A Real-Time Heart Beat Detector and Quantitative Investigation based on FPGA

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***Abstract*—A Field Programmable Gate Array (FPGA) based system for single-lead electrocardiogram signal QRS complex detection is presented in this paper. The system consists of Quadratic Spline wavelet transform, moving average filter, signed squaring and a Modulus Maxima Pair Recognition module. The parallel and pipelined architecture of the system allows a maximum throughput equals 46MS/s. The QRS Complex detection accuracy is validated using MIT/BIH arrhythmia database, in which, sensitivity of 99.35% and predictivity of 99.70% are achieved. Less than 2000 logic elements are utilized to implement this algorithm in an Altera cycloneII FPGA. The performance and resource consumption show that the design also suits for digital ASIC, which benefits in processing high volume of ECG data.**

I. Introduction

AUTOMATIC detection of the QRS complex is necessary for efficient extraction of beat-to-beat intervals (RR) from long electrocardiogram (ECG) recordings such as nighttime data or 24-hour Holter monitoring, which is useful for heart rate variability analysis, ECG classification and compression. QRS Complex is the most significant part of the ECG waveform and the detection of its position is helpful for the determination of other ECG characteristic points. In most cases, the temporal location of the *R*-wave is taken as the location of the QRS complex.

In the recent decades, many QRS complex detection approaches have been proposed; for example, algorithm base on band-pass filter and nonlinear transform [1], algorithm from the field of artificial neural networks [2], filter banks [3], etc. The performance of applying wavelet transform method to the task of QRS complex detection was reported in [4, 5]. This kind of method benefits from the time-frequency analysis property of wavelet transform. By employing several detection rules, the overall detection accuracy can exceed 99.8% [4]. However, some of these rules are too complex for hardware real-time implementation.

On the other hand, detection errors can be reduced by the application of computationally more expensive algorithms. However, particularly in the case of ASIC design, the computational complexity means larger chip area and larger power consumption. Hence, a tradeoff between complexity and detection performance needs to be carefully balanced.

The following sections will illustrate the whole profile of the QRS complex detection system, including feature extraction by linear and nonlinear transform, decision making.

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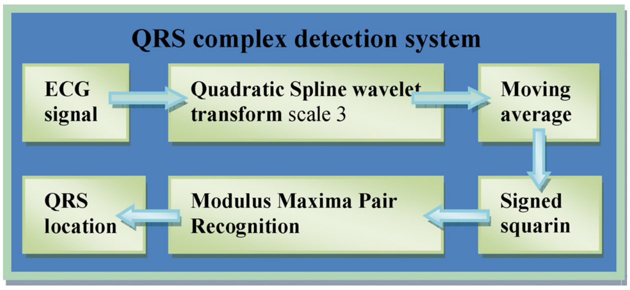

Fig. 1. System architecture of the proposed system.

Lastly, evaluation result on standard database is reported. Despite the performance of an algorithm on a database is not the ultimate answer as to its utility in a clinical environment, it provides a standardized means of comparing the basic performance of one algorithm to another [1].

II. Algorithm and Implementation

The proposed beat detection algorithm consists of Quadratic Spline wavelet transform, moving average, signed squaring and Modulus Maxima Pair Recognition. The arrangement of these functional blocks is illustrated in fig.1.

A. *Quadratic Spline wavelet transform*

In the first step, Quadratic Spline Wavelet Transform (QSWT) is chosen. Theoretically, the discrete and inflexion points of a signal can show different obvious characteristics in multi-resolution after quadratic spline wavelet transform. Making use of this advantage, the high pointed QRS complex (especially R peak) in the ECG signal, after wavelet transform, will be transformed into pairs of positive maximum and negative minimum.

The Fourier transform of Quadratic Spline Wavelet $\psi(x)$ is[6,7]

$$\Psi(\omega) = i\omega\left(\frac{\sin(\omega/4)}{\omega/4}\right)^4 \qquad (1)$$

The high pass and low pass filters $H(\omega)$ and $G(\omega)$ are Eq. 2 and Eq. 3 respectively.

$$H(\omega) = e^{i\omega/2}\left(\cos\frac{\omega}{2}\right)^3 = \frac{1}{8}\left(e^{2i\omega} + 3e^{i\omega} + 3 + e^{-i\omega}\right) \qquad (2)$$

$$G(\omega) = 4ie^{i\omega/2}\left(\sin\frac{\omega}{2}\right) = 2\left(e^{i\omega} - 1\right) \qquad (3)$$

Let $Q_j(\omega)$ be the transfer function of the equivalent filter. Then, we have

$$Q^{j=1}(\omega) = G(\omega) \tag{4}$$

$$Q^{j=2}(\omega) = G(2\omega)H(\omega) \tag{5}$$

$$Q^{j>2}(\omega) = G(2^{j-1}\omega)H(2^{j-2}\omega)...H(\omega) \tag{6}$$

From the equations above, we can derive that the equivalent filter coefficients are the integral multiple of 2 power an integer depend on the scale of wavelet j, that is,

$$FilterCoefficients = m \times 2^{-3(j-1)+1} \tag{7}$$

$$m = ... -1, 0, 1, 2...$$

This characteristic of Quadratic Spline wavelet makes it suitable for FPGA implementation, since all the equivalent filter coefficients can be represented by fixed point binary decimal without losing any information. The width of the binary decimal is equal to the absolute value of 4-3*j*. If the data being processed can be also fully express in fixed point binary form, the whole hardware filter can have the same result as the floating point version in software. This is just the case for MITBIH (Massachusetts Institute of Technology and Beth Israel Hospital) arrhythmia database, which we use to validate the proposed algorithm, because all the data collected in this database is obtained by an 11-bit ADC after an analog amplifier.

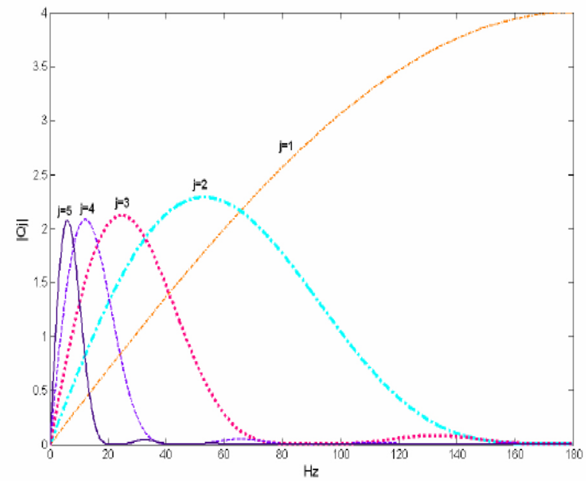

Fig. 2. The amplitude-frequency responses of equivalent filter Qj(ω) at different scales corresponding to 360 Hz sampling frequency; f=180ω/π.

TABLE I
THE BANDWIDTH OF $Q^1(\omega) \sim Q^5(\omega)$

	$Q^1(\omega)$	$Q^2(\omega)$	$Q^3(\omega)$	$Q^4(\omega)$	$Q^5(\omega)$
3dB Bandwidth	90.00~180.00	29.92~84.24	11.52~38.88	5.76~19.44	2.88~9.36

Taking the advantage of the fixed point nature of the filter and the data, the error of the hardware filter is easy to be estimated since it only consist of truncation error. We employ QSWT scale 3 in our system, the reason is not only its filter coefficients is shorter and also have the best performance in simulation while comparing the detection accuracy with other scale of QSWT. Thus only the filter in the path of wavelet transform scale 3 is implemented.

From the equation above, the coefficient of QSWT scale 3 equivalent filter is the integral multiple of 1/32. As a result, 5 bit binary decimal is enough for the representation of coefficients of the wavelet filter. To reduce the area of the circuit, we truncated the binary fraction of the output, which will induce a white noise range from 0 to -1 with a -0.5 mean. This truncation error is negligible when comparing with the amplitude of the transformed signal.

B. Moving average filter

A 6-point moving average filter (MAF) is employed after the QSWT since the 60-Hz power line interference need to be eliminated. A FIR filter is designed to implement this step.

C. Signed squaring

The equivalent filter response of step A and step B enhance the spectra of QRS complex but also cover the spectra of P and T wave. In some records of MITBIH arrhythmia database, extraordinarily strong P wave or/and T wave exist. Absolutely they will attenuate by the QSWT and MAF, but sometimes they still have amplitude which is high enough to threaten the detection accuracy of the coming Modulus Maxima Pair Recognition module. Therefore, signed squaring as blow is used to enhance the QRS complex and suppress while maintain the sign of signal for the next step.

$$y[n] = sign(x[n]) \times x^2[n] \tag{8}$$

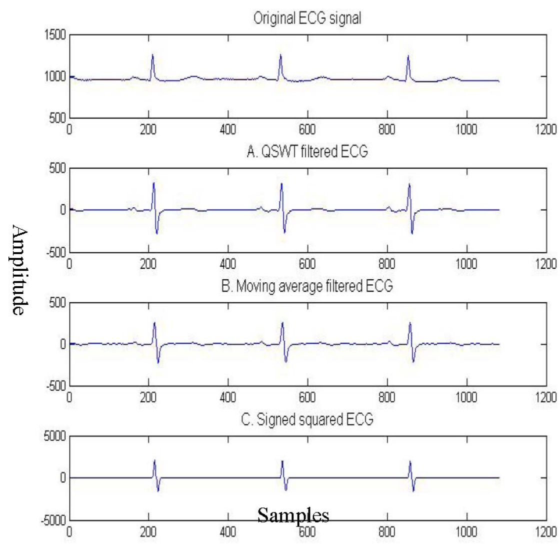

Fig. 3. Test with ECG signal from MIT/BIH Arrhythmia database record 102.

D. Modulus Maxima Pair Recognition

Compare to many other QRS complex detection algorithm with only one feature, that is the positive maximum amplitude of the transformed signal, we apply a two features recognition system, both the positive maximum and negative minimum are considered.

The detection of a QRS complex is accomplished by comparing the features against two threshold levels. In the proposed system, the threshold levels are computed to be signal dependent such that an adaption to changing signal characteristics is possible.

As a result, hardware implementation of the Modulus Maxima Pair Recognition (MMPR) module consists of two parts. The first part is threshold level computation and the second part making decision based on the comparison between transformed signal and the thresholds.

The guideline in selecting the threshold is given by empirical equations,

$$PT = APNL + 0.25APSL \tag{9}$$

$$NT = ANNL + 0.25ANSL \tag{10}$$

In (9) and (10), PT stands for positive threshold whereas NT for negative threshold. APNL is the average positive noise level and APSL is the average positive signal level; both these two levels are calculated by average of most recently 8 positive noise peaks or signal peaks. It is identical for the negative part which using average negative noise level (ANNL) and average negative signal level (ANSL). Thereby the two thresholds can be adjusted according to different signal amplitude and noise level to achieve higher detection accuracy.

The local extreme value of transformed signal has an amplitude large than this threshold is seen as Modulus pair candidate. It will be confirmed as a QRS complex if the subsequent zero crossing and opposite local extreme is found in a proper time interval. This job is accomplished by a state machine with several embedded rules. And the zero crossing between a maxima pair is considered as the location of the R peak.

The bit width of this part is minimized because it has linear correlation with the circuit area and power.

III. PERFORMANCE EVALUATION

A. *Implement Result*

The proposed system is implemented on an Altera FPGA chip. The data representation in the system is varying from module to module, since the minimum bit width requirement for enough accuracy of different module is not the same. A varying bit width can reduce the resource consumption while maintaining a low enough truncation error.

Table II describes the hardware usage, which consists of the proposed algorithm and also a UART data exchange circuit, of the proposed system. It uses about 3% of total resource for both logic elements and registers of target platform, which is a Cyclone II EP2C70F896C6N FPGA chip placed on an Altera DE2-70 board.

TABLE II
HARDWARE USAGE OF THE SYSTEM

	Total Logic Elements	Total Registers
Hardware Usage	1964	1244

B. *Verification method*

The verification data flow is MITBIH arrhythmia database stored in a PC and sends to the FPGA as fast as it can through UART. Although we already use the faster mode of UART, its speed is still much lower than the maximum processing speed of the proposed system. Thereby, the hardware can perform heart beat detection in real time. The result will be sent back to PC and compare to the standard annotations within the database to obtain detection accuracy of the proposed system. Our proposed system is a single lead detection system, thus the first channel of each record is used in the evaluation of the algorithm.

There are several modules of the system bring processing delay into the finally result, such as the QSWT, moving average filtering, MMPR modules and so on. This kind of delay will make the detected temporal location of QRS complex fall behind their real position. As a result, we move the location of detections ahead by a fixed number of samples, which depends on the total processing delay of the whole system, before it is compared with the reference annotations.

C. *Detection accuracy*

The entire hardware of the QRS detection has been tested correctly. The testing goes through all the 48 records (each lasts for 30 minutes) in MITBIH arrhythmia database to determine whether our detector has detected the beats correctly. The detected QRS complex temporal locations are considered as a true positive if they located around the corresponding reference annotation within 110 milliseconds. Thus it is not necessary to place annotations precisely on the major local extremum as in the MITBIH Data Base reference annotations [11].

$$Accuracy = 1 - \frac{FP + FN}{TB} \tag{11}$$

There are totally 109,267 heart beats has been tested, with 741 missed beats (FN) and 330 extra detected points (FP), that is a sensitivity of 99.35% and a predictivity of 99.70%. According to Eq. (11), the accuracy of the system is 99.02%. This excludes episodes of ventricular flutter that occur on tape 207. Tap 105, 108, 203 and 210 contribute more or less half of the failed detections because of these taps have poor signal to noise ratio.

IV. DISCUSSION OF SYSTEM ARCHITECTURE

There are several possible architectures, such as different filtering method or different nonlinear transform, of the system can provide real time detection. We perform quantitative investigation on some of them to see which one is better for our application. The architecture of the proposed system is finally determined after we finish this kind of experiments.

A. *Scale selection of QSWT*

Typical frequency components of a QRS complex range from about 10 Hz to about 25 Hz [12]. Therefore, from table I, only QSWT scale 3 and 4 is possible for the extraction of QRS complex from ECG signal. And it seems that QSWT scale 4 befits more this task since the centre frequency of this scale best-fits the spectrum of QRS. In particular, we evaluate the detection accuracy of the system under the same conduction for both QSWT scale 3 and 4.

Compare to scale 4, scale 3 can provide higher detection accuracy under the same validation condition. The reason is that signal after QSWT scale 4 will contain more low frequency component. As a result, the transformed signal will suffer from the interference of high P and/or T wave and thus produce more false positives (FP).

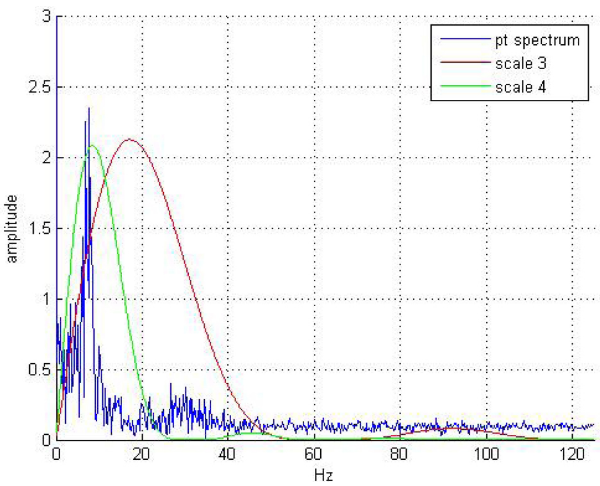

Fig. 3. The amplitude-frequency responses of equivalent filter Qj(ω) at scale 3 and 4 corresponding to 250 Hz sampling frequency; and spectrum of P and T wave of a typical ECG signal obtain from record "sel123" of MITBIH QT database.

B. *Moving Average*

The moving average stage is also necessary for the detection algorithm. By adding this filter, the high frequency noise can be attenuated and thus over 150 failed detections can be avoided.

C. *Signed Squaring*

Both QSWT and Moving Average filter are linear transform of the signal. The nonlinear transform is useful in this situation to improve the SNR of the feature signal.

Without using Signed Squaring, there are totally 596 FN and 1243 FP. Compare to the performance of system with signed squaring, the total failed detection decrease from 1884 to 1083, that is reduced by 801 failed detection or 42.52%.

The discussions above are summarized in fig.4.

V. CONCLUSION

A real-time QRS detection algorithm and its corresponding FPGA implementation are presented in this paper. The whole algorithm is written in verilog HDL and thus can operate in high speed. QRS complex can be detected reliable via this algorithm after the baseline wandering, power line noise, high P and T wave is removed by linear and nonlinear transform. The automatically threshold adjustment section enables the adaptability of decision making to diverse signal characteristics.

In the evaluation using MITBIH arrhythmia database, the algorithm failed to properly detect only 0.98 percent of the beats. The proposed algorithm is possible to transplant into ASIC because the low computational complexity and high detection accuracy of the circuit.

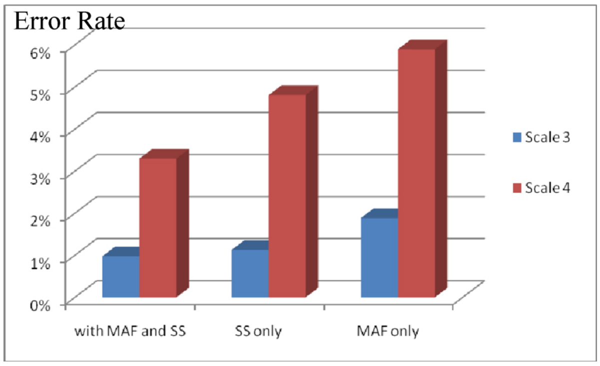

Fig. 4. Error rate of different system architecture evaluate by using MITBIH arrhythmia database; MAF stands for moving average filtering, SS stands for signed squaring.

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