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QRS Detection and Data Compression Based On Adaptive Algorithm in a Wireless Wearable Sensor

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Abstract: The paper presents the QRS detection and data compression based on LMS algorithm in a wireless wearable sensor. The proposed method achieves a high sensitivity of 99.64% and positive prediction of 99.81% ECG database. The compression algorithm is used the adaptive linear data prediction scheme, which can obtain a lossless bit compression ratio (BCR) of 2.286x and to prevent the possibility of losing any patient information of potential diagnostic value. The experimental results shows that the proposed method has better QRS detection and data compression than existing methods
Keywords: QRS detection, Lossless data compression, ECG-on- Chip, Wearable devices, Wireless Sensors.

I. INTRODUCTION

The ECG signal is extremely important for the diagnosis of the cardiac patients. However, when the ECG signal is recorded, it may be corrupted by various kinds of noises, such as, power line interference, base line wandering, electrode contact noise, motion artifacts, muscle contraction, instrumentation noise generated by electronic devices and electrosurgical noise, etc. During the diagnosis of arrhythmia or myocardial infraction, the 50 Hz power line noise can affect the ECG signal.

The frequency range of ECG signal is generally 0.05 Hz to 100 Hz, and, that of the power line interference is 50 Hz which lies in the ECG signal band. So, it has become very crucial to remove the power line interference from the ECG signal. Different types of digital filters (FIR and IIR) have been used to solve the problem [I]-[5].

However, it is difficult to apply these filters with fixed coefficients to reduce the power line interference, because the ECG signal is known as a non-stationary signal.

The main challenge involved in wearable ECG sensor is to make the device low profile, unob-trusive, easy to use with long battery life for continuous us-age. A high level of integration with inbuilt signal acquisition and data conversion is required to minimize the size, cost and power consumption of such a sensor. The major source of power consumption in such a system is the wireless transceiver, and hence it is desirable to carry out preliminary ECG analysis tasks like QRS detection [6] and R-R interval estimation locally.

This allows the transmission to be triggered only when it is deemed necessary based on cardiac rhythm analysis. Further, the large quantity of ECG data obtained by round the clock monitoring may need to be either stored lo-cally in a flash device or transmitted wirelessly to a monitor-ing gateway for further analysis. The transmission of data in-curs high power consumption, and the use of a local storage increases the device cost. The cost is further affected by the need for an on-chip SRAM which is typically used to inter-face the ECG chip with a microcontroller [7] to support burst transfer.

The rest of this paper is organized as follows. In section II, we describe the overview of the proposed method. The performance measurements introduced in sections III. Section IV gives some experimental results. Finally, a conclusion will be presented in section V.

II. PROPOSED METHOD

THE block diagram of proposed method as shown in fig.1. In the proposed method, a linear predictor is used to estimate the present sample and previous *m* samples. The estimated value is calculated between the actual sample and instantaneous prediction error then the identifying the location of QRS complex.

The QRS detection method used to identify the peaks of ECG signals and detect. ECG compression is used to minimize the ECG signal as explain each method in next section.

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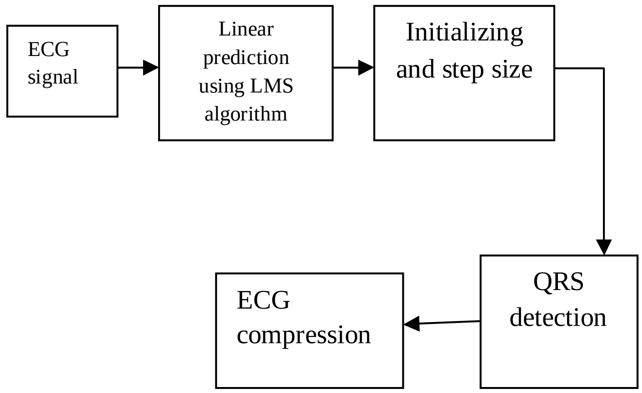

Fig.1. block diagram of proposed method

A. LMS algorithm

A significant feature of LMS is its simplicity it does not require correlation functions but it require matrix inversion. To find this, estimate the correlation matrix R and cross-correlation matrix P by instantaneous estimates i.e.

R(n) = u(n) uH (n)

P(n) = u(n) d∗(n)

Correspondingly, the instantaneous estimate of the gradient-vector is

$$y(n) = \sum_{n\ 0}^{N\ 1} w(n)x(n)$$

For updating predictor weights

$w(n+1) = w(n) + \mu u(n)[\, d*(n) - u^{H}(n)\, w(n)]$

Find the difference between the desired response and the output of the adaptive filter.

$$e(n) = y(n) - d(n)$$

$w(n+1) = w(n) + \mu u(n)\, e*(n)$

Where the estimation error e (n), present tap-weight vector w(n). μ: is the step size of the adaptive filter. $\vec{w}(n)$: Is the filter coefficients vector. $\vec{x}(n)$: Is the filter input vector

B. QRS detection

Detecting the peaks of the ECG signal based on savtizky-golay (SG) filtering and adaptive thresholding and peak detection. SG filters smoothens the incoming ECG signal by approximating the signal within a specified mask of size *L* to a polynomial of order *K*, which best matches the given ECG signal in a least-squares sense. A polynomial of order *K* is defined as

$$f_K(\mathbf{x}) = \sum_{i=1}^{K} c_i x^i$$

SG filters are beneficial in maintaining the higher order moments in the in-put signal. To select the order and frame size (*K*, *L*) of the SG filter for removing gausian noise from the prediction error, we computed the QRS detection accuracy based on ECG database for various combinations of (*K*, *L*) with *K* ranging from 3 to 6 and *L* ranging from 9 to 17.

The enhanced signal of ECG signal is given by

$$eno(n) = \sum_{n=-M/2}^{M/2} |e\_sg(n)|^2$$

Based on eno (n) to find QRS peaks based on adaptive thresholding and peak detection. The average threshold, *Thavg* is computed on the average of all detected peaks is given by

$$Th_{avg} = 0.25 * \frac{1}{4} * \sum_{k \le 3} Th_k$$

Th_k in the beginning, and a new threshold is computed based on the maximum value of the signal in a training period and every time the signal exceeds the threshold, the peak detection algorithm searches and locates the presence of a peak. The peak detection algorithm starts when the filtered signal *eno*(*n*) exceeds the threshold. It begins with finding a continually rising edge and then a continuously falling edge within a specific period of time. In order to prevent sudden peak changes from affecting the threshold adaptation, the peak amplitude considered for each detection is limited to two times the previously detected peak. For this, the *RR* intervals from past all successful detections are averaged to find *RRavg is given by*

$$RR_{avg} = \left(\frac{1}{4}\right) * \sum_{i=1}^{4} RR_i .$$

C. ECG compression

The dynamic range of the prediction error signal $e(n)$ is given by

$$e(n) = y(n) - d(n)$$

The error signal $e(n)$ is low, and centers around zero except for the segment corresponding to the QRS complex. However, it should be noted that for preserving the data without any loss, we need (M+2) bits to fully represent $e(n)$, where M is the bit-width of $x(n)$. Further, a coding scheme can be used to reduce the bit-width of $e(n)$ without incurring any data loss. Instead of transmitting the whole sample, only the coded data has to be stored/transmitted, resulting in power/memory savings. The algorithm of compression and decompression of ECG signal as shown

1) Compression

a) Initialize the SSLMS predictor

b) While new input sample do

i) Estimate new sample, $\hat{x}$, from previous sample using SSLMS predictor

ii) Read new sample, x

iii) Compute prediction error e(n)= x- $\hat{x}$

iv) Update SSLMS predictor weights

v) Clip e(n) to obtain min bit width 2's C representation

2) *De-Compression*

a) Initialize the SSLMS predictor and estimate the first sample, $\hat{x}$

b) Unpack frames using data format from Table IV, to get e(n)

c) Re construct original data with x(n)= $\hat{x}(n)$*+e(n) and feedback to the predictor.*

III. PERFOMANCE MEASUREMENTS

To evaluate the QRS detection performance, false positive (*FP*) and false negative (*FN*) detections are used. Further, by using *FP* and *FN*, the sensitivity (*Se*) and positive prediction (+P) are computed using the below equations: Here *TP* stands for true positive, i.e., the number of QRS correctly detected.

$$Se\ (\%) = \frac{TP}{TP + FN}$$

$$+P\ (\%) = \frac{TP}{TP + FP}$$

IV. EXPERIMENTAL RESULTS

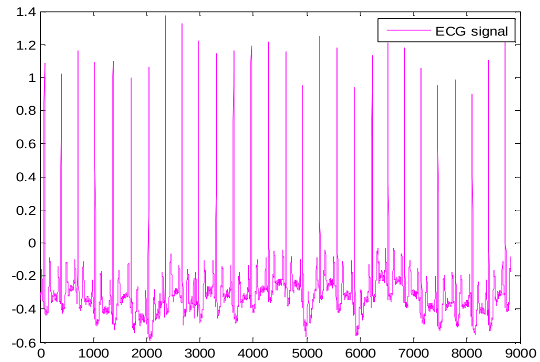

Fig.4.1 ECG signal

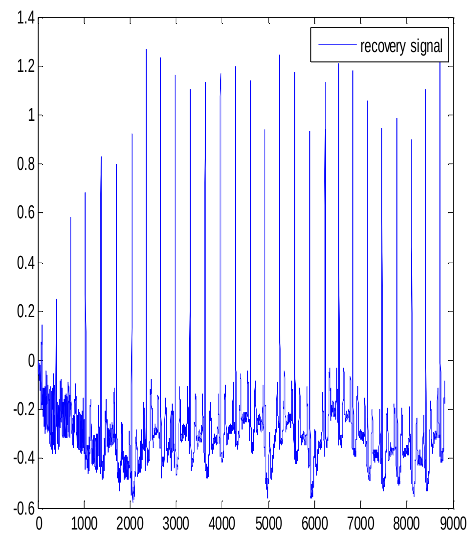

Fig.4.2 recovery signal

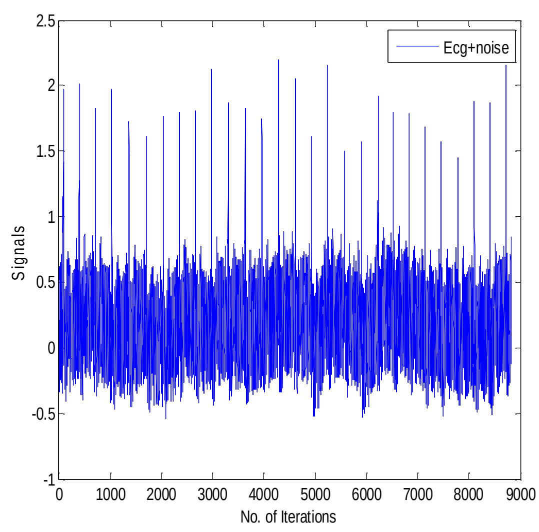

Fig.4.3 Instantaneous prediction error, $e(n)$

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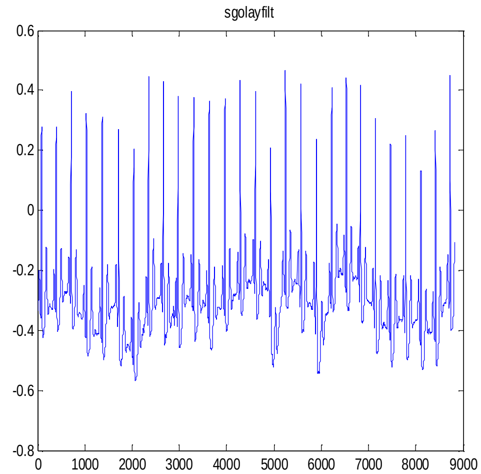

Fig.4.4 sgolayfilt ECG signal

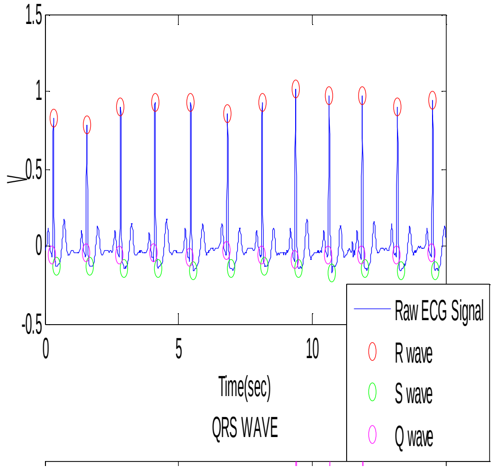

Fig.4.5 QRS detection

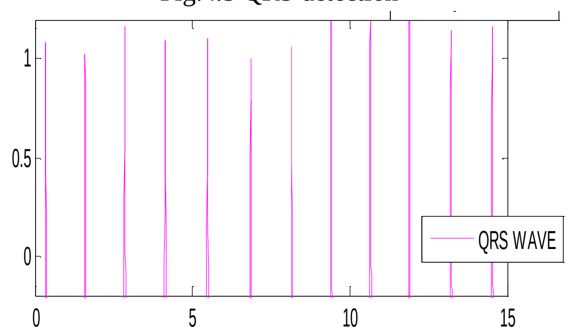

Fig.4.6 QRS wave

V. CONCLUSION

The paper presents the QRS detection and lossless data compression in a wireless wearable sensor. It achieves high sensitivity and positive prediction of ECG database. The compression algorithm is obtain a lossless bit compression and better quality of ECG signal The experimental results shows that the proposed method has better QRS detection and data compression.

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REFERENCES

[1] T. Gar, C. Thomas and M. Friesen, "Comparison of Noise Sensitivity ofQRS Detection Algorithms," IEEE Tran. Biomed. Eng., vol. 37, no.l, pp. 85-98, January 1990.

[2] R Limacher "Removal of Power Line Interference from the ECG Signal by an' Adaptive Digital Filter," in Proc. of European Tel. Conf, Garmisch-Part, pp. 300-309, M ay 21-23, 1996.

[3] j M ateo, C. Sanchez, A. Torres, R. Cervigon, and 1. 1. Rieta, "N eural Network B ased Canceller for Power Line Interference in ECG Signals," Computers in Cardiology, vol. 35, pp. 1073-1076, April 2008.

[4] M . Kaur and B . Singh, "Power Line Interference Reduction in ECG Using Combination of MA M ethod and IIR Notch Filter," Int. J. of Recent Trends in Eng., vol. 2, no. 6, pp. 125-129, November 2009.

[5] M. S. Chavan, R. Agarwala, M. D. Uplane, and M. S. Gaikwad, "Design of ECG Instrumentation and Implementation of Digital Filter for Noise Reduction," World Scientific and Engineering Academy and Society(WSEAS), Stevens Point, Wisconsin, USA, vol. 1, no. 157-474, pp. 47-50, January 2004.

[6] G. Nallathambi and J. Principe, “Integrate and Fire Pulse Train Automaton for QRS detection.,” IEEE Trans. Biomed. Eng., vol. 61, no. 2, pp. 317–326, Sep. 2013.

[7] C. J. Deepu, X. Xu, X. Zou, L. Yao, and Y. Lian, “An ECG-on-Chip for Wearable Cardiac Monitoring Devices,” 2010 Fifth IEEE Int. Symp. Electron. Des. Test Appl., pp. 225–228, 2010.