Activity Recognition in Wearable ECG Monitoring Aided by Accelerometer Data

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***Abstract*—A wearable ECG monitoring device with accelerometer aided activity recognition is proposed in this work. A 3-axis accelerometer is integrated in the Band-Aid alike wearable device which will be stuck to the user's chest. The Lead V2 ECG signal and the chest acceleration data are recorded synchronously. An activity recognition algorithm is proposed to identify certain types of daily activities, including coughing, walking, standing, sitting, squatting or lying based on the chest acceleration data. The recognition result can be further used to correlate the recorded ECG signal to the user's activity. Experiments on 13 volunteers with age of 5 to 68 show that the proposed algorithm have an overall accuracy of 96.92%. The recognition result can be further used to correlate the recorded ECG signal to the user's activities.**

***Index Terms*—wearable device, electrocardiogram (ECG), activity recognition, accelerometer**

I. INTRODUCTION

THE electrocardiogram (ECG) is a vital biomedical indicator for clinical treatment of cardiovascular diseases. Recently, wearable devices have been widely accepted and used for daily life. The Holter ECG monitor, which was first created by Normal J. Holter at the beginning of 1960s, is the earliest wearable long-term ECG monitor. For ECG signal, its bandwidth between 0.05Hz and 100Hz is used for general diagnosis applications, and its bandwidth between 0.05Hz and 50Hz is used for patient monitoring applications [1]. However, these ECG bandwidths are often being overlapped by other elements such as the 50/60Hz power line interference, baseline drifting and motion artifact. These interferences heavily decrease the quality of ECG signals, and will bring misdiagnosis or miss-diagnosis. Among all these interferences, motion artifact is particularly troublesome, because 1) in time domain, motion artifact can cause interference with large amplitude to the ECG signals; 2) in frequency domain, the low frequency noise spectrum of motion artifact overlaps with the ST segment (0.8Hz or below) spectrum of the ECG, using a high pass filter to eliminate the low frequency noise can lead to distortion of the ST segment, which contains clinical data on heart ischemia and myocardial infarction[2, 3].

Most of motion artifact is generated by the skin stretch. It has been proved that using electrode motion as the input to an adaptive filter can reduce the amount of motion artifact in the ECG [4], this method can increase the computational complexity and make the electrodes uncomfortable to wear. Built-in acceleration detection circuit with wireless ECG sensor has been designed [5], chest acceleration is collected to estimate body movements. But in [5], acceleration is only used to analysis different types of transportation the tester is taking. Daily activities recognition methods have been proposed in [10] & [13], but the accelerometer was not placed on the chest. For a ECG device, it's most likely to be placed on the chest. So an activity recognition method using chest acceleration data is proposed in this paper.

In this paper, a wearable ECG device with a built-in accelerometer is proposed. With this device, dynamic ECG and chest acceleration data are collected. Meanwhile, a data-saving chip is built in the device, which can make it work correctly either with or without the assistant of a computer. Furthermore, the low-power design ensures a long battery life.

II. WEARABLE ECG MONITORING DEVICE

A prototype wearable ECG device has been implemented which composed of an ultra-low-power micro-controller (TI MSP430F6638), a 2-channel 24-bit analog front end (TI ADS1292), a 3-axis accelerometer (ST LSM330DLC), a Bluetooth module, a 32Gbyte Flash and a rechargeable 250mAh Li-Ion Battery. The block diagram of the prototype device is shown in Fig. 1. The recorded ECG and acceleration data will be saved and processed in a computer.

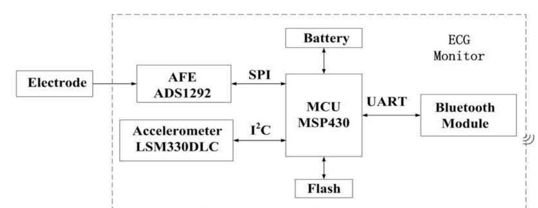

Fig. 1 Function block diagram of the wearable device

The ECG monitoring device prototype is shown in Fig.2. Three disposable Ag-AgCl electrodes are used to collect patient's Lead V2 ECG signal. Disposable Ag-AgCl electrodes are chosen in this work because they are coated

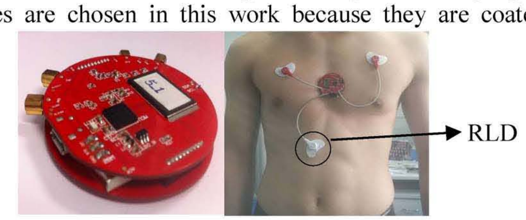

Fig. 2 ECG monitoring device prototype

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with hydrogel to maintain close adhesion between the leads and the patient's skin. Additionally, medical adhesive tape is used to fix the electrodes, lines and the monitor on the skin clingy. Except for the upper two ECG electrodes, a RLD electrode is proposed to eliminate the power line interference [6].

The ECG signal is recorded by ADS1292, which is controlled by the MCU through the serial peripheral interface (SPI), the ECG data sampling rate is 500 samples per second (SPS). Meanwhile, chest acceleration is collected by LSM330DLC, which communicates with the MCU through I^2C serial bus interface, the acceleration data sampling rate is 50 SPS. To make it accessible for other processing on the ECG signal, the ECG and acceleration signals are strictly synchronized.

The working current consumption of this wearable ECG monitor is less than 5 mA, thus with a 250mAh battery the monitor can continuously work for more than 48 hours. The max current consumption of this monitor (when the Bluetooth is turned on) is 30mA.

Table I. Performance summary of the wearable device

Diameter	48.9mm
Thickness	5.7mm
ECG sampling resolution	24 bits
ECG sampling rate	500 sps
Acceleration sampling rate	50 sps
Communication	Bluetooth 2.3
Power supply	3V
Battery Lifetime	48hours (250mAh)

The typical recorded ECG waveforms with body activities are shown in Fig. 3. The ECG data is affected by the activities, and it is significant to recognize the activity types for further analysis. A body activity recognition flow will be presented in the following section.

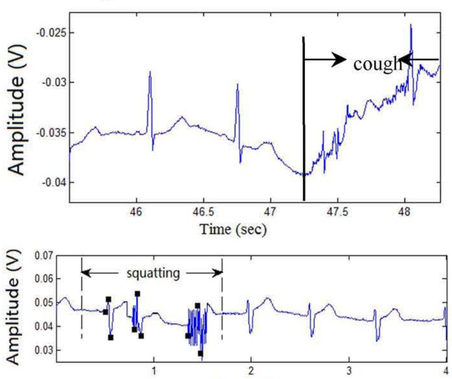

Fig. 3 ECG signals affected by body activities

III. ACTIVITY RECOGNITION FLOW

Traditional activity recognition algorithm is based on multiple wearable sensors such as accelerometers, magnetometer, gyroscopes, etc. In some circumstances, even cameras are utilized to improve the accuracy of the recognition. There is no doubt that varied types and large amount of sensors could provide much more detailed information of body movements and would be beneficial to improve recognition performance. However, wearing sensors at almost every important part of the patient such as neck, chest, arms, waist, hips or thighs could be inconvenient, especially for the patient's daily activity. The patients who are under long-term ECG monitoring would have limited daily activity, usually just the necessary activities such as standing upright, sleeping down, sitting down in a chair, squatting, walking, etc. Thus, there is no need to use multiple sensors for complex activity recognition. In this work, a single 3-axis accelerometer (which is built-in the monitor, as in Fig. 1) is employed to collect the chest acceleration, which has been proved to be efficient for activity recognition needed in this work. Fig. 4 shows the structure of the activity recognition flow.

Fig. 4. Signal processing flow of the proposed activity recognition algorithm

The details of the activity recognition are discussed as follow:

Filtering

The collected acceleration includes both posture and motion information of the patient. In this algorithm, both low-pass and band-pass filters are used to separate the information. An equiripple FIR low-pass filter with a cut-off frequency of 1Hz is employed to only preserve the posture information. On the other hand, a band-pass filter between the frequencies of 0.1 to 20Hz is applied to eliminate the low-frequency acceleration (gravity) and the high-frequency signal components generated by the noise, thus preserving the medium-frequency signal components generated by dynamic human motions [8].

Segmentation

For a long-term activity recognition, signal segmentation is necessary to improve the computing speed. Among all the segmentation techniques, sliding window technique is applied in this work [8]. In this algorithm, 64 sample windows with 32 samples overlapping between consecutive windows are chosen to segment the filtered acceleration. At a sampling frequency of 50 Hz, each window represents 1.28 seconds. Segmentation is a preprocessing for the feature extraction, and the feature computation on sliding-window with 50% overlap has demonstrated success in [9].

Feature Extraction

Features can be computed from the segmented data, usually contain time and frequency domain features including variance, mean, correlations, energy, entropy, FFT coefficients, etc.[8-10]. In this algorithm, DC feature, energy feature and sensor orientation are computed.

The DC feature is the mean acceleration value of the signal over the window. It is computed from the posture information which is the output of the low-pass filter. The DC feature is computed from Equation (1), a_x is the vertical axis acceleration, N is the window length. DC feature can be utilized to recognize the human posture, such as standing still,

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lying flat or sitting.

$$DC_{feature} = N \sum_{i=1}^{N} |a_{xi}| \qquad (1)$$

The sensor orientation is another important information to distinguish the body position, for the ECG monitor used in this work is clung closely to the skin. The orientation can be computed through equation (2), where φ is the orientation in respect to horizon, a_x is the vertical axis acceleration.

$$\varphi = arccos \frac{|a_x|}{\sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2}} \qquad (2)$$

To calculate the energy feature, we first need to calculate the signal vector magnitude (SVM), as shown in equation (3), and then the energy of a 1.28 seconds window of acceleration signal can be calculated as equation (3), where F is the FFT of SVM.

$$E = \sum_{i=1}^{64} {F_i}^2 \qquad (3)$$

Classification

In this work, classification is focused on activities which would susceptibly generate motion artifact in the ECG signal, such as coughing, sitting down, squatting down walking, etc. In [9], decision tree algorithm had been successfully applied

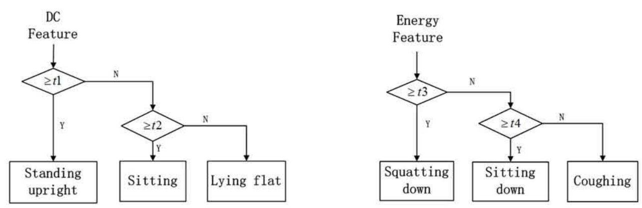

Fig. 5 (a) Posture classification (b) Preliminary recognitio

for activity classification. However, five biaxial accelerometers were used in that paper for higher recognition accuracy. In our single sensor condition, along with the Custom Decision Tree method, another pattern-match method is also introduced to ensure the accuracy. The posture and activity classification is completed through the following three steps:

- **a)** Posture classification: first, preliminary judgment is completed through the DC feature, as shown in Fig. 5(a); then, the angle φ is utilized to augment the preliminary judgment accuracy.
- **b)** Preliminary activity recognition: The Energy feature is utilized to preliminarily recognize the activity. Fig. 5(b) shows the decision tree of preliminary activity recognition.
- **c)** Final activity recognition: Since only single accelerometer is used, we cannot measure correlation feature of the acceleration between multiple body parts to improve the recognition of activities [11]. In order to improve the accuracy of activity recognition, we introduced pattern-matching module and orientation judgment to augment the preliminary

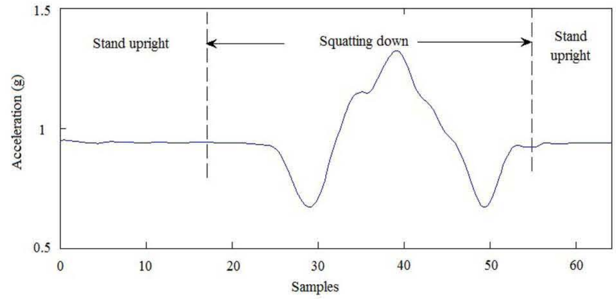

Fig. 6. Acceleration pattern of squatting down

activity recognition, paper [12] has used this method to complete fall detection. Since squatting and sitting are similar to falling, they all have obvious characteristics in the acceleration waveform, such as squatting down. The vertical acceleration of standing upright is 1g±0.1g, when squatting down, there is a decrease in acceleration followed by an increase, Fig. 6 shows the actual acceleration collected when squatting down, the waveform characteristic is obvious, so pattern-match method can be used to judge such activities. Then, the sensor orientation is utilized to recognize the activities the before and after posture to complete the final recognition.

IV. Results and Discussion

The accelerometer aided ECG recording device is utilized for the data acquisition. A total of 13 healthy subjects were chosen in the age group of 5-68 years with an average of 30 years and a standard deviation of 17.7 years. In this experiment, daily activities such as sitting, standing, squatting, coughing and walking are recorded. During the test, subjects are asked to perform these activities in different order, and we will also record the subject's activity strictly so that the performance of the algorithm could be fully verified. Some of the dictation result is shown in Fig. 7.

The following are the different activities considered in our study:

1) Standing upright;
2) Sitting still on a chair;
3) Squatting down and standing up;
4) Coughing when standing upright;
5) Walking at a gentle pace with an average speed of 1m/s on a horizontal floor.

All of the subjects are asked to repeat these activities in several times. The tests collected a total data of 137.5 min, and the valid data is 134.1 min. The DER (Detection Error Rate) is utilized to evaluate the performance of the activity recognition algorithm. FP (False Positive) means the false recognition, FN (False Negative) means the missing recognition and TP (True Positive) means the correct recognition. The DER (%) is defined as:

$$DER = \frac{FP + FN}{TP + FN} \qquad (4)$$

The result is shown in Table II.

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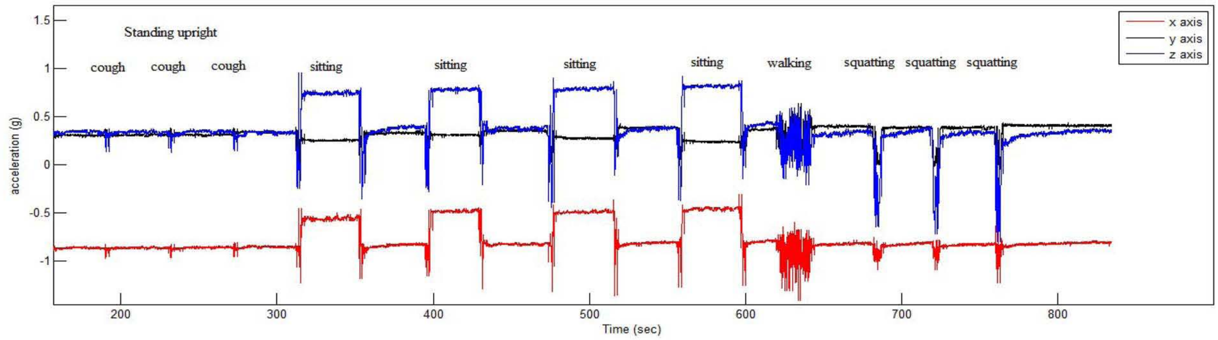

Fig. 7 Recognition results of daily activities

Table II. Activity Recognition result

Activity	FP	FN	TP	DER
Standing	2	0	81	2.4%
Lie flat	0	0	6	0
sitting	1	1	40	4.9%
coughing	1	0	42	2.4%
Sit down	1	1	35	5.6%
Squat down	1	0	31	3.2%

As shown in Table II, the average DER is 3.08%. Several activity recognition algorithms based on single 3-axis accelerometer are compared, the following Table III shows the result. It is obvious that the performance of our device is much better than the one which have its sensor on the waist. Unfortunately, because of the body structure, the acceleration of the chest is not so sensitive to the body movement in comparison to pelvic. But still, the result of our work is comparable to [10], and it is sufficient under the requirement of this work.

Table III. Activity recognition algorithm based on single 3-axis accelerometer

algorithm	Sensor position	Number of activities that can be detected	DER
2005[10]	pelvic	7	2.48%
2009[13]	waist	5	27.2%（DT）
Proposed	chest	6	3.08%

V. Conclusion

In this work, a wearable ECG monitoring device with an accelerometer is presented. The patient's daily activity can be recognized. This device has been verified on 13 volunteers including children and old people. It shows that the device is comfortable to wear and the activity recognition algorithm could classify several daily activities. Further trials will be performed to remove the interference of the body activities.

VI. Acknowledgement

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