A 0.45-V 70-nW QRS Detector Using Decimated Quadratic Spline Wavelet Transform and Window-based Extrema Difference Techniques

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Abstract—**This work presents a 70-nW QRS detector implemented in 0.45-V 0.18-μm CMOS technology. The algorithm is optimized with *decimated quadratic spline wavelet transform* (*DQSWT*) and *window-based extrema difference curve* (*WEDC*). The *DQSWT* achieves up to 60% computational unit reduction when compared to the conventional method, while the *WEDC* enhances the QRS detection accuracy while maintaining a low computational complexity. Combined with a decision-making stage with simple mechanism, the proposed algorithm achieves a sensitivity of 99.62% and a precision of 99.70% in MIT-BIH arrhythmia database.**

Keywords—ECG, Low-power, QRS Detector, Decimation, Quadratic Spline Wavelet Transform, Window-based, Extrema Difference Curve

I. Introduction

Long-term monitoring of the QRS complex in electrocardiogram (ECG) can support the diagnosis of many cardiovascular diseases [1]. This calls for the design of energy efficient QRS detectors with high detection accuracy. Apart from technology scaling and circuit-level innovations, optimization in the algorithm level is important to further reduce the hardware computation and power overhead.

Typically, the QRS complex can easily be contaminated by motion artifacts, powerline interference and electrode contact noise. Consequently, a pre-processing stage and a decision-making stage [1] are necessary to achieve accurate detection. Yet, the complicated filter taps coefficients [2] and intensive computations [3] such as derivative, squaring and search-back mechanisms can incur excessive power consumption in ASIC implementations. A detector with customized analog front-end can achieve extremely low power [4], but with reduced detection accuracy due to the process dependence and performance variability. Benefitting from the time-frequency representation and the simplicity of implementation, digital filters based on wavelet transform (WT) are widely adopted in QRS detectors [1, 5]. Yet, the QRS complex enhancement using the conventional WT is still insufficient, leading to the requirement of complicated finite state machines [1] or extra refinement modules [5] in the decision-making framework with significant hardware resources occupation and high power consumption, to ensure a satisfactory detection accuracy.

This work proposes a low-power high-accuracy QRS detector with the pre-processing stage optimized using the *decimated quadratic spline wavelet transforms* (*DQSWT*) and the *window-based extrema difference curve* (*WEDC*) techniques. The reduced hardware overhead can significantly reduce the power overhead while requiring only a simple decision-making stage to ensure high detection accuracy. Implemented in a standard 0.18-μm CMOS technology with a 0.45-V supply, simulation results using the MIT-BIH arrhythmia database show that the power consumption is merely 70 nW while achieving a detection sensitivity and a precision of 99.62% and 99.70%, respectively.

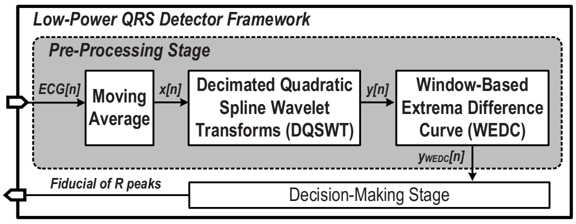

Fig. 1. Structure of the proposed system.

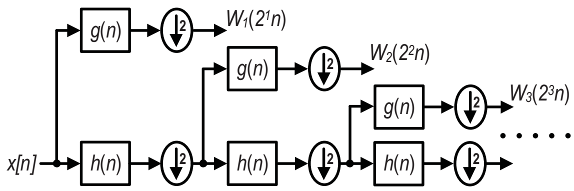

Fig. 2. Architecture of Mallat's algorithm. $g(n)$, and $h(n)$ are respectively the high-pass and low-pass filters.

II. Pre-processing Stage

A. Decimated Quadratic Spline Wavelet Transforms

Fig.1 shows the proposed QRS detector framework, where before the WT, the high-frequency small spikes are first eliminated with a moving average stage. The WT of a signal $f(t)$ can be expressed as,

$$WT_x(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt, \tag{1}$$

where $\psi(t)$ is the mother wavelet with dilation $a = 2^j$ and translation b with j as the scale number. The WT is calculated according to Mallat's algorithm [1], with the architecture from Fig. 2 using cascade filter banks. Yet, this results in high memory access and computational complexity. We selected a quadratic spline function as the mother wavelet due to its orthogonality, compact support, and one vanishing moment. And its tap coefficients can be implemented with hardware-friendly operators of adders and shifts. The frequency responses of $h(n)$ and $g(\text{n})$ are $H(\omega) = e^{i\omega/2}(cos\frac{\omega}{2})^3$ and $G(\omega) = 4ie^{i\omega/2}(sin\frac{\omega}{2})$, respectively. The equivalent filter at each scale becomes,

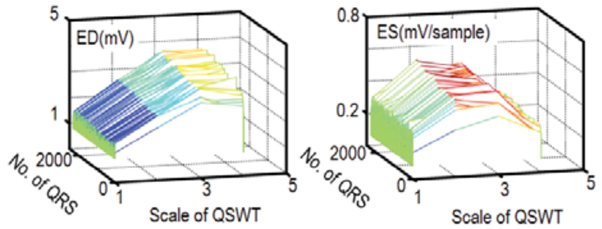

Fig. 3. Energy concentrations of the QRS complex in different scales.

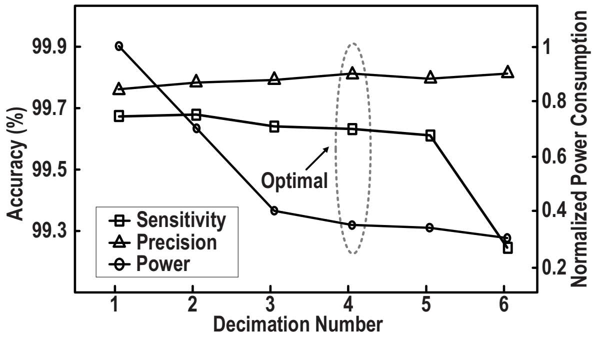

Fig. 4. Detection accuracy and normalized power consumption in different sampling rates.

$$Q_j(\omega) = G(2^{j-1}\omega)\prod_{k=0}^{j-2} H(2^k\omega). \quad (2)$$

The *QSWT* coefficients in one scale are the first derivative of a smooth function, such that the *QSWT* signal can embody the slope information of the input ECG signal. To achieve an enhanced *QSWT* signal for the ease of detection, the scale number is optimized to generate a high degree of energy concentration of the QRS complex. Based on the annotations in the MIT-BIH database with 360-Hz sampling rate, we used the record #100 to analyze the energy concentration of enhanced QRS complex in different scales with *Extrema Difference* (*ED*) and *Extrema Steepness* (*ES*), as highlighted in Fig. 3. *ED* is the max-min difference in every transformed QRS complex which reflects the sharpness of the slope change. *ES* is the average slope of extrema max-min value representing the concentration of *ED*. Simulation results confirm that scale 3 achieves its largest response in *ED* and *ES*, leading to a prominent transformation of the QRS complex.

Conventionally, automatic ECG analysis such as heart beat detection and disease diagnosis demand high sampling rates, which are far greater than the Nyquist sampling rate of the QRS complex. This can result in redundant data processing during QRS detection. In this work, we developed a decimated *QSWT* by applying a decimator on the *QSWT* signal to reduce the hardware occupation and power consumption. Fig. 4 presents the simulation of the decimation numbers in terms of the detection accuracy and power consumption. A larger decimation number can sacrifice the accuracy while a smaller value can increase the power consumption. We can observe that there exists an optimal decimation number of 4 (corresponding to 90 Hz based on the MIT-BIH database and utilized here), below which detection accuracy starts falling. In ASIC implementations, the decimation is moving forward and we only adopted the relevant *QSWT* coefficients for calculation. Fig. 5 exhibits the proposed *DQSWT* structure with a significant computation

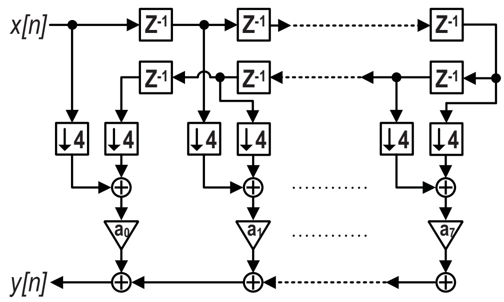

Fig. 5. Implementation architecture of the proposed *DQSWT*.

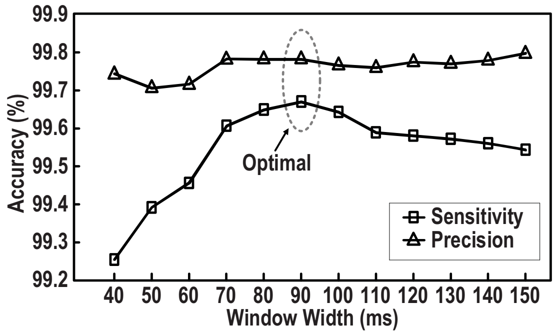

Fig. 6. Detection accuracy versus different window widths.

unit reduction of up to 60% from the conventional one without using *DQSWT*.

B. Window-Based Extrema Difference Curve

For the ease of detection, the QRS complex energy in the *DQSWT* signal is further enhanced by *WEDC*, which represents the difference between the positive and negative extrema values in a local window. The *WEDC* is calculated as,

$$y_{EDC}[n] = Max(W[n]) - Min(W[n]), \quad (3)$$

$$W[n] = \begin{cases} \{y[1], y[2], \ldots, y[n]\}, & n < d \\ \{y[n-d+1], \ldots, y[n]\}, & n \geq d \end{cases} \quad (4)$$

where $W[n]$ is the local window at position n and d is the width of the window. As the QRS complex occupies a period of ~0.12s [3], within which a modulus of positive and negative extrema can be found. A larger window width can enhance the peak energy ratio in *WEDC* and hence increase the R-peak detection accuracy, but with the penalty of more memory access that can result in a higher power consumption. Fig. 6 shows the simulated accuracy with different local window widths. It suggests an optimal width of 90ms, below which the sensitivity drops dramatically due to the loss in the modulus. Fig.7 illustrates an example of *WEDC* together with the input ECG signal. It can be observed that all the peaks in the *WEDC* are positive and are aligned with the QRS complexes of the corresponding ECG. Also, the *WEDC* signal is always positive which effectively mitigates the computational workload without the need to consider the polarity. The *WEDC* can intensify the slope of the frequency response curve of the *DQSWT* and help restrict the false positives caused by T waves with higher unusual spectral energies.

III. Decision-Making Stage

After the QRS complex is enhanced in *WEDC*, a dynamic thresholding can be employed to search for the candidate R

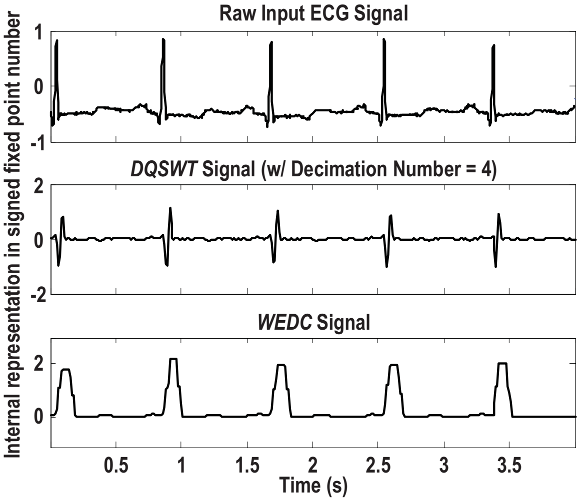

Fig. 7. Internal pre-processing signals.

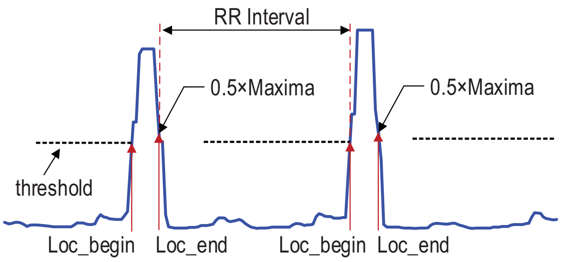

Fig. 8. Illustrative mechanism of the decision-making stage.

peaks. Fig. 8 plots the detailed mechanism. When the *WEDC* signal exceeds the threshold the location, it is denoted as Loc_begin, indicating a candidate QRS complex. Then, the system searches for the maxima in the coming peak. When the coming $y_{EDC}[n]$ is smaller than half of the detected maxima, the searching state ends, and the corresponding position is located as *Loc_end*. If the distance between *Loc_begin* and the *Loc_end* of the last R peak is less than 100 ms, this candidate peak is regarded as noise, otherwise the maxima position is denoted as a R peak fiducial. A new threshold is then calculated as $a \times R_{amp}$, where a is the scaling factor set to 0.45 and R_{amp} is the mean amplitude of 8 earlier R peaks in *WEDC*.

IV. Results and Conclusions

We evaluated the proposed algorithm according to the precision $Pr = TP/(TP + FP)$, and sensitivity $Se = TP/(TP + FN)$, where TP, FP and FN are the total heart beats, false positive and false negative, respectively. This work achieves a Pr of 99.70% and a Se of 99.62% with the MIT-BIH database. In addition, other databases (NSR, QT, Challenge 2014, and Fantasia) of 1.7 million TP with a large variety of ECG morphologies and acquisition conditions have also been tested, achieving over 99.4% Se and Pr which indicates the high robustness of the algorithm. This work was also translated into Verilog HDL and tested in the Modelsim with 99.35% Pr and 99.2% Se using the MIT-BIH database. Fig. 9 shows that it occupies 0.12 mm^2 and draws only 70 nW when implemented in a 0.45-V 0.18-μm CMOS technology [6]. Table I presents the benchmark with the state-of-the-art. The *t-PUT* algorithm [4] draws the lowest power consumption but sacrifices the detection accuracy, which is unacceptable in

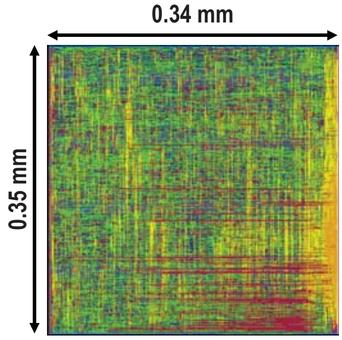

Fig. 9. Chip layout of the proposed QRS detector.

Table 1: Performance benchmark

	TBCAS'12	TBCAS'14	TEHM'15	TBCAS'17	This work
Tech.(μm)	0.35	0.13	0.13	0.18	0.18
Algorithm	QSWT	t-PUT	P-T	HWT	DQSWT + WEDC
V_{dd} (V)	1.8	0.3	0.6	1	0.45
Freq (kHz)	0.3	1	1	N/A	1
Power(nW)	830	34	764	410	70#
Se (%)	99.31	97.76#	99.85	99.6	99.62#
Pr (%)	99.70	98.59#	99.93	99.77	99.70#
Area(mm^2)	1.11	0.1	0.22	0.484	0.12

Simulation results only

many practical clinical scenarios. The *P-T* algorithm [3] achieves the highest detection accuracy thanks to the complicated pre-processing and search-back mechanisms. The *QSWT* [1] and *HWT* [5] based algorithms obtain comparable detection accuracy, but the complicated decision-making mechanisms on the contrary consume > 5.9× higher power consumption than this work.

Acknowledgment

This work is finally supported by Macau Science and Technology Development Fund (FDCT069/2016/A2) and the Research Committee of University of Macau (MYRG2017-00221-AMSV).

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