ECG Heart Beat Detection via Mathematical Morphology and Quadratic Spline Wavelet Transform

Chio-In Ieong, Mang-I Vai, Peng-Un Mak, and Pui-In Mak

***Abstract*—Presented is a novel ECG heart beat detection algorithm combining Mathematical Morphology operations and Quadratic Spline wavelet transform for hard-wired realization. Experimentally demonstrated in FPGA under the MIT/BIH Arrhythmia database, the algorithm shows 98.16% sensitivity, 99.7% predictivity and 97.29% overall accuracy.**

I. INTRODUCTION

Biomedical electronics for home healthcare [1] [2] and clinical applications not only call for accurate human-signal acquisition, recording and display, but also the capability to extract the parameters out from the acquired signals. For instance, the ECG heart beat detection involves the issue of extracting the QRS Complex, which is the key metric enabling patient monitoring and further diagnosis.

In the literature, QRS Complex detection has been studied using the derivative-based [3], filter-based [4], Mathematical Morphology [5] and Wavelet transform [6-8] methods. This paper proposes a method based on Mathematical Morphology (MM) and Wavelet transform (WT), attempting to combine the morphological analysis capability of MM and time-frequency resolution capability of WT. The algorithm befits pure hard-wired realization in Field Programmable Gate Array (FPGA) or Application Specific Integrated Circuit (ASIC); both are easy to be integrated in portable devices, body area or body sensor networks, etc. The algorithm has been successfully verified under a FPGA platform with the MIT/BIH arrhythmia database [9].

II. PROPOSED METHOD AND IMPLEMENTATION

The proposed method consists of preprocessing, transformation and decision making stages as shown in Fig. 1. The input is the digitized ECG signal in 17-bit fixed-point signed number with 360 Hz sampling rate. The output is 1-bit signal for the annotation of the occurrence of QRS Complex. It is implemented in Xilinx Virtex-4 SX35 FPGA.

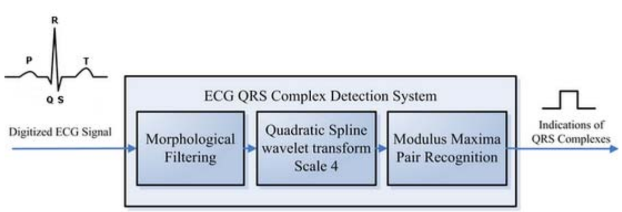

Fig. 1: System Architecture

A. Pre-processing

Noise from different geneses often pollutes the signal after acquisition, and therefore necessities signal pre-processing. The noises include power line interference, electrode pop or contact noise, patient-electrode motion artifacts, electromyography (EMG) and respiration, etc. The pre-processing is based on mathematical morphology by employing morphological operators for baseline wandering elimination and noise suppression [5].

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Morphological operators are nonlinear operators effective for impulsive noise reduction while preserving the original shape of the wanted signal. Since physiologists are interested to the shape of ECG signal, it is reasonable to detect ECG waveforms with the method for analyzing the shape of signal.

The operators exploited are shown below.

Dilation: $$f \oplus s(n) = \max_{(i)}(f(n-i)+s(i)) \tag{1}$$

Erosion: $$f \Theta s(n) = \min_{(i)}(f(n+i)-s(i)) \tag{2}$$

Opening: $$f \circ s = (f \Theta s) \oplus s \tag{3}$$

Closing: $$f \bullet s = (f \oplus s) \Theta s \tag{4}$$

Here f is the signal for filtering and s is the structuring element designed for the processing. Dilation and erosion are the basic operators of mathematical morphology, while opening and closing offers the mathematically formal way for peak or valley extraction.

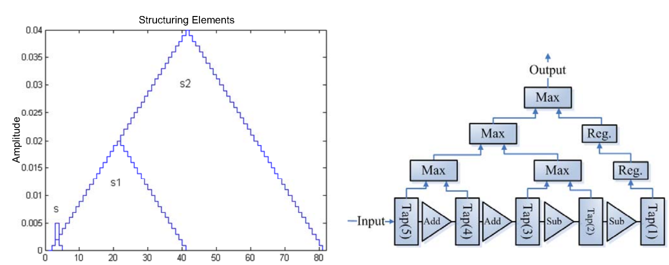
The detailed equations for the pre-processing are as follows.

$$y1 = [(x \circ s) \bullet s + (x \bullet s) \circ s]/2 \tag{5}$$

$$y2 = y1 - [(y1 \circ s1) \bullet s2 + (y1 \bullet s1) \circ s2]/2 \tag{6}$$

Here the structuring elements *s1*, *s2* and *s3* are triangular waves selected for their similarity to the shape of QRS Complex, with the length and height empirically determined as shown in Fig. 2(a). Eq. (5) is for high frequency noise filtering and Eq. (6) is for baseline wandering removals.

The circuit realization of 5-point dilation operation is shown in Fig. 2(b). Here the “Add” and “Sub” components mean adding or subtracting the differences between two consecutive values in the structuring element. “Tap” represents the registers and “Max” means finding the larger input.



(a) (b)

Fig. 2: (a) Structuring Elements (when sampling rate = 360Hz) and (b) architecture for 5-point dilation operation

B. Transformation

The transformation stage converts the ECG signal for generating the feature to facilitate heart beat detection. Quadratic Spline Wavelet transform is incorporated in the algorithm for the transform. It is the 1st derivative of the Gaussian Smooth function. It has a compact support for small computation complexity. The wavelet transform at corresponding scale is proportional to the derivative of the filtered version of the signal with a smoothing impulse response at the scale. Thus the zero-crossings of the WT correspond to the local maxima or minima of the smoothed signal at different scales, and the maximum absolute values of the WT correspond to maximum slopes in the filtered signal. Its Fourier transform is given by [6-8],

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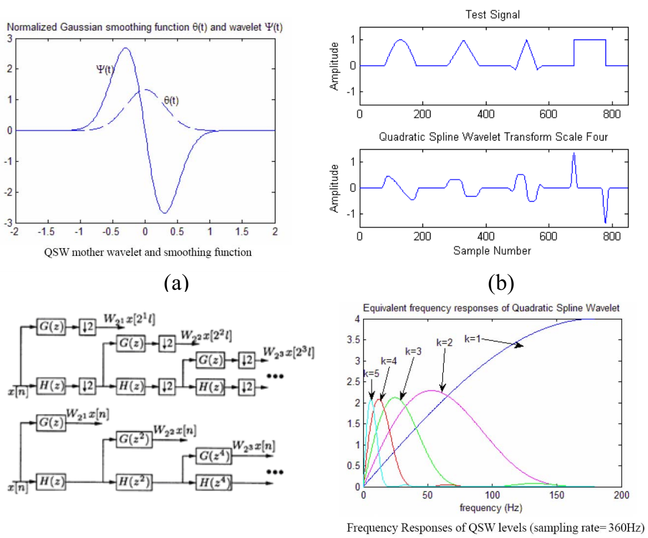
$$\hat{\psi}(\omega) = i\omega\left[\left(\sin\frac{\omega}{4}\right)/\frac{\omega}{4}\right]^4 \quad (7)$$

The corresponding highpass and lowpass filter coefficients are:

$$h(n) = [1/8 \quad 3/8 \quad 3/8 \quad 1/8] \quad (8)$$

$$g(n) = [-2 \quad 2] \quad (9)$$

The Quadratic Spline Wavelet transform is realized with filter bank with A Trous algorithm [7] for determining the coefficients. Such an algorithm is similar to Mallat's algorithm but without down-sampling. The benefit of A Trous algorithm is that it can maintain the signal representation time-invariant and can increase the time resolution in higher scales. By considering the frequency response and computational cost, the scale four of the wavelet transform coefficients (output) are passed to the next stage for recognition. The QSW, test signals, algorithm structures and QSW frequency ranges of scales are shown in Fig. 3.



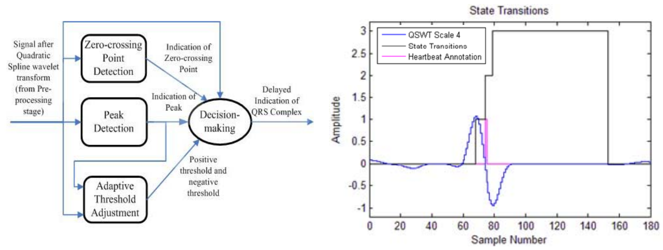
Scales	Q1	Q2	Q3	Q4	Q5
3dB BW (Hz)	90.0 – 180.0	29.9 – 84.2	11.5 – 38.9	5.8 – 19.4	2.9 – 9.4

(e)

Fig. 3: (a) Normalized Gaussian smooth function and Quadratic Spline wavelet (b) signals and their QSW transform (c) Mallat's algorithm and A Trous algorithm (d) Frequency responses of QSWT scales (e) Table showing bandwidths of scales

C. Decision Making

The decision making stage is to recognize the positive-maximum negative-minimum pair with adequate amplitude in the wavelet coefficients of scale four from the previous stage. This task is accomplished by a state machine and three sub-circuits with specialized functions for finding the zero-crossing points, zero-derivative points (peaks) and for adaptively adjusting the threshold. The architecture is shown in Fig. 4(a). According to the information from the three sub-circuits, the state machine changes state when finding a positive peak or negative peak, a zero crossing point and a peak with opposite direction to the previous one, shown in Fig. 4(b). Considering the physiological refractory period, the state machine also rejects recognizing consecutive QRS Complex within 70 ms. Finally the state machine sends out the one-bit identification of the occurrence of ECG QRS Complex.



(a) (b)

Fig. 4: State (a) machine and (b) transitions (sampling rate = 360Hz)

III. EXPERIMENTAL RESULTS

The system maximum frequency is 35.231 MHz, corresponding to 35.231-MSa/s throughput. Corresponding signals are shown in Fig. 5. The system is tested with all the recordings from MIT/BIH Arrhythmia database, with 98.16% sensitivity, 99.7% predictivity and 97.29% overall accuracy. The total power consumption is 0.75 W estimated by the Xilinx ISE Foundation design environment, and will be further optimized by dramatically slowing down the system operating frequency, simplifying the algorithm, and incorporating search-back technique in algorithm to enhance detection accuracy.

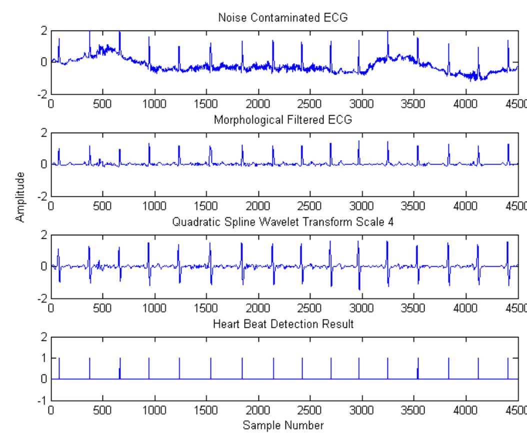


Fig. 5: Demonstration of ECG heart beat detection

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