Power Efficient Classification Method for Sensor Nodes in BSN Based ECG Monitoring System

Min Zeng*, Jeong-A Lee**° *Regular Members*

ABSTRACT

As body sensor network (BSN) research becomes mature, the need for managing power consumption of sensor nodes has become evident since most of the applications are designed for continuous monitoring. Real time Electrocardiograph (ECG) analysis on sensor nodes is proposed as an optimal choice for saving power consumption by reducing data transmission overhead. Smart sensor nodes with the ability to categorize lately detected ECG cycles communicate with base station only when ECG cycles are classified as abnormal. In this paper, ECG classification algorithms are described, which categorize detected ECG cycles as normal or abnormal, or even more specific cardiac diseases. Our Euclidean distance (ED) based classification method is validated to be most power efficient and very accurate in determining normal or abnormal ECG cycles. A close comparison of power efficiency and classification accuracy between our ED classification algorithm and generalized linear model (GLM) based classification algorithm is provided. Through experiments we show that, CPU cycle power consumption of ED based classification algorithm can be reduced by 31.21% and overall power consumption can be reduced by 13.63% at most when compared with GLM based method. The accuracy of detecting NSR, APC, PVC, SVT, VT, and VF using GLM based method range from 55% to 99% meanwhile, we show that the accuracy of detecting normal and abnormal ECG cycles using our ED based method is higher than 86%.

Key Words : Body sensor networks, Power efficiency, ECG analysis, Smart sensor nodes, Euclidean distance based classification method

Ⅰ. Introduction

As body sensor network research becomes mature, the need for managing power consumption of sensor nodes has become evident since most of the applications are designed for continuous monitoring. In contemporary BSNs, ECG monitoring is one of the most popular and well researched areas. ECG sensor node attached with a sensor board can take measurements from the patient's cardiovascular system. The collected heart beat information is continuously sent to the base station for doctors to determine any treatments if needed. Typically, a sensor node mainly consists of five components: ECG sensor module, an embedded processor, a memory unit, a wireless transceiver, and a power supply. Thus far, battery remains the main source of energy for sensor nodes, which makes it inconvenient or impossible to recharge the battery in time and limits the life time of the whole monitoring system. In addition, continuous running of the energy-hungry radio transceiver in order to connect with doctors to perform real time diagnosis further shortens the life time of sensor nodes. Based on our earlier research, in traditional continuous transmission monitoring system, power consumption percentage of each component is distributed like this (see Fig. 1).

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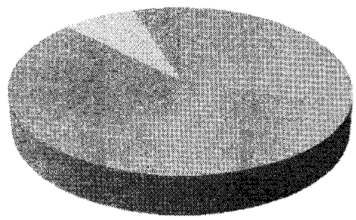

Fig. 1. Power consumption distribution of each component in traditional continuous transmission scheme

About 57% of the total power consumption of sensor nodes is attributed to the transceiver component. This is the direct result of continuously turning on the power-hungry radio transceiver component. The second biggest energy consumer is CPU component with around 30% of the total power consumption. In the continuous transmission scheme, power consumption of CPU component only includes hardware power state transitions when collecting and transmitting ECG data and there are no extra CPU cycles used for ECG analysis computation.

As proposed in [1], smart sensor nodes which can perform real time diagnosis of ECG signals do not have to communicate with base station all the time. Doctors are only notified when an abnormality is detected by sensor nodes to do further analysis and disease classification. The tasks of smart sensor nodes not only include transmitting alarm signal when necessary, but also include storing detected ECG signal and performing ECG analysis functions. The benefits of this design come from the fact that power consumption of a sensor node in processing mode is much lower than in transmitting mode. More specifically, making embedded processors run is much cheaper in terms of power than turning on the radio transceiver. Although ECG analysis method is a well researched area and many accurate algorithms have been developed, there is no proper existing method designed for resource limited sensor nodes in BSNs. ECG analysis algorithms must be designed to match the limited resource characteristic of sensor nodes.

In this paper, we describe and compare GLM based classification method and our ED based classification method applied to sensor nodes in BSNs from power consumption and classification accuracy points of view. Typically, ECG classification methods are designed for several specific cardiac diseases. The GLM based classification method is capable of categorizing normal sinus rhythm (NSR) from various cardiac diseases including atrial premature contraction (APC), premature ventricular contraction (PVC), superventricular tachycardia (SVT), ventricular tachycardia (VT), and ventricular fibrillation (VF). NSR cycles are identified in four steps. Our ED based method classifies ECG cycles into only two categories: normal or abnormal in one step. It simplifies the procedure for classification to achieve more power efficiency, while still achieving great accuracy. Through experiments we show that CPU cycle power consumption of ED based classification algorithm can be reduced by 31.21% at most and overall power consumption can be reduced by up to 13.63% when compared with GLM based method. In addition, it is shown that the accuracy of detecting normal and abnormal ECG cycles using our ED based method is higher than 86%. The accuracy of detecting NSR, APC, PVC, SVT, VT, and VF using GLM based method range from 55% to 99%.

The next section provides further background and related work. In section III, we describe system operation with real time ECG analysis on sensor nodes. Section IV presents the details of GLM based ECG analysis algorithm and our ED based method. In section V, we compare the power consumption and classification accuracy of GLM and ED based methods and present our conclusion in section VI.

II. Related Work

BSN power-reduction techniques for healthcare monitoring systems have been considered in various aspects. Many research groups are devoted to developing custom-designed BSN platforms. In earlier work, the Eco platform was proposed[2]. In later work, a BSN platform developed in [3] has the advantage of small size and low power consumption. It consists of three boards in an uniform size of 23mm in diameter. The peak active power consumption is measured as 5.68mW. Another platform developed by Wong et al.[4] achieves even lower peak active power consumption for sensor node.

A number of low power transceiver modules, sensing modules, and processors have been developed for BSN based healthcare monitoring systems, which optimize power consumption while still maintaining its normal function. In [5][6], low power but high performance transceivers were proposed for BSN sensor nodes. In [7], a coin size ECG electrode is designed for medical application sensor networks with low sensing power consumption. In [8], an optimal ultra low power processor for wireless sensor nodes is designed with power consumption of only 8.4mW when running the reference application.

Numerous power-reduction techniques aiming at MAC protocols for BSNs have been explored including avoiding collisions, shortening time for synchronization, reducing idle listening time, controlling packet overhead, etc. In [9], collision free communication is guaranteed by making sensor nodes passively reply the requests coming from base stations. In this design, sensor data is time-stamped, so global time synchronization is unnecessary. In [10], power consumption for time synchronization is completely saved by exploiting heartbeat rhythm information to perform time synchronization. In addition, power consumption problem is also managed in routing protocols. An energy-aware geographical multipath routing scheme in wireless sensor networks for smart homecare application is proposed. The remaining battery capacity is taken into consideration for next hop relay node selection, so that sensor nodes that are in serious shortage of energy can avoid being selected.

In our earlier research[11], we proposed the light-weight ED based classification method for sensor nodes in BSNs and experimental results showed 57% power consumption reduction at most of our ED based method when compared with traditional continuous transmitting sensor nodes. This paper extends our earlier work by providing more detailed classification algorithm descriptions and many new experimental results. We validate our simulation based power estimation by comparing the power reduction of our ED based classification method with that of GLM based method, and show power consumption reduction of our method in both CPU cycles and total power consumption. We also support a case for our ED based classification method by providing a classification accuracy comparison between the ED based classification method and the GLM based method.

Ⅲ. System Operation

As described in our earlier work[11], the architecture of ECG monitoring system using sensor nodes with ECG analysis functions consists of two tiers: the resource limited sensor nodes and base stations which are rich in resources (see Fig. 2).

Bottom tier sensor nodes are responsible for sensing ECG signals, performing ECG analysis, and communicating with the base station, while the main tasks of the top tier are to gather data received from the bottom tier and interact with doctors. First, ECG data is obtained continuously through sensor board with ECG sensors attached to sensor node. Then, ECG data is buffered and stored in the memory unit of sensor node and ECG analysis is performed every time an ECG cycle is located. ECG analysis is performed as two steps: the first step is to model the current located ECG cycle using autoregressive (AR) model and derive AR coefficients that reflect the characteristics of this cycle; the second step is to

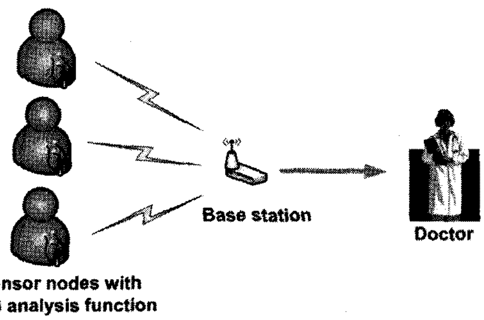

Fig. 2. System operation.

categorize this ECG cycle based on AR coefficients derived in the former step using certain classification algorithms. Finally, the transmission decision is made based on classification results. If an ECG cycle is categorized as normal, transmission is not required and sensor nodes do not have to initiate communication with the base station. In this way, communication overhead is greatly reduced and, accordingly, power consumption of radio transceiver component can be significantly lowered.

Ⅳ. ECG Analysis Algorithms

Each time before performing ECG analysis, one complete ECG cycle should be located. In current research, a complete ECG cycle consists of 300 data sensed by ECG sensors with the sampling rate 250Hz. After locating the R peak, an ECG cycle is considered as one hundred data before the peak and two hundred data after the peak. Then one ECG cycle data is fed into the AR model to generate related AR coefficients. AR model is given as

$$x[t] = \sum_{i=1}^{N} a_i x[t-i] + \varepsilon[t] \tag{1}$$

Where x[t] represents 300 data series of one ECG cycle, a_i is AR coefficients, ε[t] is zero mean white noise, and N is the AR order which is chosen as 4 according to [12]. After deriving AR coefficients based on one ECG cycle, ECG classification is performed to categorize this ECG cycle. Many algorithms for ECG classification have been developed in prior work achieving very good performance such as GLM based method while none of them is aimed at resource limited sensor nodes in BSNs. Our ED based method designed for BSNs simplifies the computation complexity by only performing a one-stop classification while still possessing high classification accuracy.

4.1 GLM Based Classification Method

GLM based classification is performed to differentiate a normal ECG cycle from those of the other five cardiac diseases - APC, PVC, SVT, VT, and VF in several steps. In each step, GLM based classification includes two stages. Fig. 3 shows the working flow of this algorithm.

In the first stage estimator β is computed as

$$\beta = (A'A)^{-1} A' Y \tag{2}$$

Where A is a matrix of AR coefficients, each row maps to one specific ECG cycle type out of six observed categories. Y is the response matrix representing the attribute of each category (belong to or not belong to). It is a column vector consists of 1 (belong to) and -1 (not belong to) in each row. β is calculated in each step of the classification. In the second stage, the output response is calculated as follow

$$Y_i = X\beta \tag{3}$$

Where X is a row vector consisting of tested ECG signal AR coefficients obtained from AR modeling. Y_i is the response of i-th step. β is the estimator calculated in the first stage. In each step, test ECG cycle is classified based on the sign of Y_i.

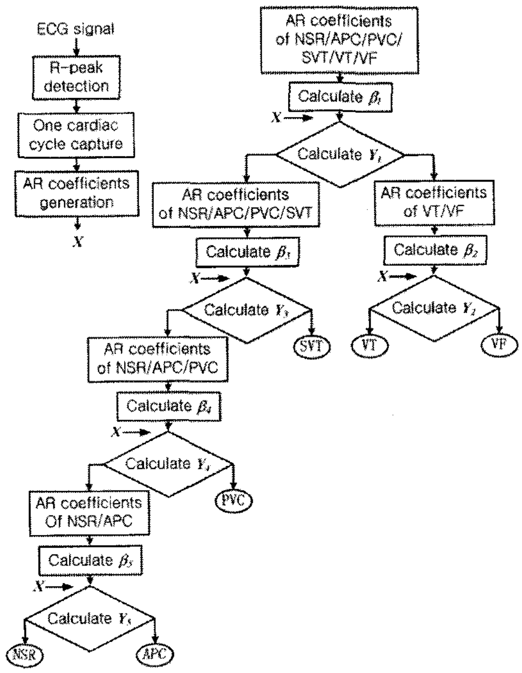

Fig. 3. ECG analysis flow chart

The total computation load is high, including floating point matrix transposition, inversion, and multiplication.

4.2 Our ED Based Classification Method

Our ED based classification method categorizes ECG cycles into abnormal or normal instead of specific cardiac diseases by computing the Euclidean distance of AR coefficients between test ECG cycles and normal sinus rhythm cycles. The Euclidean distance d between AR coefficients of current test ECG cycle $A=(a_1,a_2,a_3,a_4)$ and normal ECG cycle $B=(b_1,b_2,b_3,b_4)$ is calculated as

$$d=\sqrt{(a_1-b_1)^2+(a_2-b_2)^2+(a_3-b_3)^2+(a_4-b_4)^2} \tag{4}$$

Each time one ECG cycle is located, sensor node performs ECG analysis and determines whether this sampled cycle is abnormal or not. Only those cycles that deviate significantly from the standard normal cycles are reported to base station. A threshold δ is defined as the worst-case deviation that can be tolerated. Therefore, if the actual calculated distance d between real time cycle and the reference cycle is larger than the threshold δ, communication is initiated between the sensor node and base station to inform of the occurrence of abnormal ECG cycles. Computation of d using (4) only involves a few floating point subtractions, multiplications and square root operations.

V. Simulation Results

Power consumption is evaluated using PowerTOSSIM[13], an embedded power simulator in TinyOS for wireless sensor networks. Power consumption is mainly measured of five components: CPU, RADIO, LED, SENSOR, EEPROM. Power state of each component of the simulated mote is tracked and logged to a trace file. To determine the power consumption of each component per node, a power model is also included, which specifies the current of each working state of sensor nodes. The power consumption of each component is calculated by

$$P=\frac{time\ in\ cycles * voltage * current\ of\ each\ state}{frequency} \tag{5}$$

Where *voltage* is taken as 3V power supply; *Current* of each work state is specified in the power model generated by real hardware experiments with sensor nodes in [13]; *time* is the time duration of each state that sensor node stays and it is expressed in cycles.

In Fig. 4, power consumption of CPU cycles for ED and GLM based classification methods at 60s intervals are observed. The red line with square marks represents ED based classification method, while the blue line with round marks represents GLM based classification method. Obviously, there is a certain gap of power consumption between these two schemes and ED based method saves much more power when compared with GLM based method. On average, the CPU cycle power consumption in every 60s of using ED based method is 158.84mJ, while it is 218.88mJ of using GLM based method. Power consumption in 60s is reduced by up to 31.21% by using ED based classification method.

In Fig. 5, total power consumption includes five parts: CPU, RADIO, LED SENSOR, and EEPROM. Experimental result shows that the total power consumption difference of ED and GLM methods is smaller than that of the CPU cycles. Power consumption of ED based method can be reduced at most 13.63% in 60s when compared with GLM method. This is due to the computation delay of GLM based method. Specifically, in each cycle, a GLM based method requires around 2% more time

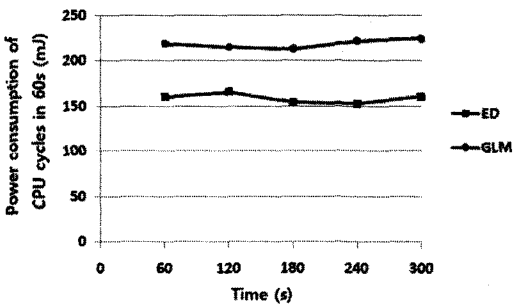

Fig. 4. Power consumption of CPU cycles every 60s.

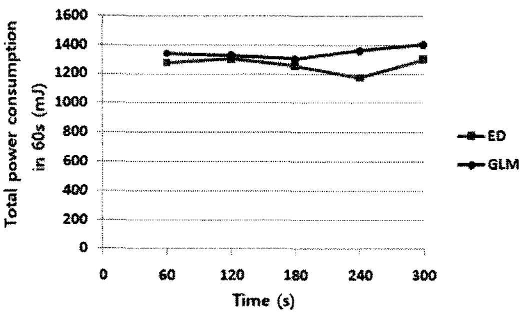

Fig. 5. Total power consumption in 60s

to finish ECG analysis. Therefore the total number of ECG cycles that can be used for diagnosis is smaller than using ED based method in specific time duration, and accordingly the power consumption of other components such as RADIO, etc is smaller than using ED based method which leads to a decrease in total power consumption. In other words, GLM based method results in smaller power consumption gap with ED based method in a specific time interval since a smaller numbers of ECG cycles are processed. This processing delay of GLM based method postpones the time of detecting any possible abnormal ECG cycles, which may lead to loss of the best treatment timing.

Test sets for ECG analysis accuracy are from MIT-BIH Malignant Ventricular Ectopy Database, Sudden Cardiac Death Holter Database, and QT Database. NSR, APC, PVC, SVT, VT, and VF cycles are acquired from these databases for ECG modeling and classification. Table 1 shows the AR coefficients for normal ECG cycles and those of various cardiac diseases.

The classification accuracy of GLM and ED based method are shown in Table 2 and Table 3. The GLM based method is tested with 118 NSR cycles, APC cycles, PVC cycles, VT cycles, and VF cycles each, which are obtained from databases mentioned above. Rows are classified by test cycles and columns are categorized by classified diseases. For example, GLM based method classifies 118 NSR cycles as 106 NSR cycles, 1 APC cycle, 9 SVT cycle, 1 VT cycle, and 1 VF cycle. The ED based method is also tested using the same test sets but only classifies them as normal or abnormal with classification threshold 1.0.

The classification accuracy comparison of GLM and ED based methods are shown in Table 4. For GLM based method, the accuracy of detecting NSR, APC, PVC, SVT, VT, and VF cycles vary from 55% to 99%. For ED based method, the accuracy of detecting normal and abnormal cycles is higher than

Table 1. AR Coefficients for ECG classes.

Classes	a(1)	a(2)	a(3)	a(4)
NSR	-2.477	2.430	-1.188	0.263
APC	-2.090	1.492	-0.227	-0.129
PVC	-2.005	0.870	0.412	-0.272
SVT	-1.946	1.204	-0.301	0.093
VT	-2.181	1.529	-0.407	0.065
VF	-1.090	-0.148	0.209	0.061

Table 2. Classification results of GLM based method.

Test cycles	Classification results					
	NSR	APC	PVC	SVT	VT	VF
NSR	106	1	0	9	1	1
APC	14	81	4	18	1	0
PVC	0	3	106	1	7	1
SVT	0	0	1	117	0	0
VT	0	0	4	0	113	1
VF	0	0	0	41	12	65

Table 3. Classification results of ED based method.

Test cycles	Classification results	
	Normal	Abnormal
NSR	112	6
APC	17	101
PVC	5	113
SVT	0	118
VT	17	101
VF	0	118

Table 4. Classification accuracy comparison.

Methods	Test cycles					
	NSR	APC	PVC	SVT	VT	VF
GLM	90%	69%	90%	99%	96%	55%
ED	95%	86%	96%	100%	86%	100%

86%. Simulation results show that ED based one-stop method is efficient in distinguishing abnormal cycles from normal cycles which is critical for sensor nodes with ECG analysis function.

Ⅵ. Conclusions

In this paper, we have described ED and GLM based ECG classification algorithms that are used for sensor nodes with ECG analysis function in BSNs, in which timely and accurately reported abnormality determines the need for emergency, sometimes even lifesaving, medical treatment from doctors. The ED based method classifies ECG cycles as normal or abnormal, leaving further diagnosis to doctors. GLM based method classifies ECG cycles into specific six classes: NSR, APC, PVC, SVT, VT, and VF. Simulation results show that using our ED based classification method, CPU cycle power consumption can be saved by 31.21% at most and overall power consumption can be reduced by up to 13.63% when compared with GLM methods. Furthermore, the classification accuracy of detecting normal and abnormal cycles with our method is higher than 86%. The accuracy of detecting NSR, APC, PVC, SVT, VT, and VF using GLM based method range from 55% to 99%. ED based method is confirmed to be more accurate in detecting abnormal ECG cycles, and more power efficient in performing ECG analysis, which is very important in BSN based ECG monitoring systems with smart sensor nodes.

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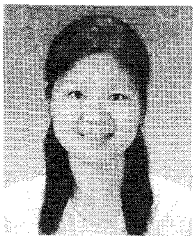

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