A system of human vital signs monitoring and activity recognition based on body sensor network

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Abstract

Purpose – The purpose of this paper is to develop a health monitoring system that can measure human vital signs and recognize human activity based on body sensor network (BSN).

Design/methodology/approach – The system is mainly composed of electrocardiogram (ECG) signal collection node, blood oxygen signal collection node, inertial sensor node, receiving node and upper computer software. The three collection nodes collect ECG signals, blood oxygen signals and motion signals. And then collected signals are transmitted wirelessly to receiving node and analyzed by software in upper computer in real-time.

Findings – Experiment results show that the system can simultaneously monitor human ECG, heart rate, pulse rate, SpO2 and recognize human activity. A classifier based on coupled hidden Markov model (CHMM) is adopted to recognize human activity. The average recognition accuracy of CHMM classifier is 94.8 percent, which is higher than some existent methods, such as supported vector machine (SVM), C4.5 decision tree and naive Bayes classifier (NBC).

Practical implications – The monitoring system may be used for falling detection, elderly care, postoperative care, rehabilitation training, sports training and other fields in the future.

Originality/value – First, the system can measure human vital signs (ECG, blood pressure, pulse rate, SpO2, temperature, heart rate) and recognizes some specific simple or complex activities (sitting, lying, go boating, bicycle riding). Second, the researches of using CHMM for activity recognition based on BSN are extremely few. Consequently, the classifier based on CHMM is adopted to recognize activity with ideal recognition accuracies in this paper.

Keywords Activity recognition, Body sensor network, ECG, Health monitor, SpO2, Telemedicine

Paper type Research paper

Nomenclature

Abbreviation

BSN = body sensor network
CHMM = coupled hidden Markov model
ECG = electrocardiogram
SpO2 = oxygen saturation
SVM = supported vector machine
NBC = naive Bayes classifier
HMM = hidden Markov model
GMM = Gaussian mixture mode
WBSN = wireless body sensor network

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1. Introduction

Body sensor network (BSN) is an application of wireless sensor network (WSN) in human health surveillance. Sensors placed on different body locations are used to collect human vital signs such as electrocardiogram (ECG), SpO2 and motion signals including acceleration and angular speed. These signals are transmitted wirelessly to personal digital assistant (PDA) or personal computer (PC). Then these signals are sent to hospital server through internet. The signals in hospital can be used to diagnose and treat patients (Yang and Yacoub, 2006).

BSN has been widely used in human health monitoring system. Katsis used BSN to monitor emotional states of car racing drivers by measuring their electromyography, electrocardiograph, respiration and skin conductivity signals (Katsis et al., 2011). Pandian developed a wearable remote physiological monitoring system to measure ECG, body temperature, blood pressure, galvanic skin response and heart rate (Pandian et al., 2008). Chung developed a WSN-based...
mobile u-healthcare system with ECG, blood pressure measurement function (Chung et al., 2008). In spite of the contribution to medical monitoring, the health monitoring systems mentioned above only consider one or more of the classical vital signs (ECG, blood pressure, pulse, oxygen saturation, blood glucose, temperature, weight) without considering behavior information.

Boyle positioned an acceleration sensor on the waist of chronic patients to monitor their daily activities (Boyle et al., 2006). Nyan utilized angular velocity sensors which were fixed on waist-chest-axillary, respectively, to recognize human falling activities and directions (Nyan et al., 2006). Jiang et al. (2011) studied the recognition methods of human activity based on BSN and Jiang (2012) developed a method to deal with installation errors of wearable accelerometers in activity recognition. But the three studies only considered behavior information without considering ECG, blood oxygen and other vital signs.

Human daily activities do not merely reflect human health condition. Some previous researches show that using BSN to recognize daily activities of elderly people (King et al., 2010), chronic patients (Steele et al., 2003), postoperative patients (Wang et al., 2010) and other patients can also effectively improve medical service qualities of those people (Atallah and Yang, 2009). Medical systems which can monitor both human vital signs and behavior information have become a hot research field in recent years. Anliker et al. (2004) developed a wearable medical monitoring system to measure ECG, SpO2, blood pressure, temperature and the level of physical activity of patients. Weber et al. (2004) designed a newly biomedical clothing VTAM based on BSN to monitor human parameters, such as ECG, breath rate, a shock/fall detection and body temperature. But the two systems mentioned above cannot recognize specific activity.

In this paper, a wearable health monitoring system is designed and the system can measure human vital signs (ECG, blood pressure, pulse rate, SpO2, temperature, heart rate) as well as recognize some simple or complex activities (sitting, lying, go boating, bicycle riding). A coupled hidden Markov model (CHMM) is adopted to recognize human activity based on BSN. The system may be used for falling detection, elderly care, postoperative care, rehabilitation training, sports training and other applications.

The rest of the paper is organized as follows: Section 2 describes the design of ECG signal collection node, blood oxygen signal collection node and activity recognition module in detail. In Section 3, experiments are conducted to evaluate the performance of the system. Finally, our work is concluded in Section 4.

2. Design of system and algorithm

The system is mainly composed of ECG signal collection node (ECG signal collection module, wireless module, power module), blood oxygen signal collection node (blood oxygen signal collection module, wireless module, power module), inertial sensor node (accelerometer, power module), receiving node (wireless module, USB communication unit), software in upper computer. Here, wireless module is composed of MSP430 microprocessor and CC2420 RF transceiver and power module is mainly composed of lithium battery and 3.3 V voltage-stabilizing chip. The structure diagram of the system is shown in Figure 1.

Figure 1 The structure diagram of system

2.1 Design of ECG signal collection node

In view of the requirement of application environment, a three-lead ECG signal collection node is designed. There are two measuring electrodes and a reference electrode, which are fixed on left arm (LA), right arm (RA) and right leg (RL), respectively. The structure diagram of the ECG signal collection node is shown in Figure 2.

A left leg drive circuit is designed to reduce interferences generated by surrounding electromagnetic devices. The preamplifier is AD627. As the bandwidth of ECG signal is 0.05-100 Hz in clinical application, a high-pass and a low-pass filter are designed. Their cut-off frequencies are set to 0.06 and 100 Hz, respectively. A 50 Hz notch filter is designed to reduce
50 Hz industrial frequency interferences generated by surrounding electrical equipments. A gain control circuit is also designed to make voltage values from 50 Hz notch filter fulfill the requirement of AD converter and make full use of the upper medium voltages outputted by AD converter. The circuits mentioned above constitute an ECG signal collection module. The ECG signal collection node is composed of an ECG signal collection module, a wireless module (MSP430 microprocessor and CC2420 RF transceiver) and a power module.

2.2 Design of blood oxygen signal collection node
Based on Lang Bert-Bill laws, a transmission-type pulse blood oxygen signal collection node is designed. Red light with 660 nm central wavelength and near-infrared light with 940 nm central wavelength irradiate finger tips alternately. \( \text{SpO}_2 \) is calculated by measuring periodical changes of the two types of light. The diagram of blood oxygen signal collection node is shown in Figure 3.

In this design, NELLCOR DB9 is used as blood oxygen probe which is driven by classical H-bridge drive circuit. A signal conditioning circuit is designed to receive light current from blood oxygen probe and transfer light current signals to voltage signals. A signal separation circuit is designed to separate the overlapping red light and infrared light. A filter circuit and an amplifying circuit of red light and infrared light are designed to collect blood oxygen signals between 0.06 and 30 Hz with no attenuation and make other frequency signals with 40 dB attenuation. These circuits constitute a blood oxygen signal collection module. The blood oxygen signal collection node is composed of a blood oxygen signal collection module, a wireless module (MSP430 microprocessor and CC2420 RF transceiver) and a power module.

2.3 Design of activity recognition module
An activity recognition module based on BSN is proposed in this paper. The process of using motion signals to recognize human activity is regarded as a classification problem. Each kind of activity to be recognized is a classification category. The diagram of activity recognition is shown in Figure 4.

2.3.1 Activity recognition hardware
Multiple inertial sensors are adopted to collect human motion signals, so it is essential to fuse multiple sensors data so as to get feature vectors. There are two kinds of common data fusion methods, namely feature layer data fusion and decision layer data fusion (Yang and Hu, 2006). But the two methods only consider the influence of each sensor on classification results, not fully consider the influence of interaction among different sensors on classification results. For this reason, the two methods above limit the recognition accuracy of classification results.

In this paper, a human activity recognition method based on CHMM is used to solve the problem of multiple sensors data fusion. This method can effectively mine association rules of motion signals from different sensors, namely synergistic movements among different body parts.

**Figure 3** The diagram of blood oxygen signal collection node

**Figure 4** The flow diagram of activity recognition

ADXL330 is small and thin, and its power consumption is extremely low. The output range of ADXL330 is \( \pm 3 \, g \), which completely meets the demands of human activity monitor based on BSN.

2.3.2 Activity recognition algorithm
There are many existent activity recognition methods, such as naive Bayes classifier (NBC), C4.5 decision tree, supported vector machine (SVM) and hidden Markov model (HMM).

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In this paper, a human activity recognition method based on CHMM is used to solve the problem of multiple sensors data fusion. This method can effectively mine association rules of motion signals from different sensors, namely synergistic movements among different body parts.

**Coupled hidden Markov model.** HMM is a probabilistic model that describes Markov progress with hidden states. CHMM is an extended model based on HMM and has been proposed by Brand et al. (1997). CHMM has been successfully used for speech recognition, image recognition and biological sequence analysis. Brand adopted CHMM to recognize complex actions and model interacting processes based on visual system (Brand et al., 1997; Brand, 1997). But the correlational researches which adopted CHMM to recognize activities based on BSN are extremely few. CHMM can model and statistically analyze random processes which contain multiple interrelated data links. There are obvious relevances among multiple data links collected from BSN. The relevances of multiple data links make us choose CHMM classification method for activity recognition based on BSN.
The structure diagram of CHMM is shown in Figure 5. \( N \) is the number of sensors as well as the number of data links; \( T \) is the length of observation sequence; \( \alpha_t^n \) is the observation of sensor node \( n \) \( (n = 1, 2, \ldots, N) \) at time \( t \) \( (t = 1, 2, \ldots, T) \). \( s_t^n \) is the hidden state of sensor node \( n \) \( (n = 1, 2, \ldots, N) \) at time \( t \) \( (t = 1, 2, \ldots, T) \). It is assumed that each hidden state variable is conditionally dependent on all hidden state variables in the previous time instance. \( s_t^n \) represents the movement pattern of human body part attached to sensor node \( n \) at time \( t \) in human activity recognition.

**CHMM parameters training.** A CHMM consists of three main parameters: \( \pi \), the initial states probability distribution; \( A \), the hidden states transition probability distribution, including states transition of the same data link and states transition between different data links; \( B \), the observation probability distribution in different states. As observations are continuous, Gaussian mixture model (GMM) is used to describe the observation probability density function. \( K \) is the number of hidden state of data link \( n \); \( T \) represents the \( i \)th hidden state of data link \( n \). \( \lambda \) is the parameters set of CHMM, namely \( \lambda = \{ \pi, A, B \} \):

- The initial state probability distribution \( \pi = \{ \pi_{in} \} \), where:
  \[ \pi_{in} = P(\alpha_t^n = i^n) \quad 1 \leq i \leq K^n, \quad 1 \leq n \leq N \]

- The state transition probability distribution \( A = \{ a_{in,jm} \} \), where:
  \[ a_{in,jm} = P(\alpha_t^n = i^n | \alpha_{t-1}^m = j^m) \quad 1 \leq i \leq K^n, \quad 1 \leq j \leq K^m, \quad 1 \leq m, n \leq N \]

- The observation probability distribution in state \( i^n \), \( B = \{ b_{in}(x_t^n) \} \), where:
  \[ b_{in}(x_t^n) = P(\alpha_t^n = x_t^n | \alpha_{t-1}^n = i^n) \quad 1 \leq i \leq K^n, \quad 1 \leq n \leq N \]

The GMM of observation symbol probability distribution in state \( i^n \) of data link \( n \) is shown as follows:

\[ b_{in}(x_t^n) = P(\alpha_t^n = x_t^n | \alpha_{t-1}^n = i^n) = \sum_{h=1}^{H^n} \omega_{in,h} N(x_t^n; \mu_{in,h}, \sum_{in,h}) \]

**Figure 5** The structure diagram of CHMM

\[ H^n \] is the number of GMM component; \( \omega_{in,h} \) is the mixture coefficient; \( \mu_{in,h} \) is the mean vector; \( \sum_{in,h} \) is covariance matrix, for the \( h \)th component.

Forward-backward algorithm, Viterbi algorithm and Baum-Welch algorithm are adopted to train model parameters \( \lambda \) when the observation sets \( X_{0} \) is given (Pernkopf, 2005). The training steps are as follows:

- **Step 1.** The initial estimation value of parameters set \( \lambda' \) is given;
- **Step 2.** Forward-backward algorithm is used to calculate the likelihood probability \( P(X_{0}|\lambda') \);
- **Step 3.** Viterbi algorithm is adopted to find a set of hidden states to maximize the likelihood probability \( P(X_{0}|\lambda) \);
- **Step 4.** Baum-Welch algorithm is utilized to re-estimate model to get a new parameters set \( \lambda'' \);
- **Step 5.** Forward-backward algorithm is used to calculate the likelihood probability \( P(X_{0}|\lambda'') \) again;
- **Step 6.** Repeatedly perform steps 3-5 until \( P(X_{0}|\lambda'') - P(X_{0}|\lambda') < \varepsilon \), where \( \varepsilon \) is a given threshold value.

**Activity recognition based on CHMM.** It is assumed that there are \( Q \) activities need to be recognized. \( X \) represents the total training data set containing observation sequences with the same length, namely feature vector sequences with action labels. \( X_q (q = 1, \ldots, Q) \) represents a subset of \( X \) and contains all training samples which belong to the \( q \)th activity. We need to make \( Q \) models since the number of activities is \( Q \). Each model describes the characteristics of one activity. \( \lambda_q \) represents the parameters set of the \( q \)th model which is trained by \( X_q \). As to unclassified observation sequence \( y \), the likelihood probability of all \( Q \) models \( P(y|\lambda_q) \), \( q = 1, 2, \ldots, Q \) is calculated, and then the maximal likelihood probability \( \hat{y} = \arg \max \{ p(y|\lambda_q) \} \) is chosen as the action label that observation sequence \( y \) belongs to.

### 3. Experiment and result analysis

**3.1 Experiment platform**

**3.1.1 Hardware platform**

The hardware platform of the system is mainly composed of ECG signal collection module, ECG cable, blood oxygen signal collection module, blood oxygen probe and inertial sensors, wireless module, USB communication unit, lithium battery (3.3 V, 1,200 mAh). The structure diagram of system hardwares is shown in Figure 6.

**Figure 6** The structure diagram of system hardwares
3.1.2 Software platform
The system software is developed in Windows XP platform and written in C#. The software can automatically initialize sensor nodes, set up wireless communication parameters (baud rate, sampling frequency, sampling time) and control the sensors when they start and end to collect data. The collected motion signals, ECG signals, blood oxygen signals, heart rate, pulse rate and SpO2 can be displayed in the software interface. In addition, data can be saved for further observation and playback.

3.2 Experiment of ECG signal test
First, ECG collection node was ensured to work well before collecting ECG signals. Second, the sampling frequency of ECG signal collection node was set to 20 Hz. This allowed us to receive sensor data with minimal packet loss. Third, two measuring electrodes and a reference electrode were, respectively, placed on two arms and abdomen of one volunteer whose actual heart rate was 80 BPM. Then, collected ECG signals were input into software in computer. Finally, the real-time ECG curve and heart rate of the volunteer were displayed in software interface, as shown in Figure 7. Horizontal axis represented the index of sampling points. Vertical axis represented the sampling value of ECG signals.

In order to validate the effectiveness and actual usability of the ECG signal collection node, 80 BPM standard ECG signals generated by MSG-210 simulator were collected by the ECG collection node and displayed on oscilloscope, as shown in Figure 8. The cycle, pulse rate and collection accuracy of ECG signals were shown in Table I. There are obvious T wave, P wave, QRS complex waves in ECG curve displayed on oscilloscope as shown in Figure 8. The collection accuracy of standard ECG signals is 98.75 percent, which shows that the ECG collection node can collect standard ECG signals precisely.

Figure 7 clearly shows T wave, P wave, QRS complex waves in real-time ECG curve and heart rate with 71 BPM in software interface. The collection accuracy is 88.75 percent, which shows that the ECG collection node can collect human ECG signals reasonably. The power consumption of the ECG collection module is 132 mW. The high collection accuracy and low power consumption verify the effectiveness and actual usability of the ECG collection node.

However, the collection accuracy of human ECG signals is 88.75 percent, which is 10 percent lower than that of standard ECG signals. Hence, how to improve the hardware to collect human ECG signals more precisely and how to improve the software to display human ECG signals and calculate heart rate more accurately are our future work.

3.3 Experiment of blood oxygen signal test
First, it was necessary to guarantee that the blood oxygen probe was driven effectively. Second, the sampling frequency of blood oxygen signal collection node was set to 20 Hz. This allowed us to receive sensor data with minimal packet loss. Third, finger tip of the same volunteer whose actual pulse rate was 80 BPM was put into probe. Fourth, the blood oxygen signals were collected and then collected signals were input into the software. Finally, the curve of blood oxygen signals, pulse rate and SpO2 were displayed in software interface in real-time, as shown in Figure 9. Horizontal axis represented the index of sampling points. Vertical axis represented the sampling value of blood oxygen signals.

In order to test and verify the effectiveness and actual usability of blood oxygen collection node, oscilloscope was utilized to display collected blood oxygen signals, as shown in Figure 10. CH1 represented blood oxygen signals of the volunteer. CH2 represented the 80 BPM standard blood oxygen signals generated by MSG-210 simulator. The cycle, pulse rate and collection accuracy of blood oxygen signals were shown in Table II. The collection accuracies of human blood oxygen signals and standard blood oxygen signals are 93.75 and 96.25 percent, respectively, which show that our blood oxygen collection node can collect both human blood oxygen signals and standard blood oxygen signals precisely.
Figure 9 explicitly shows that human blood oxygen signals, SpO₂ and pulse rate can be displayed by the system software in real-time. The collected pulse rate is 89 and SpO₂ is 0.67, with the collection accuracy of 88.75 percent. The power consumption of the blood oxygen module is 105.6 mW. The high collection accuracy and low power consumption validate the effectiveness and actual usability of the blood oxygen collection node.

The collection accuracy of human blood oxygen signals is 2.5 percent lower than that of standard blood oxygen signals. The collection accuracy of human blood oxygen signals displayed in software is 5 percent lower than that displayed on oscilloscope. So, how to improve our hardware to collect human blood oxygen signals more precisely and how to improve our software to display human blood oxygen signals and calculate heart rate and SpO₂ more accurately are our further work.

3.4 Experiment of human activity recognition
3.4.1 Data collection
To provide training data of physical activities, we recruited eight subjects (four males and four females) to perform a series of activities. For this study, we selected nine common daily activities, namely standing (A1), sitting (A2), lying (A3), walking (A4), go upstairs (A5), go downstairs (A6), jogging (A7), bicycle riding (A8) and go boating (A9). Activities A4-A7 were more complex than other activities and needed to be performed with the coordination of upper limbs, lower limbs and chest. In order to describe complex activities, five inertial sensors which were worn on left wrist, right wrist, chest central, left ankle and right ankle of the subjects were chosen to collect acceleration signals, as shown in Figure 11(a). The sampling frequency was set to 20 Hz with minimal packet loss. Every activity lasted for 20 s and was repeated three times.

3.4.2 Data processing and feature extraction
In order to verify the effectiveness of CHMM classifier, we compared CHMM classifier with HMM, NBC, C4.5 decision tree, and SVM. Both feature layer data fusion and decision layer data fusion were utilized to fuse the features of four contrastive classifiers.

The collected acceleration signals were processed to get feature vector sequence which could be recognized by classifiers. Each activity contained five sets of triaxial acceleration signals, as shown in Figure 11(b). A feature vector extracted from triaxial acceleration signals in an observation window contained 12 features, namely mean, variance, kurtosis in x, y, z-axes and three covariances among x, y, z-axes. In order to avoid losing information in window edge, there were 50 percent overlap between two adjacent observation windows.

Figure 9 The real-time blood oxygen signals displayed in software
Data fusion of CHMM. A sliding window with 32 sampling points split each set of acceleration signals into observation windows with the same length. Every observation window only contained the acceleration signals of one sensor. A 12 dimension feature vector was extracted from an observation window as an observation of CHMM model. Every ten adjacent feature vectors formed an observation sequence. There were five overlapping feature vectors between two adjacent observation sequences.

Feature layer data fusion of NBC/C4.5 decision tree/SVM. A sliding window with 160 sampling points split five sets of acceleration signals into observation windows with the same length. Every observation window contained the acceleration signals of five sensors. A 60 dimension feature vector was extracted from an observation window as a sample of one activity.

Feature layer data fusion of HMM. A sliding window with 32 sampling points split five sets of acceleration signals into observation windows with the same length. Every observation window contained the acceleration signals of five sensors. A 60 dimension feature vector was extracted from an observation window. Every ten adjacent feature vectors formed an observation sequence as a sample of one activity. There were five overlapping feature vectors between two adjacent observation sequences.

Decision layer data fusion of NBC/C4.5 decision tree/SVM. A sliding window with 160 sampling points split each set of acceleration signals into observation windows with the same length. Every observation window contained the acceleration signals from one sensor. A 12 dimension feature vector was extracted from an observation window as a sample of one activity.

Decision layer data fusion of HMM. A sliding window with 32 sampling points split each set of acceleration signals into observation windows with the same length. Every observation window contained the acceleration signals of one sensor. A 12 dimension feature vector was extracted from an observation window as a sample of one activity. There were five overlapping feature vectors between two adjacent observation sequences.

Figure 10 The real-time blood oxygen signals displayed on oscilloscope

Table II The cycle, pulse rate and accuracy of blood oxygen signals

<table>
<thead>
<tr>
<th>Signal cycle</th>
<th>Pulse rate (BPM)</th>
<th>Collection accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CH1</td>
<td>0.8 s</td>
<td>75</td>
</tr>
<tr>
<td>CH2</td>
<td>0.78 s</td>
<td>77</td>
</tr>
<tr>
<td>Figure 9</td>
<td>-</td>
<td>0.67</td>
</tr>
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</table>

Data fusion of CHMM. A sliding window with 32 sampling points split each set of acceleration signals into observation windows with the same length. Every observation window only contained the acceleration signals of one sensor. A 12 dimension feature vector was extracted from an observation window as an observation of CHMM model. Every ten adjacent feature vectors formed an observation sequence. There were five overlapping feature vectors between two adjacent observation sequences.

Figure 11 (a) Sensors position; (b) a set of acceleration signals of “jogging”
3.4.3 Recognition result
CHMM classifier, NBC, C4.5 decision tree, SVM and HMM were used to recognize nine activities, respectively. Ten-cross validation method was adopted to calculate recognition accuracies of the five classifiers. Recognition results were shown in Table III.

It can be clearly seen from Table III that recognition accuracies of A1-A3, A8-A9 are not the highest, as all limbs are basic static in A1-A3, and only the amplitude of movement in lower limbs or upper limbs is relatively big in A8 or A9. The interactions among different limbs are too few to make full use of the advantages of CHMM classifier. As to A4-A7, CHMM classifier achieved the highest recognition accuracy. As the four activities are performed with the interactions among different body parts, they make full use of the advantages of CHMM classifier. The average accuracy of CHMM classifier is 94.8 percent, which is higher than the other four classifiers. Results show that CHMM classifier is better than other four classifiers in activities recognition especially in interactive activities recognition.

3.5 Evaluate performance of the system hardware
In the design of the system, power consumption and wireless transmission distance are important indicators to evaluate its performance. First, we measured the power consumption of main modules, as shown in Table IV. The system was powered by a lithium battery (3.3 V, 1,200 mAH). Table IV shows that the total power consumption of the system is 346.5 mW and the system can work nearly 11.5 hours continuously. Low power consumption extends battery life. Second, we measured the wireless transmission distance of wireless module which was up to 20 m indoor and 100 m outdoor. It can enhance the mobility and flexibility of patients. Except that, matchbox-sized modules can improve the portability of device.

The monitoring system has been adopted by the citizens in a community service center, Shenyang, Liaoning province. The system is regarded as a practical and convenient apparatus by the users. Properties of the monitoring system are very well and the system meets design requirement. It is expected to be commercialized.

4. Conclusion
Although there exist many similar studies on health monitoring system, most of them do not integrate activity recognition with ECG and blood oxygen as a whole. Consequently, a human health monitoring system based on BSN is developed in this paper and the system can measure human vital signs and recognize some simple or complex activities.

The system is mainly composed of ECG signal collection node, blood oxygen signal collection node, inertial sensor node, receiving node, and upper computer. Three collection nodes are used to collect ECG, blood oxygen and motion signals. Then the collected signals are transferred wirelessly to receiving node which is connected with upper computer via USB communication unit. EGC signals and blood oxygen signals are processed by software in upper computer to display heart rate, pulse rate, SpO2, ECG curve and blood oxygen curve. As to motion signals, they are processed to get feature vectors which can be recognized by classifier. A classifier based on CHMM is adopted to recognize human activity. The average accuracy of CHMM classifier is 94.8 percent and higher than the four contrastive classifiers with feature layer data fusion and decision layer data fusion. As we all know, there are more than one inhabitant in a house, so how to recognize multiple people interactive activities is a challenge in health monitor system. Compared with other classifiers, CHMM classifier is more suitable to recognize complex activities, such as multiple people interactive activities recognition. At present, few studies has adopted CHMM as a classifier to recognize multiple people interactive activities in BSN. In conclusion, CHMM classifier algorithm is a good choice for us to recognize multiple people interactive activities based on BSN in future studies. As some activities are too similar to be easily recognized only by activity recognition classifier, ECG and blood signals are

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**Table III** Recognition accuracies of the five classifiers (%)

<table>
<thead>
<tr>
<th>Data fusion</th>
<th>Classifier</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
<th>A6</th>
<th>A7</th>
<th>A8</th>
<th>A9</th>
<th>Average</th>
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<tr>
<td>Feature layer data fusion</td>
<td>NBC</td>
<td>96.3</td>
<td>94.6</td>
<td>95.4</td>
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<td>86.1</td>
<td>87.1</td>
<td>86.4</td>
<td>87.8</td>
<td>89.9</td>
<td>89.8</td>
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<tr>
<td></td>
<td>C4.5</td>
<td>98.7</td>
<td>96.3</td>
<td>97.5</td>
<td>90.0</td>
<td>91.2</td>
<td>93.1</td>
<td>92.4</td>
<td>92.8</td>
<td>91.9</td>
<td>93.8</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>95.4</td>
<td>96.2</td>
<td>95.9</td>
<td>86.9</td>
<td>87.0</td>
<td>90.0</td>
<td>91.4</td>
<td>93.9</td>
<td>93.3</td>
<td>92.3</td>
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<tr>
<td></td>
<td>HMM</td>
<td>94.8</td>
<td>95.6</td>
<td>95.2</td>
<td>91.1</td>
<td>90.1</td>
<td>92.4</td>
<td>90.1</td>
<td>91.4</td>
<td>92.2</td>
<td>92.5</td>
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<tr>
<td>Decision layer data fusion</td>
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<td>95.9</td>
<td>93.9</td>
<td>94.9</td>
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<td>90.8</td>
<td>90.9</td>
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<td></td>
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<td>97.0</td>
<td>89.4</td>
<td>88.3</td>
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<td>88.5</td>
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<td>91.7</td>
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<tr>
<td></td>
<td>HMM</td>
<td>95.2</td>
<td>95.0</td>
<td>95.0</td>
<td>91.3</td>
<td>92.5</td>
<td>93.2</td>
<td>93.3</td>
<td>92.7</td>
<td>92.7</td>
<td>93.4</td>
</tr>
<tr>
<td></td>
<td>CHMM</td>
<td>97.4</td>
<td>96.9</td>
<td>97.1</td>
<td>92.9</td>
<td>93.0</td>
<td>95.3</td>
<td>94.1</td>
<td>93.1</td>
<td>93.2</td>
<td>94.8</td>
</tr>
</tbody>
</table>

**Table IV** The power consumption of main modules in the monitoring system

<table>
<thead>
<tr>
<th>Modules</th>
<th>Power consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECG module</td>
<td>40 mAh*3.3 V = 132 mW</td>
</tr>
<tr>
<td>Blood oxygen module</td>
<td>32 mAh*3.3 V = 105.6 mW</td>
</tr>
<tr>
<td>Five inertial sensors</td>
<td>5<em>2 mAh</em>3.3 V = 33 mW</td>
</tr>
<tr>
<td>Wireless module</td>
<td>23 mAh*3.3 V = 75.9 mW</td>
</tr>
<tr>
<td>Total</td>
<td>105 mAh*3.3 V = 346.5 mW</td>
</tr>
</tbody>
</table>
collected as a secondary rule to distinguish them and improve recognition accuracy. Consequently, our system can be used in similar activity recognition. The monitoring system presented in this paper may be used for falling detection, elderly care, postoperative care, rehabilitation training, sports training and other fields.

References


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