing and walking postures. A dead-reckoning method was adopted to determine the human position in a room. For practical applications, however, a simple, light-weighted and reliable posture estimation system is still a challenging task.

In this paper, we present a method for posture estimation based on a wearable sensor module attached to the human body. A signal processing algorithm is proposed to process measured posture signal and classify human posture using time-frequency analysis of wavelet transform. The developed human posture recognition system aims to combine with a home assistant robot. Activity analysis thus provides a powerful tool for the robot to understand the elderly and can consequently be used as a robot-human interaction device.

2. Wearable sensor system

The hardware sensor module consists of a two-axis accelerometer, an 8-bit microcontroller and a RF transmission module. The sensor module is integrated into a small box and can be attached to the thigh of a human being. Figure 1 shows the mounted sensor module on a human in testing. This sensor

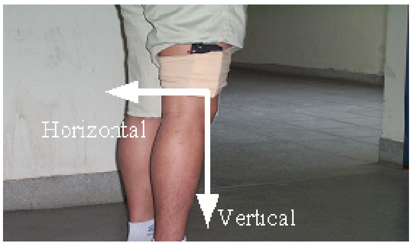

Figure 1. The mounted sensor module

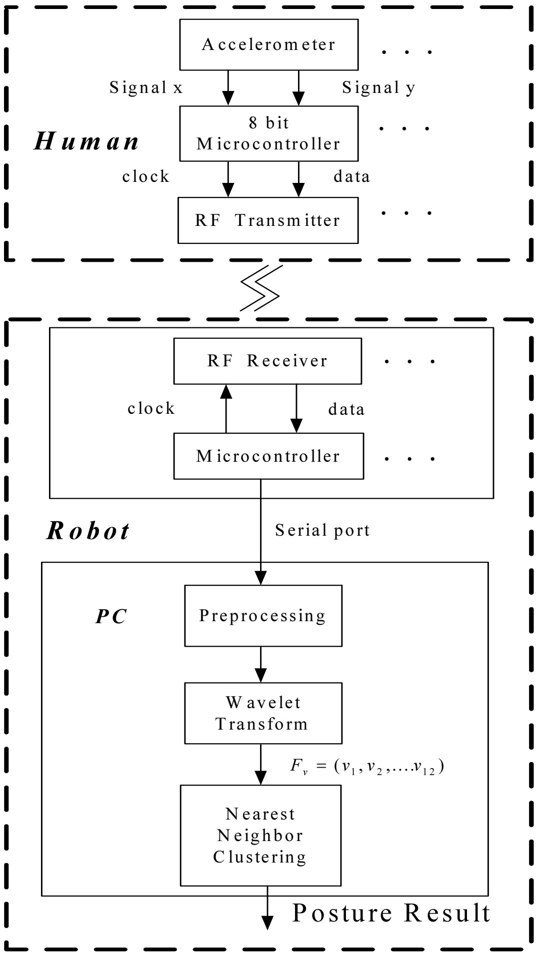

Figure 2. Architecture of the posture recognition system

module measures body accelerations in the horizontal and vertical directions. The transmitted signal is received by a receiver module through RF wireless link. The receiver module consists of a RF device to receive the signal and an 8-bit microcontroller. A RS232 interface was utilized for delivering data to the robot onboard computer for signal processing and recognition. The onboard computer is responsible for recognizing five types of human postures, namely move upstairs, downstairs, walking, standing and sitting. The system architecture of the complete system is illustrated in Figure 2. In the signal processing part, a batch of 1000 data is received and recoded for every recognition cycle and the low-frequency components are extracted using wavelet transform. We extract six-frequency band wavelet coefficients for feature extraction in the horizontal and vertical directions respectively. In this study, five postures are trained using K-Nearest Neighbor method. The detailed design will be described in the following sections.

The hardware of complete sensor system consists of the posture measurement module and the receiver module. The posture measurement module is composed of a two-axis accelerometer, a microcontroller and a RF module. Figure 3 shows the photo of the implemented sensor/transmitter module. The receiver electric circuit includes a RF module, microcontroller and circuitry for RS232 link. Figure 4 shows a photo of the receiver module.

A two-axis accelerometer ADXL202JE from Analog Devices was used in this design. Its output is a PWM wave form. From the duty cycle of the PWM, one can calculate the acceleration value. Since the PWM signal period of is fixed, one can use a timer and interrupt function to count the duration of its high state. A 9V battery was used for power supply of the system. Since the accelerometer as well as the microcontroller needs a voltage of 5V, a 7805 voltage regulator was used to reduce the voltage from 9V to 5V. The RF IC requires a power supply of 1.9~3.6 V,

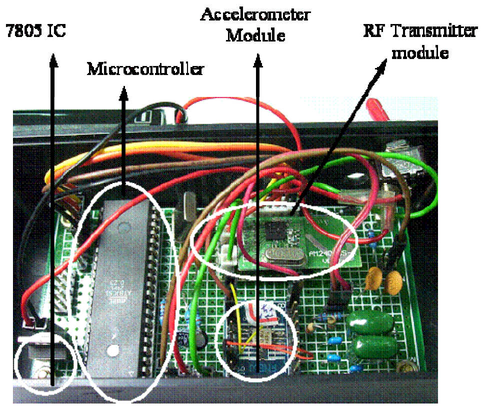

Figure 3 Photo of the transmitter module

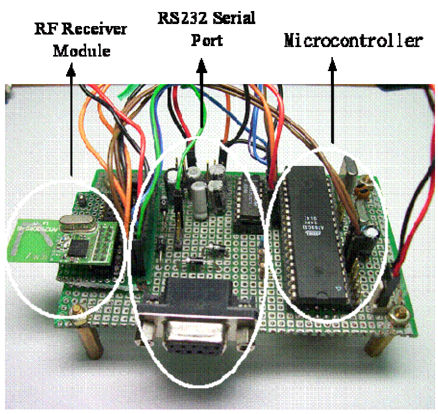

Figure 4. Photo of the receiver module

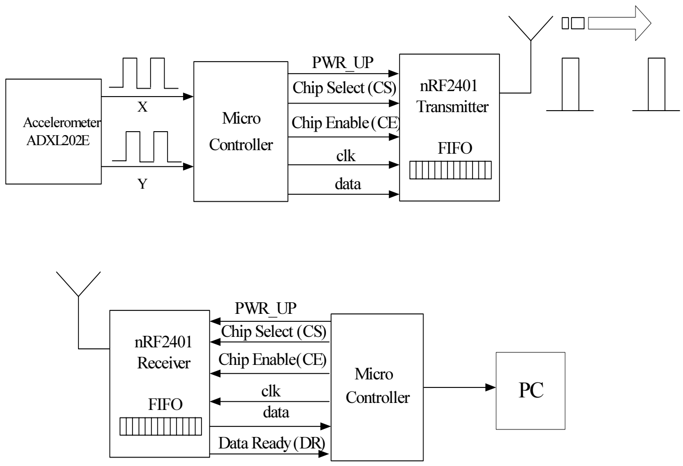

Figure 5. Interface design of the transmitter and receiver

so we reduce 5 V to 2.6V using 4 diodes. Figure 5 shows the interface design of the RF transceiver and receiver module. Popular 89C51 microcontrollers were adopted as the core of this interface design. The transmitter microcontroller is responsible for calculating the acceleration values of two directions and delivering the acceleration data to the RF module for transmission. In this design, we first set the RF configuration via three pins on the RF IC, namely PWR_UP, CE, and CS. Set PWR_UP, CS high but CE low,. for one transaction, the RF module in the transmitter mode will send 12 bytes data at 1Mbps. These data include information about transmission mode, frequency band, CRC bits, address and the size of data. In this design, the data size is 4 bytes in each transmission of acceleration values in two directions. The *Interrupt0* and *Interrupt1* of the microcontroller were applied to calculate high-level duration of horizontal and vertical acceleration signal. The *Interrupt0* detects the high level rising edge in the vertical direction acceleration signal. It starts the *Timer0* accordingly. The *Tmer0* stops counting when *Interrupt0* detects the falling edge of the high level acceleration signal. The counter value is expressed by 2 bytes. After *Timer0* calculation completes, *Timer1* calculates the high-level duration of horizontal direction acceleration signal in a similar way. The measured two-axis acceleration values are transmitted by 4 bytes data to the host computer through the RF module. The processing procedure will be described in section 3. In the host computer, a RF receiver module was installed. The microcontroller in the receiver module receives the data from the RF link. As shown in Fig. 5, when data come to the RF receiver from transmitter RF, the DR pin will send a high-level signal to the microcontroller.

The RF transmitter/receiver IC used in this work is from Awin, serial number AM2400BS-RA transceiver module. The microcontrollers provide clock to the RF transveivers and transmit/receive data to/from the data pin. In the PC side, the microcontroller provides data to the processor for pattern recognition through the serial port

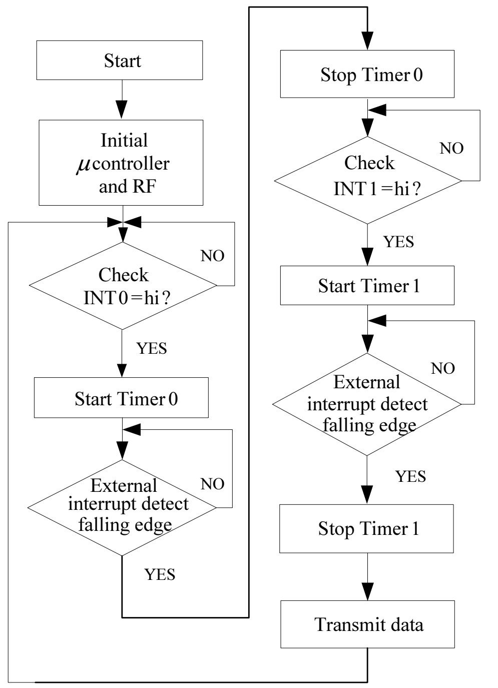

Figure 6. Flow chart of the accelerometer interface program

with a baud rate of 57600 bps. Figure 6 illustrates the programming of th e accelerometer module using the microcontroller 89C51.

3. Signal Processing

3.1 Wavelet transform

In this work, we extract features in different frequency bands of time-frequency domain to recognize the posture by using wavelet transform. Fourier transform and short-time Fourier transform(STFT) have been widely used for transforming signals from time domain to frequency domain in order to obtain frequency spectrum information. However, Fourier transform is suitable for stationary signals, while the posture patterns are too short to use Fourier transform. The frequency resolution will be too poor to obtain effective information for classifying posture patterns. On the other hand, although STFT may be employed to analyze non-fixed signals, a time window needs to be specified. For a non-stationary signal, STFT will not be suitable in this case. We adopted wavelet transform in this work to extract posture features for pattern recognition. Wavelet analysis is based on two basic functions, the mother function and the scaling function as shown below:.

$$\psi(t) = \sqrt{2}\sum_{n} g(n)\psi(2t-n) \tag{1}$$

$$\phi(t) = \sqrt{2}\sum_{n} h(n)\phi(2t-n) \tag{2}$$

In discrete wavelet transform, the scaling function and the wavelet function are determined to reconstruct the signal. The wavelet function is then given by:

$$\psi_{j,n}(t) = 2^{j/2}\psi(2^{j}t - n), \quad j,n \in R \qquad (3)$$

The scaling function is expressed as :

$$\phi_{j,n}(t) = 2^{j/2}\phi(2^{j}t - n), \quad j,n \in R \qquad (4)$$

In the discrete wavelet transform, a signal is split into an approximation signal and a detail signal using the coefficients of a discrete low-pass filter and a high-pass filter. The approximation signal is then itself split into a second level approximation signal and the detail signal. The process is repeated, as shown in Fig. 7.

3.2 Posture recognition design

Figure 8 shows the posture recognition procedure. On the human body, the acceleration-measuring device is attached to measure horizontal and vertical acceleration signals. The acceleration value is obtained after microcontroller processing and then transmitted to the host computer by wireless RF transmission. In the computer, wavelet decomposition is applied to obtain six components of low frequency bands. The wavelet coefficients of these frequency bands are used as features for recognition. In the training phase, each posture generated by a tester goes through ten cycles of training. Each posture is trained by using twelve feature parameter vectors, six for each measuring direction. In this study, five postures were considered for feature parameter vectors, namely, F_{sit} , F_{stand} , $F_{upstair}$, $F_{downstair}$ and F_{walk} . In applications, the measured signals are compared with the trained samples, exploiting the K-Nearest Neighbor classification principle.

3.3 Preprocessing

In preprocessing, the wavelet coefficients are obtained from on-line acceleration signals. We take 2000 bytes of acceleration data in a cycle of pattern recognition. Each direction of acceleration contains 1000 bytes data. If too few signal data are acquired, it will degrade the recognition rate due to not enough features. If too many data are used, the system will take too much time to recognize a posture. For the current implementation, it takes about 8~9 seconds for a cycle of posture recognition. Figure 9 depicts the preprocessing of both horizontal and vertical acceleration data. Original 2000 bytes data are decomposed into six low frequency components in each direction. As shown in Fig. 10, six levels of signal are selected after the wavelet decomposition: A5 (0~1.56Hz), D5 (1.56~3.12Hz), DA4 (3.12~4.68Hz), DD4 (4.68~6.25Hz), DA3 (6.25~9.38Hz), DD3 (9.38~12.5Hz). With acceleration signals from two perpendicular directions, twelve elements are obtained to form a feature vector. The feature vector is then exploited for posture recognition.

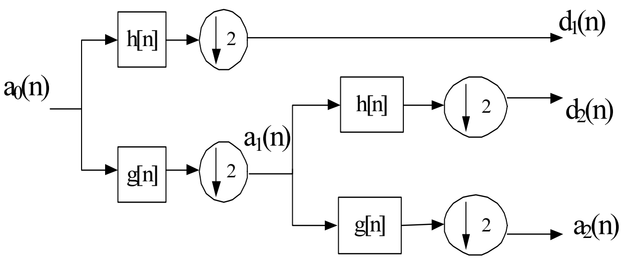

Figure 7. Discrete wavelet transform

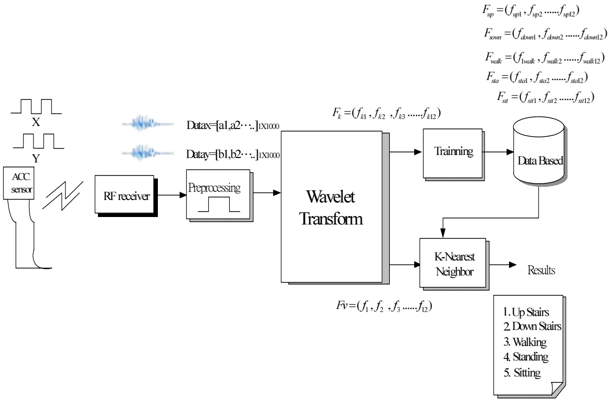

Figure 8. Posture recognition procedure

3.4 K-nearest neighbor clustering

There are several popular classification method including nearest neighbor method (K-Nearest Neighbor, KNN)[9], maximum and minimum distance method[9], Hidden Markov model based method[10], etc. In this work, we adopted the KNN approach considering the system only

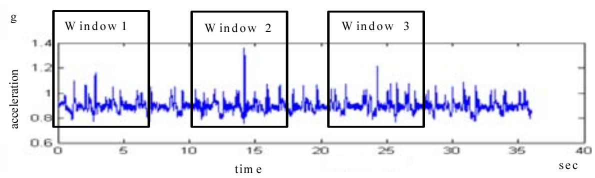

Figure 9. Signal preprocessing

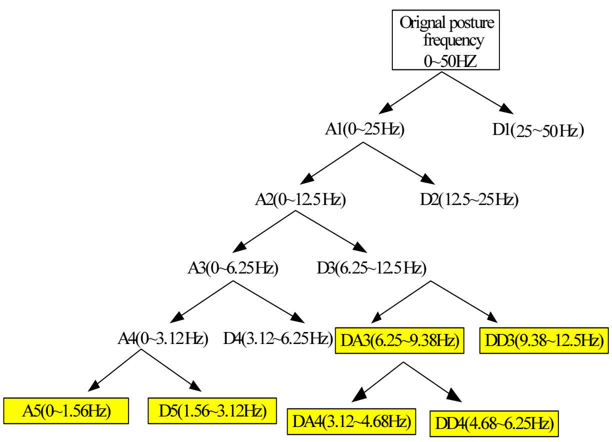

Figure 10. Wavelet decomposition

needs to classify several (five) kinds of postures with only one-dimensional information. The main steps in KNN are as follows:

1.) Training stage: In this stage, training data are collected for each tester and for all five postures. The 12-dimensional feature vectors established using wavelet transformation are used in the training stage. For each posture, ten training cycles are performed. The mean of these ten values are used as the feature vector of recognition. We obtain F_{sit} 、 F_{stand} 、 $F_{upstair}$ 、 $F_{downstair}$ and F_{walk} five groups of postures feature vectors.

2.) Recognition stage: In the recognition stage, test data of 12-dimentional vectors are obtained on line. With the test feature vector, the distance between it and five trained standard vectors are calculated. The one with the smallest distance will be classified as the posture.

4. Experimental Results

This section describes the experiments and experimental results of the human posture recognition system. In the prelliminary phace, we verified the system recognition rate by following two experiments.

1). In the first experiment, the sensor module was attached to the thigh of testers to acquire acceleration signal. Five testers were asked to walk normally, upstairs, downstairs, stand still and sit down in order to collect data of five postures. Each posture was then to be recognized for twenty times, and the statistics of recognition rate for each tester as well as an average recognition rate of five testers are calculated. Figures 11-15 depict the experimental results of, respectively, upstairs, downstairs, walking, standing and sitting. Table 1 shows the average recognition rate of five testers.

2). In the second experiment, a tester was asked to move with different postures continuously. Recognition rates of six testers were collected. Each tester made continuous posture change including sitting, upstairs, standing, downstairs and walking. In the experiment, each posture was recognized twice; therefore for each posture there are twelve recognition results. Finally we calculate the average recognition rates, as shown Table 2.

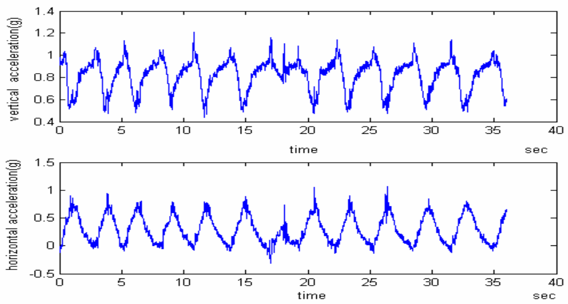

Figure 11. Measured signal of walking upstairs

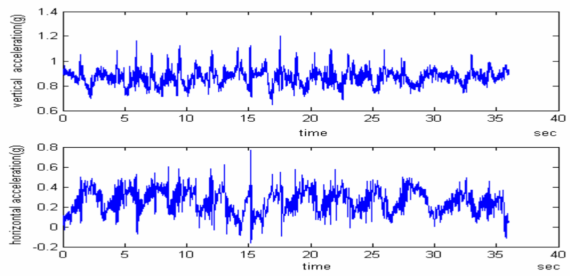

Figure 12. Measured signal of walking downstairs

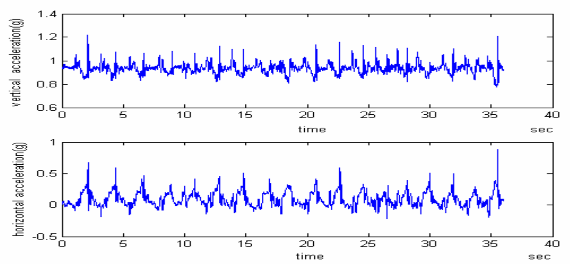

Figure 13. Measured signal of walking

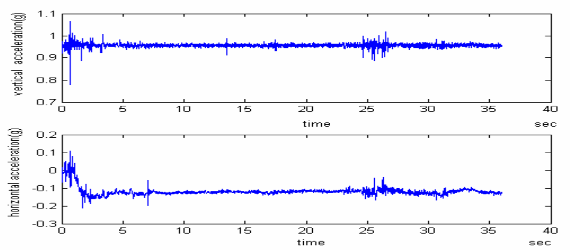

Figure 14. Measured signal of standing

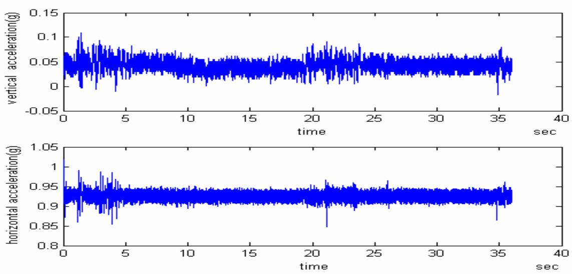

Figure 15. Measured signal of sitting

Table 1. Average recognition rate

Real posture / Recognition result	Upstairs	Down stairs	Walking	Standing	Sitting
Upstairs	70	11	2	0	0
Downstairs	28	84	1	0	0
Walking	2	5	89	9	0
Standing	0	0	8	91	0
Sitting	0	0	0	0	100
Recognition rate	70%	84%	89%	91%	100%

It can be seen from the experimental results that very high recognition rate can be obtained for stand and sit postures. This is mainly due to the acceleration is asserted in different directions respectively by the

Table 2. Average recognition rate of different posture in a continuous motion

Recognition result \ Real posture	Sitting	Upstairs	Standing	Down stairs	Walking
Sitting	12	0	0	0	0
Upstairs	0	10	0	5	0
Downstairs	0	1	0	6	0
Standing	0	0	12	0	0
Walking	0	1	0	1	12
Recognition rate	100%	83%	100%	50%	100%

gravity. When a human is standing, the acceleration in vertical direction is asserted by gravity and one obtain larger coefficient in low frequency bands. As a human is sitting, the horizontal signal is affected by gravity and one gets larger coefficient in low frequency bands. For postures of up, down stairs and walking, because the dynamic states vary not much, these three postures inherently are more difficult to recognize. But the proposed system still can find out the differences in the low-frequency components of horizontal signals.

5. Conclusions

This paper proposes a body posture recognition system. A portable acceleration sensor module has been designed and implemented to measure human body motion. A wavelet-based algorithm has been proposed to exbstract features from 2-D motion signals for recognizing human postures. The presented system can recognize five postures including upstairs, downstairs, walking, sitting and standing. Experimental resuls collected from five testers reveal satisfactory recognition rate except fro the cases of upstairs and downstairs motion. However, several limitations are also observed for the system. Firstly, the motion needs to be smooth. For rapid posture change and sudden jumps, the recognition rate will decrease significantly. Secondly, signal transmission distances are not sufficient. A more powerful RF module needs to be employed. There also several places for future improvement. On one hand, the proceeissing time needs to be reduced. For the present system, it takes about 8 seconds for one cycle. It can be reduced if less data samples are needed for recognitiog or a faster data transmission can be used. On the other hand, dynamic posture recognition can be achieved if combining more sensors, such as gyroscopes and accelerometers.

6. References

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