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Peak Detection of ECG Signals with Data Compression

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ABSTRACT: The proposed work presents a joint QRS detection and data compression scheme for ECG signals. Since QRS detection and data compression is done together, it reduces the average computational complexity and power consumption of the devices. The joint approach uses sharing of a single step adaptive linear predictor for both detection and compression. ECG data is taken from MIT/BIH Arrhythmia Database. Here a Joint QRS Detection Compression (JQDC) scheme is used. The proposed algorithm reduces the average complexity by sharing the computational load among multiple essential signal processing tasks needed for wearable sensors. The compression algorithm achieves a bit compression ratio of 2.03xx. The algorithm also achieves a Sensitivity (Se) of 100% and Positive Prediction (+P) of 100% in almost all the ECG tapes tested.

KEYWORDS: ECG Signal; Wearable Devices; QRS Detection; Sensitivity; Positive Prediction; Lossless Data Compression; Bit Compression Ratio (BCR)

I. INTRODUCTION

Cardiovascular disease is the main cause of death in the UK and it accounts for 39% of all death each year. Among patients who had heart attacks, about 30% of them died even before reaching to the hospital. Although heart attack can happen suddenly without apparent indications, cardiac rhythm disturbances can often be found before the event. They can potentially be used as the precursor to major cardiac episodes. Currently, ECG (Electrocardiogram) Holter monitoring is the most widely used technique for providing ambulatory cardiac monitoring for capturing rhythm disturbances. A wireless sensor network (WSN) (sometimes called a wireless sensor and actor network (WSAN)) are spatially distributed autonomous sensors to monitor physical conditions like EEG, EMG, blood pressure, respiratory rate, heart rate etc.The realization that the proprietary designed WSN are not ideally suited for monitoring human body and its internal environment has led to the development of a wireless body sensor network (BSN) platform. BSN architecture aims to set a standard of development of a common approach towards pervasive monitoring.

The BSN node ensures the accurate capturing of data from sensor to which it is connected, carries out low level processing of data and wirelessly transmit this information to a local processing unit (LPU). The data in this way from all the sensors are collected, processed and transmitted to a central monitoring server through a wireless LAN, Bluetooth or mobile phone.One of the major use of wireless BSN is in cardiology.Healthcare spending is increasingly becoming the major contributor of expenditure in many countries. U.S. alone spends roughly 18% of its GDP on healthcare. This can be achieved by proactive and long-term monitoring of individual's cardiovascular health using low-cost wearable electrocardiogram (ECG) sensor devices. The main features of the ECG, i.e., the P, Q, R, S, and T points, give information about the cardiac health of the person. Electrocardiography is the process of recording the electrical activity of the heart over a period of time using electrodes placed on a patient's body. These electrodes detect tiny electrical changes on skin that arise from heart muscle depolarizing during each heartbeat.

A wearable ECG sensor, as shown in figure.1, can be used to acquire, process, and wirelessly transmit ECG signal to a monitoring center. The main challenge involved in the development of the sensor is to make the device low profile, unobtrusive, easy to use with long battery life for continuous usage. 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

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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 and RR interval estimation locally. This allows the transmission to be triggered only when it is deemed necessary based on cardiac rhythm analysis.

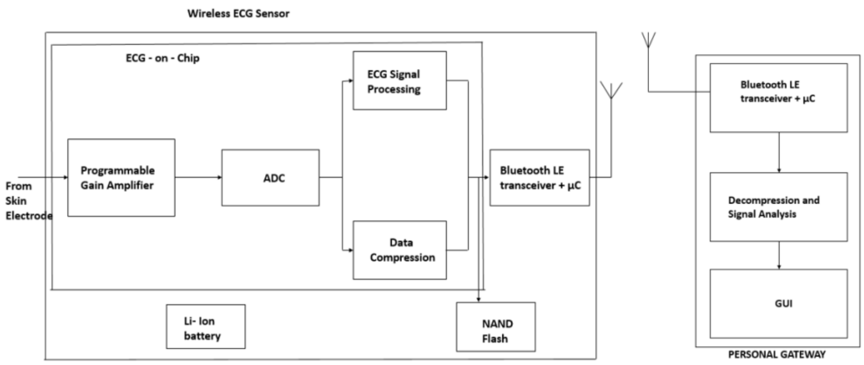

Fig. 1. Wearable ECG monitoring system

Further, the large quantity of ECG data obtained by round the clock monitoring may need to be either stored locally in a flash device or transmitted wirelessly to a monitoring gateway for further analysis. The transmission of data incurs 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 interface the ECG chip with a microcontroller to support burst transfer [1].

II. Related work

In [2] authors introduced a low-power wearable ECG monitoring system has been developed entirely from discrete electronic components and a custom PCB. This device removes all loose wires from the system and minimizes the footprint on the user. The monitor consists of five electrodes, which allow a cardiologist to choose from a variety of possible projections. Clinical tests to compare our wearable monitor with a commercial clinical ECG recorder are conducted on ten healthy adults under different ambulatory conditions, with nine of the datasets used for analysis. The cardiac monitor is designed using a flexible PCB. It has an “L”-shaped board, which is 11.4 cm tall and 5.1 cm wide in the vertical section, and 11.4 cm long and 3.8 cm wide in the horizontal section. The board is designed in an “L” shape to allow the clinician to choose one of several possible ECG vectors to record, depending on a patient’s specific needs. The board can be mounted on the user’s chest in two preferred configurations. The first configuration (type 1) consists of the “A”-axis aligned with the sternum and the “B”-axis underneath the left pectoralis muscle. The monitor can also be rotated 90^o clockwise, so the “A”-axis rests horizontally above the left pectoralis and the “B”-axis is aligned along the sternum (type 2). In [3] authors introduced a wireless ECG plaster that can be used for real-time monitoring of ECG in cardiac patients. The proposed device is light weight (25 grams), wearable and can wirelessly transmit the patient’s ECG signal to mobile phone or PC using ZigBee. The device has a battery life of around 26 hours while in continuous operation, owing to the proposed ultra-low power ECG acquisition front end chip. The prototype has been verified in clinical trials. The overall system includes two parts: (1) a wireless ECG acquisition plaster, and (2) a personal gateway (or remote station). The ECG plaster contains a custom designed ECG front-end chip, a microcontroller, and a ZigBee transceiver. The personal gateway can be either a mobile phone or a PC with an USB ZigBee interface. The plaster records the ECG and wirelessly transfers the data to remote data center through the personal gateway. The ECG acquisition chip is designed for low power use. The proposed device is wearable, light weight and can wirelessly transfer the patient’s ECG signal to a remote monitoring station, where it can be analyzed in detail. The device has a battery life of around 26 hours using a 650mAH rechargeable Lithium Ion battery while performing continuous ECG recording.In [4] authors presented a down-sampling QRS complex detection algorithm. It is based on wavelet transform. This algorithm reduces the power consumption and memory size to a great extend. WT is calculated by a cascade filter bank to get the detail and approximation part of the signal. The down sampling methods used include WT

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and Low-Power QRS Complex Detection, Parameters Selection of WT, Low-Complexity and Low-Power Filter Design and Detection of QRS Complex. Based on our algorithm, the reduction of data volume saves hardware resource and lowers the demand of work frequency.In [5] authors presents a novel Dual-Slope QRS detection algorithm with low computational complexity, suitable for wearable ECG devices. The Dual-Slope algorithm calculates the slopes on both sides of a peak in the ECG signal; And based on these slopes, three criterions are developed for simultaneously checking 1)Steepness 2)Shape and 3)Height of the signal, to locate the QRS complex. In [6] authors presented the impact of MIT-BIH arrhythmia database. The MIT-BIH Arrhythmia Database was the first generally available set of standard test material for evaluation of arrhythmia detectors, and it has been used for that purpose as well as for basic research into cardiac dynamics at about 500 sites worldwide since 1980. It has lived a far longer life than any of its creators ever expected. Together with the American Heart Association (AHA) Database, it played an interesting role in stimulating manufacturers of arrhythmia analyzers to compete on the basis of objectively measurable performance, and much of the current appreciation of the value of common databases, both for basic research and for medical device development and evaluation, can be attributed to this experience. In this work, authors briefly review the history of the database, describe its contents, discuss what have been learned about database design and construction, and take a look at some of the later projects that have been stimulated by both the successes and the limitations of the MIT-BIH Arrhythmia Database. In [7] authors proposed another peak detection method that uses decision rules to discriminate the QRS complex from noise events. There is a pre-processor section which performs linear and nonlinear filtering of ECG signal. The decision rule is based on the output of the pre-processor. QRS complexes has steep amplitude, but simple peak detection algorithm falsely detects multiple peaks due to ripples in the wave. A simple local maxima peak detector is used here which can detect small- amplitude peaks. Both peaks results from same QRS complex, but one peak is classified as QRS complex and other as noise. Low pass filtering helps to reduce the ripples and multiple peaks. Instead of using a filter, in this work, a peak detection algorithm is used. It will find peaks in final output of filtering stage and these peaks define an event. The algorithm stores maximum levels and new peak is defined only after half the maximum of that height is crossed. MIT/BIH tapes are pre-processed and for each detected peaks a 2-dimension vector is defined. QRS detectors may be optimized with respect to false positives and negatives. Here the decision rules are optimized to minimize sum of false negative and false positive detections. Peak level estimator is used to predict next QRS peak from previous one. Here peak detection is done using mean, median and iterative prediction. Similarly RR interval is also calculated. The results shows that the detector produces 340 false negative detections and 248 false positive detections for a sensitivity of 99.69% and positive prediction of 99.77%.

III. PROPOSED JQDC SCHEME

Wearable ECG monitoring systems have been implemented on a large scale in recent years. Several studies have been conducted in this field and there are more yet to come. Literature review gives a brief information regarding different methods of ECG data collection and about the type of sensors. In all these works QRS detection and data compression are done separately and this increases the system complexity and power consumption. In this work, a joint approach for QRS detection and ECG compression algorithm for use in wireless sensors is used. The central idea of the proposed algorithm is to use a single technique for processing of QRS detection and data compression, instead of using two distinct approaches. The algorithm lowers the average computational complexity per task by sharing the computational load among two operations. This is done using a shared adaptive linear predictor for performing both ECG beat detection and lossless data compression. In addition, a novel fixed-length data coding-packaging technique for convenient representation of the signal entropy is used [1].

In these approaches, a forward predictor is used to estimate the current sample of the ECG signal, x(n), from its past m samples, i.e.,

$$\hat{x}(n) = \sum_{k=1}^{m} h^k \, x(n-k) \qquad (1)$$

where, $\hat{x}(n)$ is the estimate of x(n) and h^k is the predictor coefficient. Upon convergence, the predictor is able to closely estimate the future samples, including the P, T wave segments and the slow baseline variations in the ECG

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signal. Therefore, the instantaneous prediction error e(n), which is the difference between the actual sample and its estimate will be minimal in these regions. The prediction error is given in eq.(2).

$$e(n)= x(n) - \hat{x}(n) \qquad (2)$$

For signal regions with steep amplitude variations, like the QRS segment, the predictor statistics are considerably different and hence will result in a higher prediction error.Therefore, the prediction error can be used as a marker to locate the QRS complex in the ECG signal. The complete JQDC scheme is shown in figure 2.

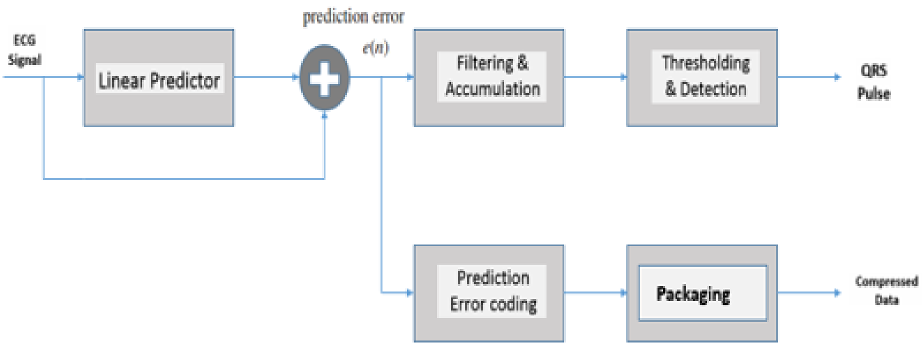

Fig.2 JQDC scheme: Overall block diagram

Several factors affect the detection accuracy, CR, and hardware complexity in the proposed joint detection and compression algorithm. In the following, we analyze the effect of linear predictor selection, order of the predictor, and step size. In the proposed JQDC scheme, an adaptive predictor is used, so that predictor self-adjusts output based on the incoming signal statistics. The predictor is realized by using a tapped-delay line structure. For updating predictor weights, LMS algorithm and its variants were considered. Sign Sign Least Mean Square (SSLMS) algorithm is used here as its implementation complexity is the lowest.

$$\text{SSLMS } h(n+1) = h(n) + \mu.\ \text{sgn}\ (e(n))\ .\text{sgn}\ (x(n)) \qquad (3)$$

Here, μ and β are the step sizes, and h(n+1) and h(n) are updated and current predictor coefficients, respectively. An Adaptive Linear Predictor is shown in figure 3.

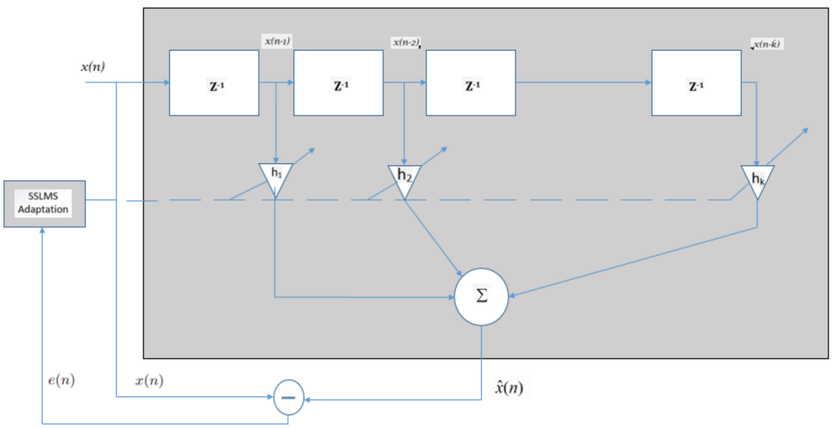

Fig.3. Adaptive Linear Predictor

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The order of linear predictor is highly related to performance of proposed JQDC and hardware cost. The performance increases as the order is increased till 4 and started to gradually decline thereafter. As the order increases QRS segment becomes more and more predictable, and hence, the instantaneous error contains less signal component of the QRS complex, which results in a lower detection accuracy. Adaptive techniques require several cycles to converge to the optimal point based on the incoming signal characteristics.

A simple coding-packaging scheme is used here, which gives a practical, fixed-length 16-bit output and has low hardware complexity. The coding-packaging routine is summarized in Table 2. Here, the 2's complement representation (e_2c(n)) of the error signal is used. Since most error samples centers around zero, it can be represented in only a few bits. Therefore, we only retain the necessary LSB's and remove any MSBs that do not carry information. However, the problem in using this approach is that the bit clipped, 2's complement encoded samples are of varying bit widths and cannot be stored continuously in a memory as it lacks the prefix-free nature of the Huffman codes. Hence, we introduce a simple bit packaging scheme which can pack data samples of varying bit widths dynamically to produce a fixed-length data output of 16 bits. Each individual data packet will be marked with a unique header so as to easily identify and decode the data while decompressing. The lossless data compression scheme is shown in figure 4 and data packaging format is listed in table I.

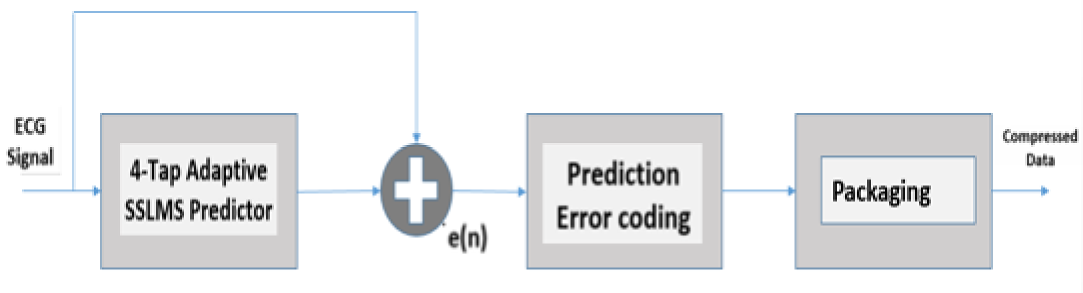

Fig.4. Lossless Data Compression Scheme

Frame Type	Header	Data (Bits)
A	1	5 or 4
B	01	7 or 6
C	0001	3
D	0000	2
E	0011	12

Table.I. Data Packaging Format

Simplified Data Packaging Routine
1) Receive 2'sC coded prediction error, e_2c(n), into a 6–word local memory.
2) If the memory is full go to Step 3), else go to Step 1)
3) If -2 ≤ e_2c (n−5 ≤ i ≤ n) ≤ 1, append header '0000', use framing format D form Table IV and go to Step 1) else Step 4)
4) If -4 ≤ e_2c (n−3 ≤ i ≤ n) ≤ 3, append header '0001', use framing format C form Table IV and go to Step 1) else Step 5)
5) If -16 ≤ e_2c (n−2 ≤ i ≤ n) ≤ 15, append header '1', use framing format A form Table IV and go to Step 1) else Step 6)
6) If -64 ≤ e_2c (n−1 ≤ i ≤ n) ≤ 63, append header '01', use framing format B form Table IV and go to Step 1) else Step 7)
7) If -65 ≥ e_2c (n) ≥ 64, append header '0011', use framing format E form Table IV, replacee2c(n)with corresponding x(n) and go to Step 1)

Table.II. Simplified coding- packaging routing

The dynamic data packaging scheme uses a simple priority encoding technique to frame fixed-length data from samples of multiple bit widths. As and when the error data are received, the algorithm checks whether the maximum amplitude of a signal group (e_2c (n – j ≤ i≤ n)) exceeds the value that particular frame format can accommodate from table I based on the packaging routine given in table II. If not, the algorithm proceeds with the next best framing option. Full data frames of Type E can be sent periodically at a predetermined interval to add resilience against transmission

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errors.But in normal cases fixed length coding cannot be used since the simultaneous signals in the ECG data are not of fixed length and hence decoding becomes more complex, but it provides better CR. Otherwise same bit length codes have to be found out and arranged according to the table and the same should be applicable while decoding. Here just the header is added before the code and fixed length coding is not used. Each samples of ECG signal is considered. The algorithm first checks the first sample and according to the number of bits of the sample, headed is selected. Before adding the header, the 2's complement of the data is found out and is converted into binary form. Since most of the samples centers around zero value, it can represents only a few bits and hence it is necessary to retain LSB's and remove MSB's that do not carry any information. Header is added to the data. Similarly it is done for all the samples and the entire data is combined into a single output data. The coded data is transmitted to the monitoring center and the same table can be used to decode the data and reconstruction of signal is done.

Compression
1) Initialize the SSLMS predictor
2) While new input sample do
  a. Estimate new sample,$\hat{x}(n)$, from previous sample using SSLMS predictor
  b. Read new sample, x
  c. Compute prediction error e(n) = x(n) $-\hat{x}(n)$
  d. Update SSLMS predictor weights
  e. Clip e(n) to obtain min bit width 2's C representation
  f. Package using routine in Table 3.3

De-Compression
1) Initialize the SSLMS predictor and estimate the first sample, $\hat{x}(n)$
2) Unpack frames using data format from Table 3.2, to get e(n)
3) Reconstruct original data with x(n) = $\hat{x}(n)$+ e(n) and feedback to the predictor.

The coded signal is transmitted to the monitoring center and it is decoded using the same header table. First the algorithm checks the header and accordingly number of bits are assumed and using loop function that much bits are taken and converted into decimal form and inverse 2's C is found out. Similarly all the samples are decoded and the signal is reconstructed again using linear predictor. From the error signal and the predicted sample the original signal can be reconstructed as in eqn.11,

$$x(n) = \hat{x}(n) + e(n) \qquad (4)$$

The bit clipping of error signal is removed before reconstruction. The reconstructed signal is fed back to the linear predictor and error signal is calculated from which QRS detection is done. The error signal consists of impulse noises. To remove impulse noises moving average filtering is done and the smoothened signal is enhanced by squaring and moving sum method. Adaptive thresholding and peak detection is done.

The instantaneous prediction error, e(n), from the adaptive SSLMS predictor is used for locating the QRS complex. This is because the error corresponding to QRS segment is relatively higher than that of P, T wave and baseline variations. The prediction error also contains high frequency impulse noise, which has to be filtered out so as to easily locate the QRS complex. Typically, moving average filters are effective in removing impulse noises and smoothening of such signals. However in doing so, it also smoothens and distorts the shape and the height of the error peaks corresponding to the QRS complex. It is important to preserve the integrity of the signal content corresponding to QRS, while smoothening the high-frequency and impulse noise that corresponds to the other regions of ECG. To achieve these goals, a Moving Average filter is employed to remove the high-frequency impulse noise from the prediction error. Once the impulse noise is removed, the signal is further enhanced by using a squaring and moving sum operation for adaptive thresholding and peak detection. The block diagram of the QRS detection scheme is illustrated in Fig.5.

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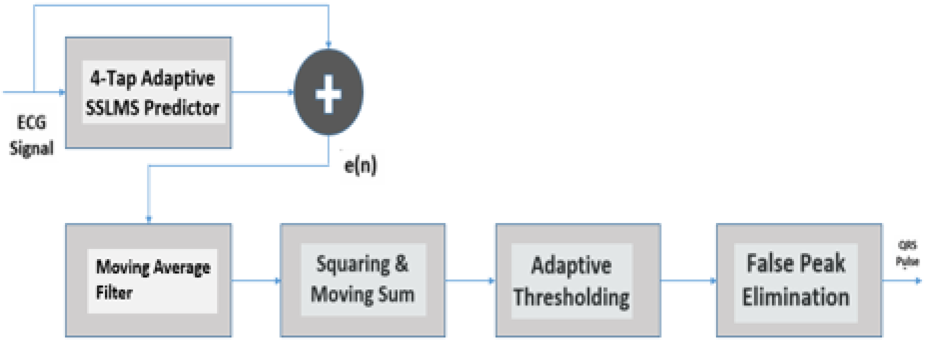

Fig.5. QRS detection block diagram

The moving average is the most common filter in DSP, mainly because it is the easiest digital filter to understand and use. Given a series of numbers and a fixed subset size, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by "shifting forward"; that is, excluding the first number of the series and including the next number following the original subset in the series. This creates a new subset of numbers, which is averaged. This process is repeated over the entire data series. The plot line connecting all the (fixed) averages is the moving average. M is the number of points or span of averaging filter.

$$e\_sg(n) = \frac{1}{M}\sum_{j=0}^{M-1} x[n+j] \quad (5)$$

Once the high-frequency impulse noise is suppressed, the signal is further enhanced by squaring and taking the moving sum of the signal before the thresholding operation. The instantaneous signal samples are squared, as in, to provide a nonlinear amplification to the prediction error, which helps to further magnify the QRS component in the signal relative to the other segments. Furthermore, moving window integration is done to obtain a smooth waveform for thresholding and peak detection.

$$eno(n) = \sum_{n=-\frac{m}{2}}^{\frac{m}{2}} |\, e\_sg(n)|^2 (6)$$

The enhanced signal, eno(n), is continuously scanned to find QRS peaks. As the signal amplitudes vary across patients and based on external conditions, an adaptive threshold is used for detection. The threshold is initialized with a default value, Th_{def} in the beginning, and a new threshold is computed based on the maximum value of the signal in a training period of first 2 s, i.e., the threshold is updated to 25% of the maximum value during this period. Every time the signal exceeds the threshold, the peak detection algorithm searches and locates the presence of a peak, T_{amp} , as described later. The average threshold , Th_{avg} is computed as 25% of the average of last four detected peaks, and is given in eqn.5,

$$Th_{avg} = 0.25 * \frac{1}{4} * \sum_{k\leq 3} Th_k \quad (7)$$

In order to prevent sudden amplitude changes from affecting the threshold adaptation, the peak amplitude considered for each detection is limited to two times the previously detected peak An automated threshold reduction mechanism is employed to ensure that a decrease in the peak amplitude of the signal corresponding to QRS peaks does not cause a lockup condition, whereby subsequent peaks are not detected due to a higher threshold. For this, the RR intervals from past four successful detections are averaged to find RR_{avg} .

$$RR_{avg} = \frac{1}{4} * \sum_{i=1}^{4} RR_i (8)$$

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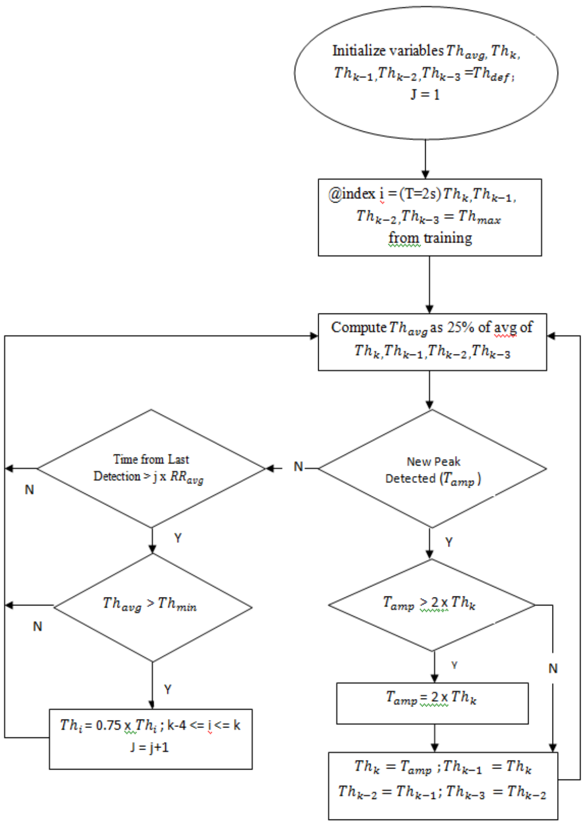
For every RR_{avg} duration, if a new peak is not detected, then the average threshold is reduced to 75% of its current value. Initially threshold is set as the 25% of maximum value of amplitude of the smoothened signal and this initial threshold is updated based on the incoming samples. Once a signal crosses the threshold value the signal is selected. The threshold is made 25% of maximum of first 500 samples to get more accurate results. All the peaks whose value is lesser than threshold value is removed, hence smaller peaks get removed. Average width is signal is taken 35 and if any signal width exceeds this limit, it is removed. Hence wider peaks are removed. For the remaining signals peak detection is done. When signal amplitude goes above threshold value, the algorithm checks for 3 continuously rising points and wait for 100ms and checks for continuously falling points. If the condition is satisfied, the peak is detected. It is then compared with the peak of the original signal. The following figures shows the threshold adaptation routine and peak detection and false peak cancellation for QRS detection.



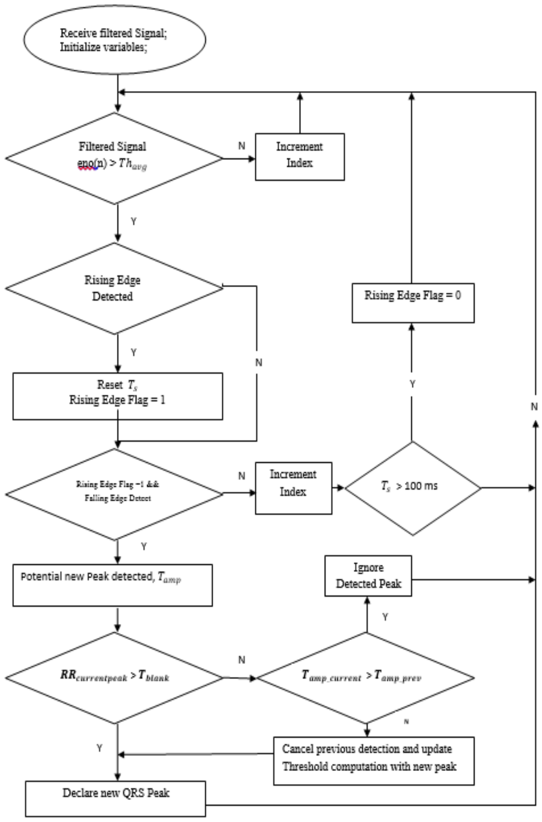


Fig.6. Thershold adaptation routinefor QRS detectionFig.7. Peak detection and false peak cancellation routine

IV. Simulation Results

MATLAB r2007b is used as the simulation tool. MATLAB (Matrix Laboratory) is a programming language developed by Math Works. It started out as a matrix programming language where linear algebra programming was simple. It can be run both under interactive sessions and as a batch job. MATLAB(matrix laboratory) is a fourth-generation high-level programming language and interactive environment for numerical computation, visualization and programming. It allows matrix manipulations; plotting of functions and data; implementation of algorithms; creation of user interfaces; interfacing with programs written in other languages, including C, C++, Java, and Fortran; analyze data; develop algorithms; and create models and applications.

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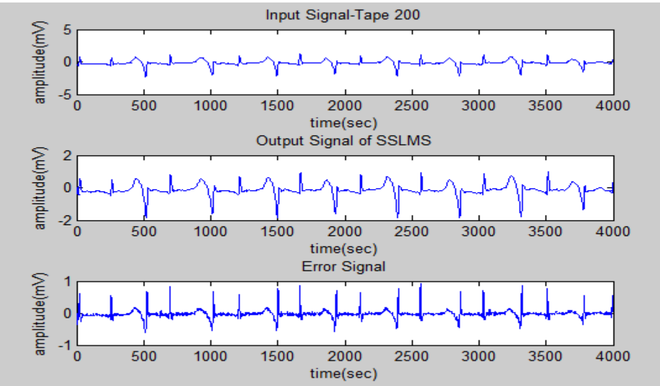
Initially ECG data is loaded from the MIT/BIH arrhythmia database. Here Tape 200 is used. These recordings have 11-bit resolution over 10 mV and are sampled at 360 Hz. After sampling, the signal is defined at discrete instants of time. Out of 30000 samples from the tape, 4000 sample values are stored to a variable N. Predictor coefficients are defined. A row matrix of zeros is defined and for loop is initialized. First data is stored in matrix and convolution is done similarly it is done till the length of N. Error signal is obtained as difference of actual and predicted signal.The error signal is bit clipped to obtain minimum bit width 2's complement representation.



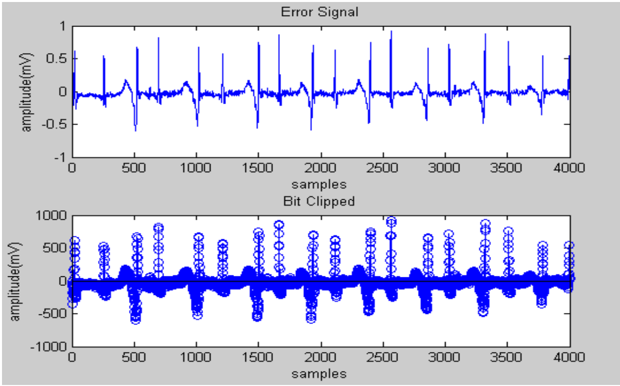
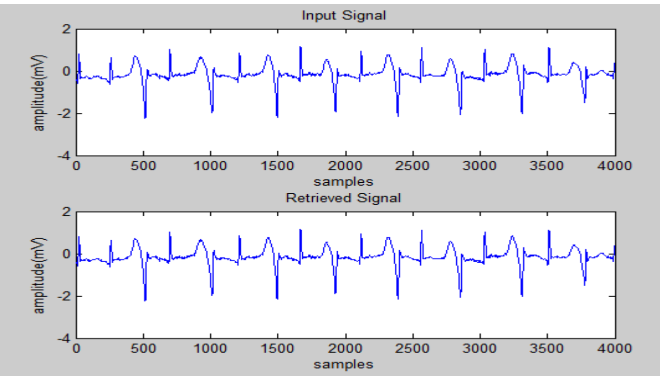


Fig.8. Error signal from actual signal and predicted signal

Fig.9. Error signal and its bit clipped representation

Simple bit packaging scheme is used. Length of bit clipped error signal is calculated and for loop is initialized. First signal is taken and its range checked and accordingly bits are assigned. Two's complement is calculated and it is converted into binary value.According to number of bits of error signal, header is added. Similarly all the signals are coded and the coded signals are combined into single code and transmitted. Decompression is done at the monitoring center. While loop is initialized and check if it is less than length of code. An empty matrix and a variable i=1 is defined. Header is checked and according to the header, no. of bits are taken as from previous table. The code without header is assigned to a variable .It is converted into decimal value. Again two's complement is find out to obtain original code. It is stored in the empty matrix and value of variable is incremented till starting of header of next code. Similarly it is done till the end code length and entire code is unpacked using data format of previous table and stored in the matrix.Reconstruction of original signal is done. Clipping of error signal is removed and the predictor coefficients are initialized. Input signal is obtained from error signal and predicted signal and is fed back to predictor. QRS detection is done from reconstructed data. Retrieved signal is fed back to the 4-tap linear predictor.



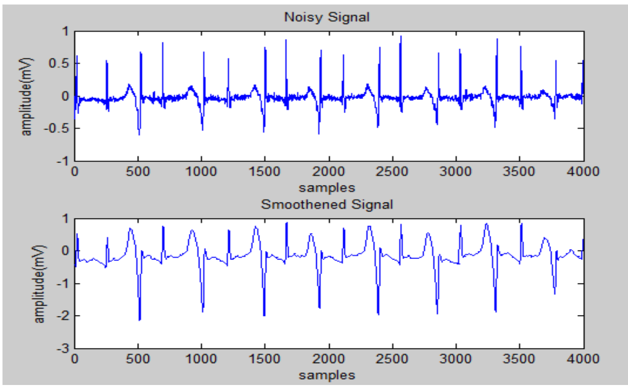


Fig.10. Reconstructed Signal

Fig.11. Smoothened Signal

Squaring and moving sum method is done.Instantaneous signal samples are squared to amplify prediction error. QRS component is magnified. Window integration is done to obtain a smooth waveform. M corresponds to the width of the

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QRS complex. Threshold amplitude is set as 25% of maximum of first 500 samples of the signal. Continuously check for signal. If signal with amplitude less than threshold amplitude occurs, then it is eliminated. Hence smaller peaks are removed.

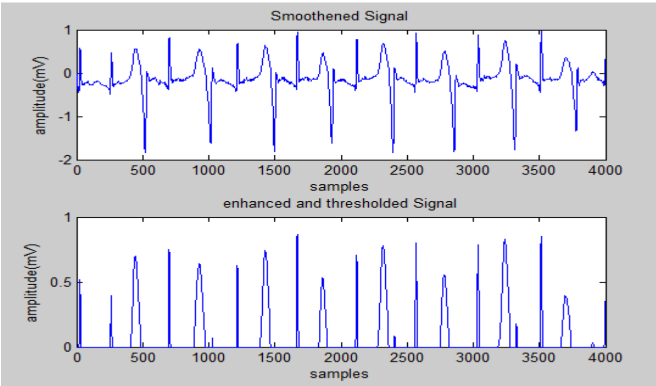

Fig.12. Enhanced and Thresholded Signal

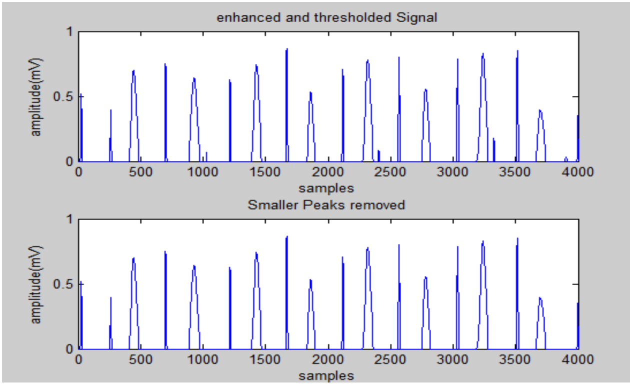

Fig.13. Smaller Peaks removed signal

Again average height is calculated. If signal width greater than 34 (that is sample difference) then it is eliminated. Hence wider peaks are removed .QRS peaks with large slope will remain. QRS peak detection is done in the enhanced signal. Checks for continuously rising and falling points. Peak of original signal is also located for comparison.

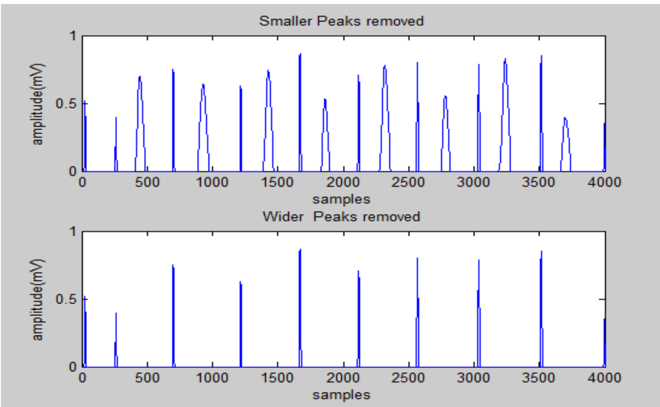

Fig.14. Wider Peaks removed signal

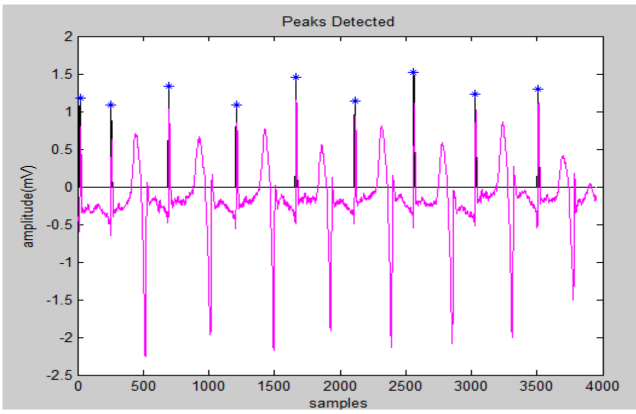

Fig.15. Peak Detected Signal

Sensitivity (Se) and Positive Prediction (+P) is calculated and Se and +P is high (100%) in 15 ECG tapes tested and 95% in tape 234. Bit compression Ratio (BCR) is found to be 2.0311 for tape 200. Initially TP, FP and FN is 0. If retrieved signal peak is between the previous and next value of the original signal's peak, TP is incremented. Otherwise FP is incremented. If original signal peak is between the previous and next value of the retrieved signal's peak, FN is incremented. Sensitivity and + Prediction is calculated using formula.Final output showing ECG signal, error s/g, moving average filter o/p and peak detection is obtained. Sensitivity is the true positive rate, it is the measure of the proportion of positives that are correctly identified. Positive prediction shows the proportion of positive results in a test.

$$Se\ (\%) = \frac{TP}{TP + FN} \tag{9}$$

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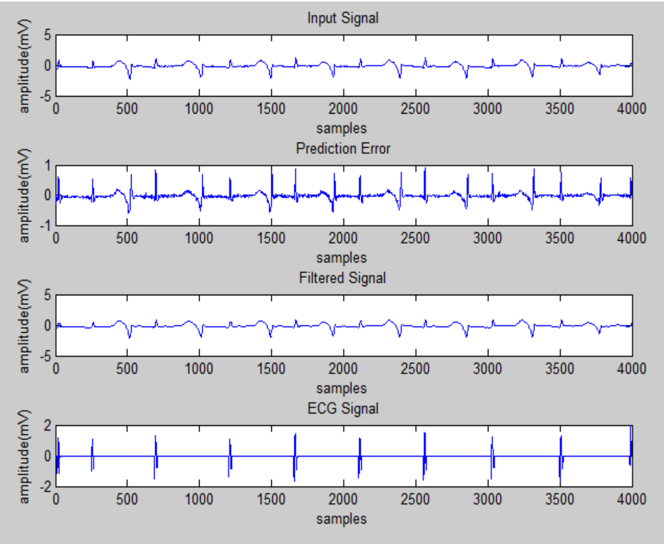
$$+P\ (\%) = \frac{TP}{TP+FP} \quad (10)$$

The proposed data compression algorithm is tested using the MIT/BIH Arrhythmia database for analyzing the compression performance. The bit compression ratio (BCR) is computed as in eqn.9:

$$BCR = \frac{\text{No of uncompressed Samples} \times BW_{uncomp}}{\text{No of compressed Samples} \times BW_{comp}} \quad (11)$$

where, BW_{comp} and BW_{uncomp} refers to the bit widths of compressed and uncompressed samples, respectively.



ECG TAPE	EXISTING METHOD [1]	ENHANCED METHOD	BCR
101	100	100	2.0627
102	100	100	2.1489
111	91	100	2.0016
113	99.94	100	2.0671
118	100	100	1.8104
200	84	100	2.0311
201	95	100	2.0118
234	91	95	2.1592

Fig.16. Final Output

Table. III. Comparison of Se and+P for existing and enhanced methods and BCR

V. Conclusion and Future Work

This paper presents a joint approach for QRS detection and ECG compression algorithm for use in wireless sensors. The algorithm lowers the average computational complexity per task by sharing the computational load among two operations. Adaptive linear filter is used for both ECG data compression and peak detection. In order to obtain more accurate results smaller and wider peaks are removed while doing peak detection. This will result in more precise results by considering only large slope peaks. High Sensitivity and positive prediction of 100% is obtained for different tapes. Bit Compression Ratio of 2.03xx has been obtained. Future scope includes compressed sensing, which will further reduce the complexity.

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