Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Body Sensor Network Based Context Aware QRS Detection

Huaming Li and Jindong Tan

Abstract—**In this paper, a Body Sensor Network (BSN) based context aware QRS detection scheme is proposed. The algorithm uses the context information provided by the body sensor network to improve the QRS detection performance by dynamically selecting the leads with best SNR and taking advantage of the best features of two complementary detection algorithms. The accelerometer data from the BSN are used to classify the patients' daily activity and provide the context information. The classification results indicate both the type of the activities and their corresponding intensity, which is related to the signal/noise ratio of the ECG recordings. Activity intensity is first fed to lead selector to eliminate the leads with low SNR, and then is fed to a selector for selecting a proper QRS detector according to the noise level. MIT-BIH noise stress test database is used to evaluate the algorithms.**

I. INTRODUCTION

Heart disease is the leading cause of mortality in the United States. It accounts for 30.4% deaths in the United States in 1999, which is ranked No. 1 [1]. Driven by the finance and quality issues, there are large demands to change the traditional physician/hospital based heart disease therapies into in-home and personal prevention, early detection and fitness healthcare services [2].

Recent progresses in wireless sensing/monitoring and wearable/implantable biosensors have enabled Body Sensor Networks (BSN), a promising personal and ubiquitous healthcare candidate solution. BSNs are capable of sensing, communicating and processing different physiological parameters through biosensor nodes and helping physicians to make clinical decisions. Due to their miniature sized and flexible nodes, body sensor networks are able to provide real-time context aware, noninvasive and ubiquitous health monitoring, hence help to early detect, evaluate and diagnose heart diseases. Several recent works focused on BSN based wearable medical monitoring hardware platforms, BSN energy efficient communications or body activity classification [9, 10].

In this paper, we investigate the higher level application of BSNs and propose a scheme that utilizes the context information (body activity) obtained from a body sensor network to help detect QRS complex (the most significant waveform within an ECG) in a daily ambulatory environment. Body activity information is used to select the optimal lead and the proper detector. Other context information such as blood pressure, ambient and body temperature, and brain activity etc. are also collected and added along with the activity information to the ECG annotations. In this way, each patient is able to possess a context aware personalized heart diary, which eases the heart disease early detection and provides the physicians valuable information for further analysis and diagnosis. Fig. 1 illustrates the proposed idea. The heart function can be looked as a black box which reacts to all kinds of incoming stimulus, such as daily activity, physical stress test, mental stress and environmental changes (temperature, air pressure, etc). By continuously sensing, recording and analyzing different vital signs that represent the heart reactions to different stimuli, BSNs are capable to evaluate the heart function and diagnosis potential problems effectively.

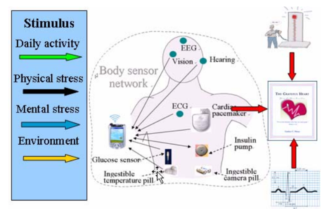


Figure 1. Body Sensor Network based heart activity analysis and recording.

This paper is organized as follows. In Section II, background and related works will be introduced. The body sensor network based context aware QRS detection algorithm will be presented in section III. Simulation results are given in Section IV. Conclusions are given in Section V.

II. BACKGROUND AND RELATED WORKS

There are several issues in testing and diagnosing heart diseases that attract our attention. First, although many heart disease problems have well-known patient aware symptoms, such as angina, shortness of breath, weakness or dizziness and nausea, many patients may suffer from silent attacks, heart diseases in the absence of any typical symptoms [3,4]. Second, coronary arteriogram is traditionally considered as the definitive "gold standard" diagnostic test. Other invasive procedures including coronary angiogram, bypass surgery, and angioplasty are widely used as testing and therapies for heart diseases. These surgeries are not only expensive, aggressive and traumatic for the patients, but sometimes proved to be overused and unnecessary according to several recent studies [5]. Therefore, noninvasive, safe and affordable heart disease diagnosis and testing approaches are highly desired. The approaches should be able to assist physicians to decide whether to refer the patient for more invasive testing and therapy.

Traditionally, exercise test and ambulatory ECG are two of the most widely accepted noninvasive procedures for identifying patients with probable heart disease [5]. During an exercise test,

The authors are with the Department of Electrical and Computer Engineering, Michigan Technological University, Houghton, MI, 49931 USA (phone: 906-487-3115; e-mail: jitan@ mtu.edu).

patients' heart rate (HR) and heart variability (HRV) are usually monitored to make the evaluation. Exercise tests and corresponding ECG processing are usually performed in a lab environment and are under the supervision of physicians. This may cause so-called White Coat Syndrome which may affect the accuracy of the test result due to mental stress. Moreover, the test may only be performed occasionally due to the cost and schedule issues. By introducing body sensor network, all the tests can be done at anywhere and anytime.

III. DISCRIPTION OF THE ALGORITHM

Ambulatory ECG records are prone to be corrupted with various types of noises, including baseline wandering (BW), muscle (EMG) artifacts (MA) and electrode motion artifacts (EM) [14, 15]. Electrode motion artifacts are considered as the hardest one to attack, because its frequency spectrum coverage is very similar to the QRS complex. MA and EM artifacts are usually caused by the movements of the patients, which is very common in a daily life, especially during an exercise test.

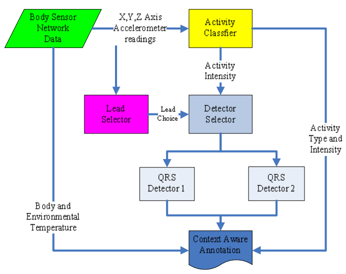


Figure 2. Block diagram of the context aware QRS complex detection

The MA and EM artifacts can be reasonably assumed to be proportional to the intensity of the body activity; hence the body activity intensity can serve as a real-time indicator of the signal to noise ratio (SNR) the QRS detector algorithms are experiencing. Many QRS detectors are shown to be complementary under variable signal contexts, which can be different combinations of QRS morphologies and clinical noise [12]. Instead of depending on a complicated all-purpose QRS detector, applying proper detectors under their optimal working condition may be a better choice.

In this paper, two complementary detectors are adopted: one is very sensitive and provides best performance when the SNR is high; the other is on the contrary, robust to noisy environment and has higher positive predictivity when the signal quality is poor. Benefiting from the context information provided by the body sensor network, it is possible to improve the QRS detection performance by dynamically selecting the leads with the best SNR and taking advantage of the best features of two complementary detection algorithms. Fig. 2 shows the block diagram of the proposed algorithm.

A. Activity Classfication

Accelerometers have been shown to be effective for body activity recognition [10]. In laboratory settings, most of the prevalent human daily activities, such as sitting, lying, standing, walking and running, have been successfully classified using one or more accelerometers [9]. The classification results indicate both the type of the activities and their corresponding intensity, which is related to the signal-to-noise ratio of the ECG recordings. Due to the miniaturized design, triaxial accelerometers can be embedded into every ECG lead in a body sensor network, so that lead-specific acceleration data can be obtained and used to make the intelligent lead and detector selection. As nodes in a wireless network, the leads can communicate with a network coordinator (a PDA or smart phone) and with each other if needed.

The measure of signal variations in the XYZ axes is suitable for distinguishing the activity intensity. In this paper, the normalized signal magnitude area (SMA) [9] is selected to represent the activity intensity.

$$SMA = \frac{1}{t}\left(\int_0^t |x(t)|\,dt + \int_0^t |y(t)|\,dt + \int_0^t |z(t)|\,dt \right) \quad (1)$$

where x(t), y(t) and z(t) is the X, Y, Z axis accelerometer readings, respectively.

If SMA is above a certain threshold, the subject is deemed to enter an active state. Z axis signal data can be further processed to detect cyclic motion, such as waling, cycling and running. By measuring the angle between the Z axis vector and the gravitational vector, postural orientation information can be deduced to distinguish lying, sitting and standing [9]. Detailed classification results as well as other context information from the body sensor network, such as ambient temperature and body temperature, will be recorded together with the ECG analysis output to form the context aware heart diary.

B. Leads Selection

Because the accelerometers are embedded in the ECG leads, their readings directly indicate the local condition of the lead. Activity intensity (SMA) is fed to a lead selector for selecting the leads with optimal SNR. Only the ECG recordings from the leads whose SMA are lower than a threshold will be used for QRS complex detection. Based on the collected SMA value, the body sensor network coordinator adjusts the threshold dynamically to guarantee the appropriate leads are selected. The number of leads that will be selected is configurable to support potential multi-leads QRS detection algorithms.

C. Candidate Detectors

SMA is also fed to a detector selector for selecting the appropriate QRS detection algorithm from two candidates according to the noise level. Two complementary QRS detection algorithms are adopted: the first is robust to noisy environment and has higher positive predictivity when SNR is low; the second is very sensitive and provides best performance when the signal/noise ratio (SNR) is high.

The first detector is based on the algorithm proposed in [12]. The ECG is passed through a differentiator fist:

$$y0(n) = x(n) - x(n-4) \quad (2)$$

Then a digital low-pass filter is applied:

$$y1(n) = y0(n) + 4y0(n-1) + 6y0(n-2)$$
$$+4y0(n-3) + y0(n-4). \quad (3)$$

The absolute value of the derivative is compared with an adaptive threshold. If the threshold value is exceeded, a candidate QRS onset is stored. Then a search is started to count further crossings to the same threshold. The QRS candidates are classified by the cross counts. If no other threshold crossings occur within the 160 ms search period, the candidate is considered as a baseline shift. If there are 2, 3 or 4 crossings, the candidate is classified as a true QRS complex. Otherwise, the candidate is considered as noise. Noise ends when the threshold is not exceeded for 200ms. After a detection of QRS the threshold is updated as:

$$Threshold_{new} = (7 \times Theshold_{old} + M/4)/8 \quad (4)$$

where M is maximum slope found in any complex. If no candidates are found within a certain period of time, the threshold will be lowered gradually to make the algorithm more sensitive.

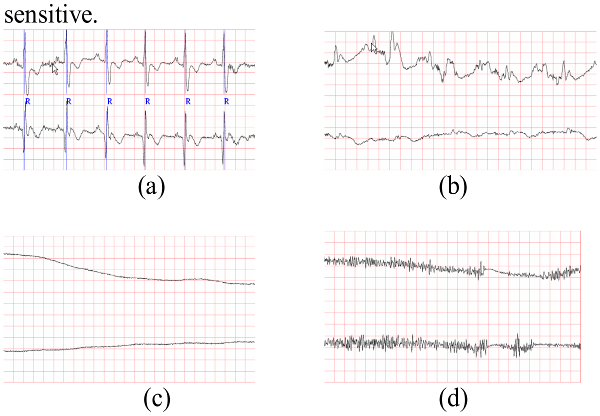


Figure 3. Noisy electrocardiograms: (a) orignal record (MIT-BIH Arrhythmia Database 118); (b) electrode motion artifact; (c) baseline wander; (d) muscle (EMG) artifact (MIT-BIH Noise Stress Test Database, 118e12)

The second detector is adapted from the algorithm developed in [13], which is composed of three parts: a low-pass filter, nonlinearly scaled curve length transformation (LT), and decision rules.

The second order recursive low-pass filter is given in the difference equation:

$$y(n) = 2y(n-1) - y(n-2) + x(n)$$
$$-2x(n-5) + x(n-10) \quad (5)$$

The curve length transformation of a continuously differentiable over the time interval [a, b] function y(t) is represented by:

$$L(w,t) = \int_{t-w}^{t} \sqrt{1+\left(\frac{dy}{dt}\right)^2}\, dt \quad (6)$$

where w is the duration of the time window, w << b-a and a+w < t < b. The ECG curve length feature can be used for QRS detection.

An adaptive LT threshold is used to find a possible QRS position and local search strategies are used to locate the QRS onset. A LT threshold is set as three times the mean value of the LT signal for the initial 10 seconds. Then the threshold base value is adjusted dynamically according to the maximum LT value of each detected QRS complex. The actual threshold is set to 1/3 of the base value. From the LT threshold-crossing point, the algorithm searches backward and forward for 125ms to get the difference (LA) between the maximum (Lmax) and minimum (Lmin) value. Then repeat the above steps to locate the positions where the LT value drops monotonically to Lmin+ LA/100 and increased to Lmax-LA/100, respectively. The two positions are considered as the base value of QRS onset and end.

D. Detector Selection

The detector selection decision is made based on the ongoing activity intensity (SMA) fed to the selector. SMA is assumed to be inversely proportional to SNR:

$$SNR = k \times \frac{1}{SMA} \quad (7)$$

where the coefficient k can be determined by an initial calibration procedure.

Then the decision is made by comparing the deduced SNR in (7) with a threshold N. When SNR < K, which indicates a noisy environment, the first algorithm is selected. When SNR >= K, the second is selected for its good sensitivity. In this study, N is empirically set to 17 dB.

TABLE I
ALGORITHM 1 & 2 PERFORMANCE COMPARISION (RECORD 118)

	24 dB	18 dB	12 dB	6 dB	0 dB	-6 dB
SE1 (%)	99.32	98.49	96.66	91.23	77.3	63.47
PP1 (%)	99.79	99	97.78	81.11	71.34	72.04
SE2 (%)	100.00	100.00	99.90	99.63	99.53	89.93
PP2 (%)	99.64	99.46	89.32	73.34	57.68	52.01

TABLE II
ALGORITHM 1 & 2 PERFORMANCE COMPARISION (RECORD 119)

	24 dB	18 dB	12 dB	6 dB	0 dB	-6 dB
SE1 (%)	100.00	99.28	98.25	96.33	89.58	78.09
PP1 (%)	98.17	98.04	97.37	89.99	75.38	66.27
SE2 (%)	100.00	99.88	99.28	99.63	99.28	98.01
PP2 (%)	99.58	98.99	88.52	70.24	53.38	49.14

IV. EXPERIMENT RESULT

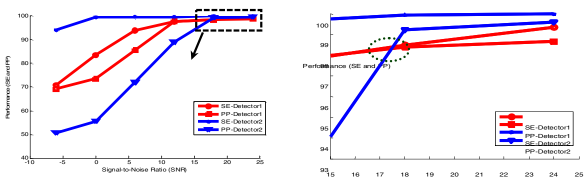
The MIT-BIH Noise Stress Test Database and MIT-BIH Arrhythmia Database are used to evaluate the algorithms. An

ECG episode with various noises is shown in Fig. 4. Bxb, a standard beat annotation comparison utility provided by PhysioNet is used for performance evaluation. Parameters are carefully chosen to make sure the two candidate detectors achieve optimal performance.

Two widely accepted benchmarks, the sensitivity (SE) and positive predictivity (PP), are adopted to evaluate the algorithms mentioned in the previous section.

$$SE = \frac{TP}{TP + FN} \qquad PP = \frac{TP}{TP + FP} \tag{8}$$

where TP is the number of true positives (correct detections), FN is the number of false negatives (missed detections), and FP (false detections) is the number of false positives. The results for the noisy ECG records 118 and 119 are listed in Table I and II, respectively. Averaged SE and PP also plotted in Fig. 4 to ease the analysis.



(a) (b)

Figure 4. Detector performance analysis under different SNR. SE refers to sensitivity and PP refers to positive predictivity. (a) SNR from -10dB to 25dB; (b) SNR from 15dB to 25dB.

As expected, algorithm 1 shows its immunity to the noise and still demonstrates a acceptable sensitivity and positive predictivity when the SNR drops to 0 and even -6 dB. This is mainly due to its rigid threshold crossing counting criteria, in which all the QRS candidates that have greater than 4 crossings are classified as noise. Algorithm 2 is very sensitive and keeps almost 100% sensitivity in the entire SNR range. However, the positive predictivity (PP) drops dramatically when the SNR is lower than 18 dB. When the SNR reaches 0 dB, the positive predictivity drops to around 50% and the results become unusable. The deterioration of PP is mainly due to the increase of FP when SNR is decreased.

Fig. 4 (a) demonstrates the trend clearly. In Fig. 4 (b), the dashed box in (a) is zoomed in. A crossing can be observed at around 17 dB, as shown in the dashed circle. This is where the detector should be switched. When SNR is above 17 dB, detector 2 is selected, and when SNR drops below 17 dB, detector 1 will be used.

V. Conclusion

A novel body sensor network based context aware QRS detection scheme has been developed. The algorithm uses the context information provided by the body sensor network to improve the QRS detection performance by dynamically selecting the leads with the best SNR and taking advantage of the best features of two complementary detection algorithms.

The two candidate algorithms are chosen to be relatively simple on purpose, because they impose lower computation requirements on the hardware, which is helpful to conserve the precious energy in BSNs and prolong the overall network life. Although the two candidate algorithms used in this paper may not be the best choice, this work demonstrates that using multi-channel ECGs and context information obtained from BSNs can improve the performance of existing QRS detectors by dynamically selecting the leads with the best SNR and switching between two complementary detection algorithms.

References

[1] Data from Centers for Disease Control and Prevention (CDC), 1999.

[2] IMIA Yearbook of Medical Informatics 2005: Ubiquitous Health Care Systems. pp. 125-138, 2004.

[3] Peter F. Cohn, Kim M. Fox; Silent Myocardial Ischemia. Circulation, 108:1263, 2003.

[4] Berman DS, Rozanski A, Knoebel SB. The detection of silent ischemia: cautions and precautions, Circulation, 75(1):101-5, 1987

[5] Marcus R, Lowe R 3rd, Froelicher VF, Do D. The exercise test as gatekeeper. Limiting access or appropriately directing resources? Chest. 107(5):1442-6, May 1995.

[6] Cole CR, Blackstone EH, Pashkow FJ, Snader CE, Lauer MS. Heart-rate recovery immediately after exercise as a predictor of mortality. The New England journal of medicine. 341(18):1351-7. Oct, 1999.

[7] Vivekananthan DP, Blackstone EH, Pothier CE, Lauer MS. Heart rate recovery after exercise is a predictor of mortality, independent of the angiographic severity of coronary disease. Journal of the American College of Cardiology. 42(5):831-8, Sep, 2003.

[8] Makikallio TH, Huikuri HV, Makikallio A, Sourander LB, Mitrani RD, Castellanos A, Myerburg RJ. Prediction of sudden cardiac death by fractal analysis of heart rate variability in elderly subjects. Journal of the American College of Cardiology, 37(5):1395-402. Apr, 2001.

[9] Karantonis, D.M. Narayanan, M.R. Mathie, M. Lovell, N.H. Celler, B.G. Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring. IEEE Transactions on Information Technology in Biomedicine, Issue: 1, 156-167, 2006.

[10] Parkka J, Ermes M, Korpipaa P, Mantyjarvi J, Peltola J, Korhonen I. Activity classification using realistic data from wearable sensors. IEEE transactions on information technology in biomedicine, 10(1):119-28, 2006.

[11] Pan, J., and Tompkins, W. J. A real-time QRS detection algorithm, IEEE Trans. Biomed. Eng., BME-32(3), pp. 230–236, 1985.

[12] W.A.H. Engelse and C. Zeelenberg, A single scan algorithm for QRS-detection and feature extraction, Computers in Cardiology 6:37-42, 1979.

[13] W. Zong, G.B. Moody, D. Jiang. A robust open-source algorithm to detect onset and duration of QRS complexes, Computers in Cardiology 30:737-740, 2003.

[14] Friesen, G., Jannett, T., Jadallan, M., Yates, S., Quint, S., and Nagle, H. A comparison of the noise sensitivity of nine QRS detection algorithms, IEEE Trans. Biomed. Eng., 37, pp. 85–98, 1990

[15] Portet F, Hernandez AI, Carrault G. Evaluation of real-time QRS detection algorithms in variable contexts. Med Biol Eng Comput. 43(3):379-85. May 2005.

[16] Kohler, B.-U.; Hennig, C.; Orglmeister, R. The principles of software QRS detection, IEEE Eng. Med. Biol. Mag., 21(1), pp. 42–57, 2002.