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A New Combinatorial Algorithm for QRS Detection

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***Abstract*— QRS detection is the most important step for analyzing electrocardiogram (ECG) signals. In this paper, a new combinatory algorithm based on Pan-Tompkins' method and wavelet transform is proposed to keep their strengths and avoid the weakpoints. It consists of two stages: preprocessing and decision. In the preprocessing stage, the wavelet transform is used to remove undesired details of the ECG signal and amplify QRS complexes. Then, the local energy of the signal is computed by using a Gaussian kernel. Finally, in the decision stage, similar to Pan-Tompkins' method, an adaptive threshold selection algorithm is employed to detect QRS complexes. Experimental results on the MIT-BIH database demonstrated outstanding solution quality of the proposed algorithm compared to a number of QRS detection algorithms. Furthermore, interesting properties such as low computational burden and straightforward implementation nominate the proposed algorithm as an appropriate candidate for real-time QRS detection applications.**

Keywords: Electrocardiography; QRS Detection; Pan-Tompkins's Method; Wavelet Transform

I. INTRODUCTION

The QRS complex is the most important part of the electrocardiogram (ECG). Its shape and occurrence time provide much information about the heart function. Due to the unique characteristic shape, QRS detection is the fundamental part of almost all automated ECG analysis algorithms such as heart rate variability and cardiac cycle classification. A typical ECG waveform is shown in Fig.1.

A typical QRS detection algorithm usually consists of two stages: preprocessing and decision [1]. Generally, the former includes some sort of filtering while the later attempts to specify the location of QRS complexes in the ECG signal. Until now, a wide variety of methods such as linear filtering [2-4], neural networks [5], and wavelet transform [6-8] have been proposed by researchers for QRS detection.

For example, a large number of QRS detection algorithms initially use linear filtering to remove undesired parts of the ECG signal. Then, QRS complexes are determined by applying a suitable threshold to the resultant signal. Pan-Tompkins' method [2], [3] is the most well-known algorithm of this category. A good comparison between Pan-Tompkins' method and other algorithms in the same category can be found in [4].

Recently, a number of QRS detection algorithms were proposed based on the wavelet transform. They analyze the ECG signal by using the multi-scale sub-band data provided by the wavelet transform [6-8]. Furthermore, a number of combinatory algorithms were proposed by researchers in order to use the benefits of both the linear filtering and wavelet transform [9, 10].

Generally, QRS detection is a not a trivial task. It may be distorted by noise due to the electrode artifact, baseline drift, and power line interference. Furthermore, the ECG signal may be improperly deformed because of pathological changes, e.g. signals with small QRS complexes or suddenly variable levels. Therefore, providing a reliable and efficient QRS detection algorithm is still an open problem.

In this paper, a new algorithm which combines Pan-Tompkins's method and wavelet transform is proposed. First, the wavelet transform is applied to the ECG signal to weaken undesired frequency content. We used the fourth scale of the wavelet bior1.5 for this aim. Then, the local energy of the filtered signal is computed. Finally, QRS complexes are determined by using the blanking and double thresholding method. According to experimental results on MIT-BIH arrhythmia database [14], the proposed algorithm provided outstanding performance in terms of both solution quality and CPU time.

The remainder of the paper is organized as follows: Sections 2 and 3 present an overview of Pan-Tompkins' method and wavelet transform, respectively. The proposed combinatory algorithm is stated in Section 4. Section 5 is devoted to experimental results and finally, conclusions are drawn in Section 6.

II. PAN-TOMPKINS' METHOD

Pan-Tompkins' method is actually a linear-filtering based algorithm for QRS detection. In the preprocessing stage, first, it improves the signal-to-noise ratio by using a band-pass filter. In more detail, the ECG signal is filtered by a low-pass filter and a subsequent high-pass filter with cut-off frequencies of 25Hz and 5Hz, respectively.

Then, the resultant signal is differentiated and, in turn, squared to further magnify the amplitude of the QRS complex. Next, the local energy of the signal is obtained by applying an integration window on the squared signal.

Finally, in the decision stage, the QRS complexes are detected by using an adaptive thresholding method.

III. WAVELET TRANSFORM

Similar to the Fourier transform, the wavelet transform decomposes a signal by using a set of basis functions

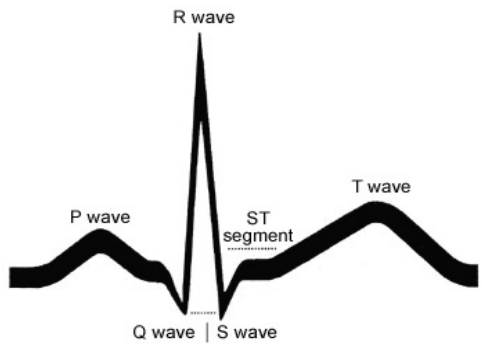

Figure 1. A typical QRS waveform

which are obtained by dilation and translation of the mother wavelet $\psi(x)$ with bounded support [7]. The continuous wavelet transform (CWT) of the signal $x(t)$ is defined by [6, 7]:

$$\mathrm{CWT}(x(t);a,b) = x(t) * \psi(t) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\psi^*(\frac{t-b}{a})dt \quad (1)$$

where $a,b \in R$ ($a \neq 0$) are the translation and dilation parameters, respectively. Generally, the wider basis function, with larger a, in the time domain, provides the lower frequency content and vice versa.

The dyadic wavelet transform (*DyWT*) is obtained by discretizing a with the sequence of 2^j (j=1,2,…). Therefore, *DyWT* of $x(t)$ is given by:

$$\mathrm{DyWT}(x(t); a = 2^j, b) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} x(t)\psi^*(\frac{t-b}{2^j})dt \quad (2)$$

Similarly, by using the above equation for discrete signals, the discrete wavelet transform (DWT) is obtained which can be efficiently computed by Mallat's method [11, 12].

IV. Proposed Algorithm

It was shown that if the wavelet is the first derivative of a smoothing function, for highly variational parts of the signal (e.g. the QRS complex in the ECG signal), DWT will provide local maxima at several successive scales [6].

Furthermore, most energy of the QRS complex is usually exposed in the third and, especially, fourth wavelet scales (i.e. a=23 and 24) [7, 8]. For example, the record 108 of MIT-BIH is shown in Fig. 4. It seems that because of abnormally high amplitude of P waves, the QRS complexes cannot be easily detected in the source ECG signal. However, in the fourth wavelet scale, they can be straightforwardly distinguished from P waves for their stronger energy content.

Therefore, we can use the wavelet transform instead of the linear filtering to improve the performance of Pan-Tompkins' method. It is the main idea of the proposed algorithm whose block diagram is shown in Fig. 2.

In the preprocessing stage, first, the fourth wavelet scale of the ECG signal is computed. We use the wavelet bior1.5 because of the biorthogonal, compact, regular, and symmetric properties. Thus, for the ECG signal x(t), we can write:

$$y(t) = \mathrm{DWT}_{bior1.5}\left(x(t); a = 2^4\right) \quad (3)$$

where y(t) is the resultant signal of the wavelet transform.

Since the QRS complexes appear as the local extremums, in contrast to Pan-Tompkins' method, there is no need to further differentiate the resultant signal. Furthermore, differential is actually a high-pass filter which can strengthen the noise effect on the signal.

To compute the energy signal e(t), we convolved the square of y(t) with a Gaussian kernel as follows:

$$e(t) = G_\sigma(t) * y^2(t) \quad (4)$$

where σ indicates the standard deviation of the Gaussian kernel Gσ(t). Compared to the sharp averaging window used in the Pan-Tompkins' method, the Gaussian window better estimates the local energy of the signal for its smoothed shape in both the time and frequency domains.

In the decision stage, to detect QRS complexes in the energy signal, we take advantage of the adaptive thresholding algorithm of Pan-Tompkins' method. In more detail, every peak of the energy signal, with the amplitude greater than a specified threshold (θ1), determines a QRS complex. If no QRS complex is detected within a specified time interval, a back-search process is performed in which the above procedure is repeated by using a smaller threshold (θ2), i.e. a fixed fraction of θ1. Furthermore, the time distance between every pair of subsequent QRS complexes should be longer than 200ms because of the physical constraints. Thus, in each pair of QRS complexes which denies the above criterion, the weaker one in terms of the energy value is truncated.

V. Experimental Results

We used the MIT-BIH database to evaluate the performance of the proposed algorithm. It contains 48 half-hour annotated tape of two-channel ambulatory ECG recordings with the sampling rate of 360 Hz, totally including 110 k beats (i.e. on average about 2280 + 450 per patient) [14]. However, we used only the first channel data of 10 first tapes (i.e. the records of 100-109) for experimental results.

To evaluate the solution quality of the proposed algorithm, we used the sensitivity and positive predictivity measures which are defined, respectively, as follows [13]:

$$Se = \frac{TP}{TP + FN} \times 100\% \quad (5)$$

$$+P = \frac{TP}{TP + FP} \times 100\% \quad (6)$$

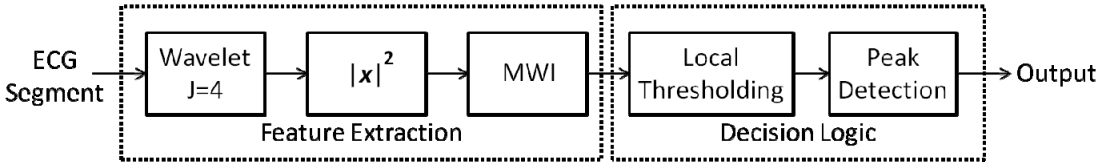

Figure 2. Block diagram of the proposed algorithm.

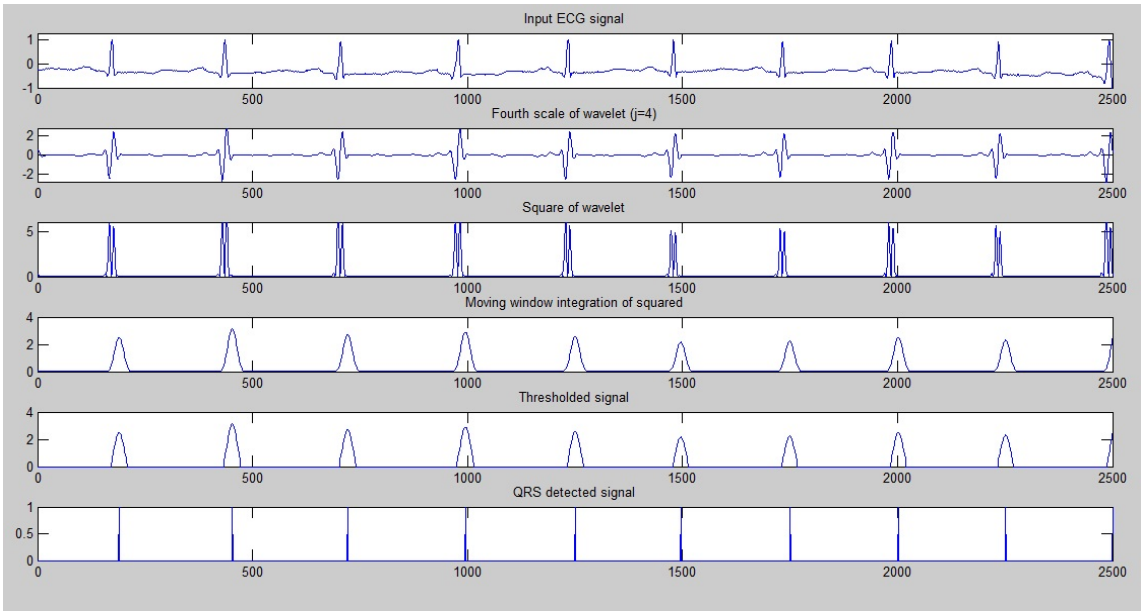

Figure 3. Results of the proposed algorithm for record 100.

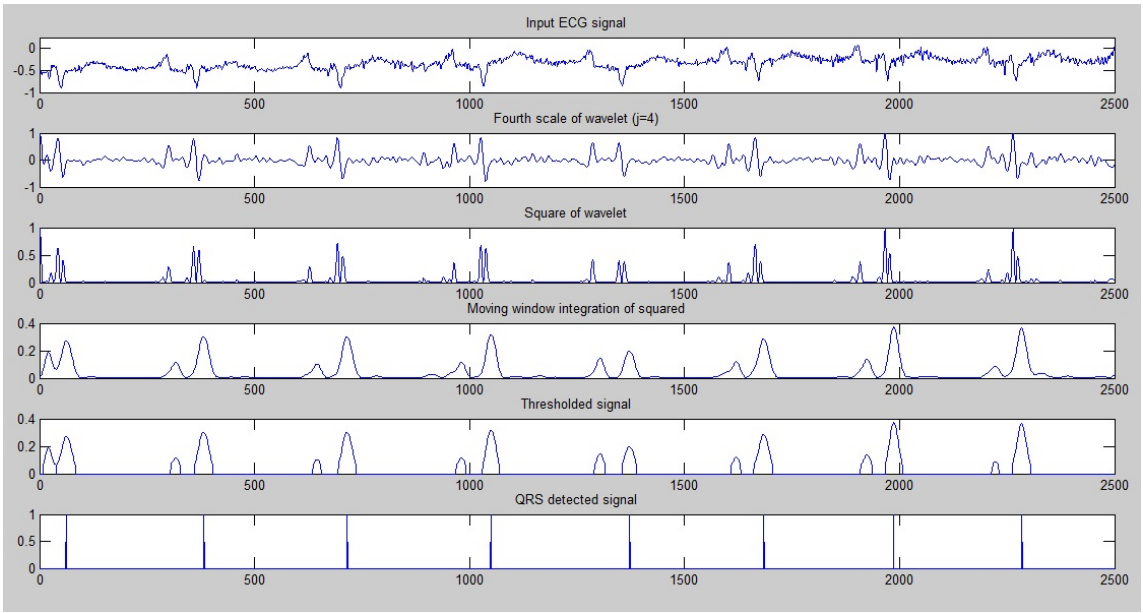

Figure 4. Results of the proposed algorithm for record 108.

where *TP*, *FN*, and *FP* denotes the number of true positives, false negatives, and false positives, respectively. All experimental results are obtained by an Intel Core-i3 2.13GHz PC with 1GB main memory using MATLAB environment. The results of the proposed method for some parts of the records 100 and 108 are illustrated in Figs. 3 and 4, respectively. It is further compared with Pan-Tompkins' method and a wavelet based QRS detection algorithm suggested by Li *et al*.

As shown, the proposed algorithm beats Pan-Tompkins' method in terms of both sensitivity and positive predictivity. Furthermore, it provided better positive

TABLE I. COMPARING THE PROPOSED ALGORITHM AND ITS TWO COUNTERPARTS INCLUDING PAN-TOMPKINS' AND LI'S METHODS FOR 10 BENCHMARK RECORDS FROM THE MIT-BIH DATABASE.

		Proposed Algorithm				Pan-Tompkins' method [2]				Li's method [6]			
Tape	Total	FN	FP	Se (%)	+P(%)	FN	FP	Se (%)	+P(%)	FN	FP	Se (%)	+P(%)
100	2273	1	0	99.96	100	0	0	100	100	0	0	100	100
101	1865	0	1	100	99.95	3	5	99.84	99.73	0	1	100	99.95
102	2187	0	7	100	99.68	0	0	100	100	0	0	100	100
103	2084	1	0	99.95	100	0	0	100	100	0	0	100	100
104	2229	17	0	99.24	100	0	1	100	99.96	2	8	99.91	99.64
105	2572	0	2	100	99.92	22	67	99.14	97.44	13	15	99.49	99.42
106	2027	13	1	99.36	99.95	2	5	99.91	99.75	3	2	99.85	99.90
107	2137	1	0	99.95	100	2	0	99.91	100	0	0	100	100
108	1774	0	1	100	99.94	22	199	98.76	89.80	15	13	99.15	99.27
109	2532	4	1	99.84	99.96	1	0	99.96	100	0	0	100	100
Total	21680	37	**13**	99.82	**99.93**	52	277	99.76	98.74	**33**	39	**99.85**	99.82

predictivity compared to Li's method. It is interesting to note that the QRS complexes of the noisy record 108 were detected with a very low error rate.

The proposed algorithm is significantly straightforward and efficient. In more detail, the average CPU time, for processing one benchmark record (with 648000 samples), was only 5.466s.

VI. CONCLUSION

In this paper, we introduced a new combinatory algorithm based on Pan-Tompkins' method and wavelet transform. The basic idea was substituting the linear filtering step of Pan-Tompkins' method with the wavelet transform to improve its performance. Experimental results demonstrated superior performance of the proposed algorithm compared to Pan-Tompkins' method and Li's method (a wavelet based QRS detection algorithm). The proposed method is a suitable approach for real-time QRS detection because of efficiency and straightforward implementation.

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