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Intelligent sensor node based a low power ECG monitoring system

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Abstract: This paper presents a novel two-tier low power electrocardiogram (ECG) monitoring system which consists of a sensor nodes layer and a base station layer by employing a simple but effective Euclidean distance model. To save transmission power, a sensor node only transmits sensed data to a base station when the sensed data shows abnormality. For the low power implementation of the abnormality detection on a local power-hungry sensor node, we propose light-weight computation of Euclidean distance between a sensed ECG signal and a reference ECG signal. Experimental results show that the proposed scheme can reduce power consumption by 39-57% of the sensor nodes and accordingly prolongs the lifetime of the whole monitoring system.

Keywords: low power, body sensor networks, ECG analysis

Classification: Science and engineering for electronics

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1 Introduction

With the development of wireless communication, sensor design, and energy storage technologies, wireless sensor network (WSN) has become a reality. Currently, the monitoring of human body physiological parameters is becoming a new interesting application of WSN. However the well designed WSNs are not ideally suited to the human body monitoring and it is necessary to develop a wireless body sensor network (BSN) to meet the needs of the human body monitoring. As ECG is the most significant information to diagnose the heart disease, monitoring ECG during everyday life would be very useful to manage people's chronic health conditions. Therefore many BSNs have been designed for continuously ECG monitoring. The "Code Blue" project at Harvard University has developed a medical sensor network that incorporates wireless pulse oximeter sensors and ECG sensors to continuously monitor and record vital sign and cardiac information [2]. The "CardioNet" is also a mobile outpatient telemetry system to provide continuous real-time ECG monitoring [3].

All these schemes are traditional ECG monitoring systems. The ECG sensors are attached to the patients' body and these sensors are also connected to a BSN sensor node which is an embedded system integrating small processor, wireless transmitter, and battery. The BSN node with the ECG sensors can capture the data from the sensors and transmits this signal to a base station. The base station is used to collect ECG signal and send this information to the doctor via wireless networks. As mentioned in [4], a key design criterion for such a system is the power consumption of the sensor nodes. Typically a sensor node has four work modes: Listen mode, Processing mode, Transmit mode, Sleep mode. The power consumed by each mode is different. The current consumption in listen and transmit mode is much higher than in processing or sleep mode. So if the radio is continuously active in transmission, power would be used up soon. It is obvious that the mote should be turned to the processing or the sleep mode most of the time to save the power. Nowadays, most of the ECG monitoring schemes and projects aim at 24-hour monitoring and sensor node has to detect and transmit ECG signal to the base station continuously. Hence the lifetime of the sensor node becomes a critical problem for such ECG monitoring systems.

The proposed low power ECG monitoring system in this paper put some intelligence on a sensor node to reduce the number of transmissions. The sensor node is mostly put into the processing mode and just connects the base station when necessary. In this way the power can be saved and the lifetime of the system can be prolonged.

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2 System design

Fig. 1 (a) shows the two-tier architecture of the proposed system. The upper tier is the base station. It is assumed to be rich in computational, communication, and storage resources. The task of this tier is to gather data from the bottom tier and answer queries posed by the user. The bottom tier is the sensor nodes. The sensor nodes are low-power mote platforms, such as Mica2 mote, MicaZ mote, Telos mote etc, equipped with ECG sensors, microcontroller, flash storage, wireless radio and batteries. The tasks of this tier are to sense data and transmit them to base stations when appropriate, while archiving all data locally in flash storage. The sensor node can also do some local ECG analysis, so that continuous transmission is not always necessary. Only when the node

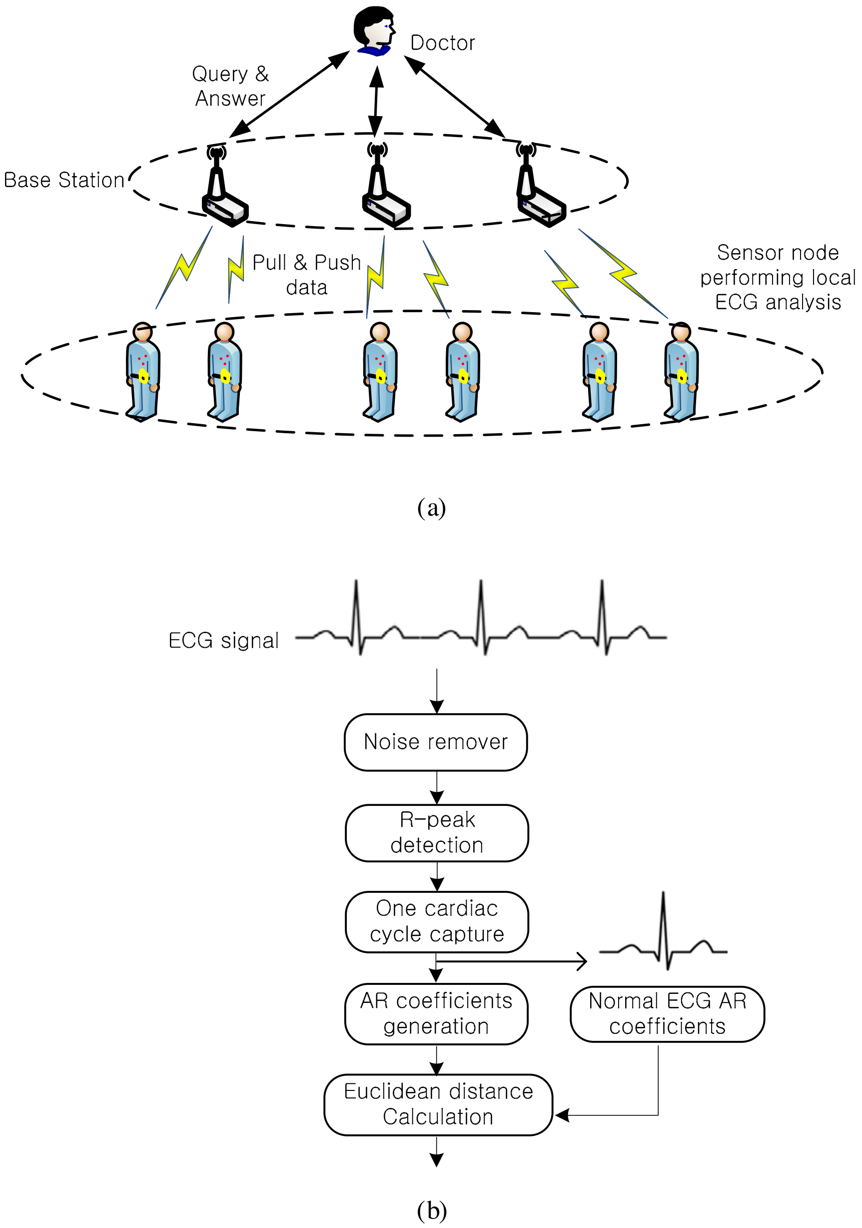

Fig. 1. System overview: (a) System architecture, (b) Local ECG analysis flow chart

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determines that the signal is abnormal, the transmission would be launched. In a word, the sensor node trade communication for computation. Since the processing mode is far energy efficient than the radio transmission mode, much power can be saved in this way.

Before modeling, the ECG signal should be preprocessed to remove noises such as baseline wonder, muscular noise or electrode motion artifact and so on [5]. Then the peak within 300 samples is detected and it is considered as the R peak. One cardiac cycle is captured as one hundred samples before the R peak and 200 samples after the R peak. Currently it is adequate to capture most of the information from a particular cardiac cycle [6]. Next the autoregressive model (AR) is used to model the ECG signal and Burg's algorithm is used to calculate the AR coefficients. Compared with other complex models, this model is more suitable for our source limited system. AR models is given by [6]

$$v[k] = \sum_{i=2}^{P+1} a_k v[k-i+1] + n[k] \tag{1}$$

Where $v[k]$ is the ECG time series, $n[k]$ is zero mean white noise, a_k is the AR coefficients, and P is the AR order. As mentioned in [6], AR order chosen as 4 is enough to model the ECG signal. Finally the classification is performed by computing the Euclidean distance between the tested ECG signal AR coefficients obtained above and the normal ECG signal AR coefficients of the same person generated by his former normal record. The Euclidean distance d between points $A = (a_1, a_2, \cdots, a_n)$ and $B = (b_1, b_2, \cdots, b_n)$ is given by

$$d = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \cdots + (a_n - b_n)^2} \tag{2}$$

We choose Euclidean distance as the measure of similarity because of two reasons: (i) this method achieves accurate clusterings with large dimensionality reduction. In [6], the Euclidean distance based ECG classification method achieves the accuracy of 93.2% to 100%; (ii) specific and complex classification method is not suitable with our resource restricted sensor node. If the computation load is too much, the power consumption of it would be comparable to that of the wireless radio. Fig. 1 (b) shows the local ECG analysis algorithm on sensor node by using R-peak detection, autoregressive model and Euclidean distance. If abnormal EC G signal is detected, alarm is transmitted to the doctor.

3 Results

We have implemented and simulated a prototype of the proposed system in NesC on TinyOS. The sensor node tier uses Hybus Mote, each consisting of a MSP430 processor, a 2.4 GHz CC2420 radio, and 512 kB EEPROM. The sampling rate is 250 Hz. The experimental results are shown in Fig. 2 and Table I.

Fig. 2 (a) shows that the node without ECG analysis function always transmits the ECG signal as soon as it is detected. It is much energy demanded as radio transmission is high power cost. Simulations are done with

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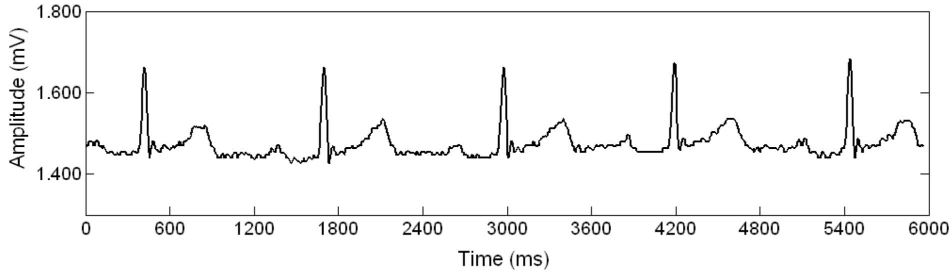
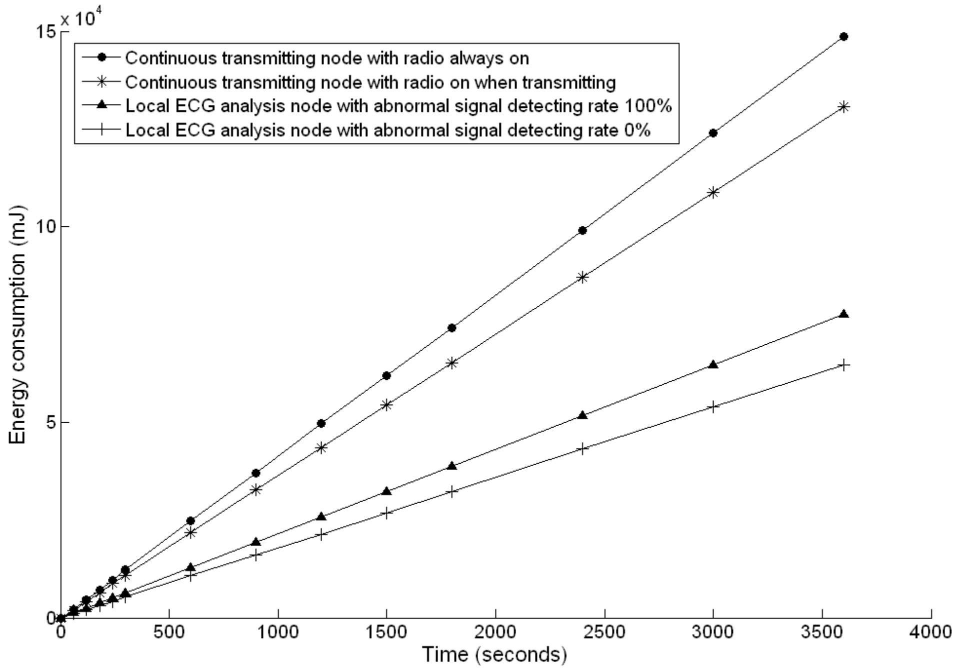


(a)



(b)

Fig. 2. Experimental results: (a) ECG signal sent by the mote without local ECG analysis function, (b) Power consumption: Local ECG analysis node vs Continuous transmission node

PowerTOSSIM to estimate the energy consumption of each node. PowerTOSSIM is a power modeling extension to TOSSIM simulator in TinyOS. It is proved to be an efficient power simulator for TinyOS applications. The power consumption is measured of five components — CPU, radio, led, sensors, EEPROM. The estimated power consumption of the proposed system sensor node and the sensor node performing continuous transmission is shown in Fig. 2 (b). The power consumption of each component is presented in Table I as well. The data are captured after analyzing one hour-long ECG signals. It shows that the proposed scheme trade computation for transmission. But totally the proposed system is more energy efficient saving about 57% energy at most and the local ECG analysis node will achieve longer lifetime. This table also shows the longer the monitoring time, the more power can be saved.

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Table I. Power consumption: Local ECG analysis node vs Continuous transmission node

Components	Power Consumption (mJ)			
	A	B	C	D
cpu	44565.1	44511	54345.5	54295.5
radio	84848.2	67009	1115.4	0
led	11869.6	11855.2	11859.3	0
sensor	7445.5	7436.5	7440.5	7435.1
eeprom	0	0	2840.6	2833.5
total energy	148728.4	130811.7	77601.3	64564.1

A: Continuous transmitting node with radio always on

B: Continuous transmitting node with radio on when transmitting

C: Local ECG analysis node with abnormal signal detecting rate 100%

D: Local ECG analysis node with abnormal signal detecting rate 0%

4 Conclusion

This paper described a two-tier low power ECG monitoring system. In contrast to existing techniques, our work put some intelligence on an energy restricted sensor node in order to save power by trading computation for transmission. We design an ECG analysis algorithm on embedded mote platforms and these platforms are always resource restricted. The novel aspect of our work is the use of autoregressive model to model the ECG signal and the Euclidean distance as a simplified preliminary classification method. Our experiments showed that this local ECG analysis algorithm yields an improvement in saving about 39-57% energy of the sensor node and prolongs the lifetime of the ECG monitoring system. As part of the future work, we plan to extend the sensor node with another flash board to archive a larger amount of historical data at extremely low energy cost and smaller delay.

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