QRS Detection by Lifting Scheme constructing Multi-resolution Morphological Decomposition

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***Abstract*—QRS complex detecting algorithm is core of ECG auto-diagnosis method and deeply influences cardiac cycle division for signal compression. However, ECG signals collected by noninvasive surface electrodes areusually mixed with several kinds of interference, and its waveform variation is the main reason for the hard realization of ECG processing. This paper proposes a QRS complex detecting algorithm based on multi-resolution mathematical morphological decomposition. This algorithm possesses superiorities in R peak detection of both mathematical morphological method and multi-resolution decomposition. Moreover, a lifting constructing method with Maximizationupdating operator is adopted to further improve the algorithm performance. And an efficient R peak search-back algorithm is employed to reduce the false positives (FP) and false negatives (FN). The proposed algorithm provides a good performance applying to MIT-BIH Arrhythmia Database, and achieves over 99% detection rate, sensitivity and positive predictivity, respectively, and calculation burden is low. Therefore, the proposed method is appropriate for portable medical devices in Telemedicine system.**

I. Introduction

QRS Complex detection is the most important stage in ECG analyzing process. Accurate detection of QRS Complex is the precondition of detecting other ECG waves. This is the basis of ECG automatic classification and diagnosis [1,2]. Meanwhile, it ensures dividing cardiac cycles correctly, which is usually the first step before ECG compression, and has deep impact on utilization of correlations between cardiac cycles or different leads. QRS Complex detection consists of R peak detection and onset/offset decision, and we focus on R peak detection in this paper.

There are many algorithms designed for QRS detection purpose. Before Wavelet techniques are adopted, the derivative and its related information of ECG are mainly used for QRS detection, as it can access the deep slops of the R waves [3,4]. Such kind of methods has the characteristics of less calculation and easy implementation, but with lower positive rate and noise immunity. QRS detection algorithms based on Wavelet Techniques have been popular since last decade. The main idea is that QRS Complex's analyzing components are different between levels, and by choosing the level with local maximum, it is easier to distinguish modulus maximum that are related to QRS Complexes [5,6]. However, for QRS Complex with steep slope, methods based on Wavelet techniques are likely to mix it with EMG or other noise, and result in leak detection. Mathematical morphology (MM) methods have been introduced into ECG signal processing field in 1980s [7]. Mostly, algorithms based on MM methods are adopted in the pre-processing for its robustness and self-adaptability in extracting morphological information [8]. And then QRS detection based on MM method was mainly implemented by triangle structure elements (SE) [9]. In 2002, Goutsias et al proposed nonlinear multi-resolution signal decomposition scheme based on MM [10], which can achieve good performance for ECG signals, especially in ECG pre-processing [11]. QRS complex detection can also be realized by multi-resolution decomposition scheme based on MM (MDMM) [12]. However, QRS complex detection methods based on MM distinguish steep R peaks more easily than gentle ones.

This paper proposes a QRS complex detection method to improve FP and FN caused by abnormal ECG signals. This method is based on lifting scheme constructing MDMM with Maximization updating operator, which is implemented after ECG signal pre-processing by algorithm described in [11](LMW algorithm for short). Furthermore, an effective R peak search-back algorithm is adopted to reduce the false positives (FP) and false negatives (FN).

II. Method

A. Lifting Scheme Constructing MDMM for ECG signals

Define ECG signal as$f(n), n=0,1,\ldots,N-1$, symmetrical SE as $B(m), m=0,1,2,\ldots,M-1$, erosion and dilation of ECG signal can be denoted as following

$$(f\Theta B)(n)=\min_{m\epsilon 0,1,\ldots,M-1}\{f(n+m)-B(m)\} \tag{1}$$

$$(f\oplus B)(n)=\max_{m\epsilon 0,1,\ldots,M-1}\{f(n-m)+B(m)\} \tag{2}$$

Opening operator is $f\circ B=(f\Theta B)\oplus B$ while closing operator is $f\cdot B=(f\oplus B)\Theta B$.

According to multi-resolution morphological decomposition theory, ECG signals at level$j$can be decomposed as following

$$x_{j+1}=\psi_j^{\uparrow}(x_j)=MF_j(x_j) \tag{3}$$

$$y_{j+1}=\omega_j^{\uparrow}(y_j)=x_j-MF_j(x_j) \tag{4}$$

where$MF_j(f)$ is definedas multi-resolution morphological filter at level j.

$$MF_j(f)=\frac{1}{2}\left(f\circ B_j\cdot B_j+f\cdot B_j\circ B_j\right) \tag{5}$$

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whereB_j is a linear SE with length equals to $j+1$ while x_j is the approximate signal and y_j is the detail signal at level j. More improvements in specified performance of algorithms such as noise suppression and QRS detection accuracyand so on, are able to be achieved by adopting lifting scheme constructing method with appropriate operators. Consider lifting scheme constructing new detail and approximate component at level j as

$$y_j^{'} = y_j - \pi(x_j) \quad (6)$$

$$x_j^{'} = x_j - \lambda(y_j^{'}) \quad (7)$$

where$\pi: V_j \rightarrow W_j$ is the predicting operator and $\lambda: W_j \rightarrow V_j$ is the updating operator. Reconstructions at level j and $j-1$ are defined as

$$\hat{x}_j = x_j^{'} + \lambda(y_j^{'}) \quad (8)$$

$$\hat{x}_{j-1} = \psi_j^{\downarrow}(\hat{x}_j) + \omega_j^{\downarrow}\left(y_j^{'} + \pi(\hat{x}_j)\right) \quad (9)$$

B. ECG signal pre-processing by LMW algorithm

Noise suppression in ECG signals can be divided into two steps: (1) remove the baseline wander caused by electrodes movement and respiration; (2) Suppress high frequency noise caused by EMG and other interference. Therefore, LMW algorithm first does baseline wander correction by using the following MM filter [8]

$$f_b = f_0 \circ B_0 \cdot B_c \quad (10)$$

where$f_0$is the original ECG signal, $f_b$is the detected baseline wandering, $B_0$and$B_c$are two linear SEs which depend on the duration of characteristic waveforms in ECG signalsT_ω and sampling rate F_s. Commonly, $T_\omega < 0.2s$, therefore, let $B_0 = 0.2F_s$ and $B_c = 1.5B_0 = 0.3F_s$. ECG signals after baseline correction can be decomposed at level j as following

$$x_0 = f_0 - f_b \quad (11)$$

and let $x_1 = x_0$.

Then high frequency noise suppression is conducted by lifting scheme constructing MDMM. Block effect is the main cause of waveform distortion in morphological filter based ECG pre-processing method. To address this issue, a novel updating and predicting operator based on cubic spline interpolation is proposed as

$$\pi(x_j)(n) = x_j(n) - x_j(n+1) \quad (12)$$

$$\lambda(y_j)(n) = \text{spline}(x_j(n-1), x_j(n+1)) \quad (13)$$

where the predicting operator is the difference between adjacent samples; and updating operator is the interpretation according to the forward and backward sample. Because of the smoothing characteristic of cubic spline interpolation, LMW algorithm can reduce the block effect and improve the waveform distortion. The good performance in noise suppression is also proved by our previous work [11].

Take Sample 222 in MIT-BIH with visible baseline wander and high frequency noise as example, as is shown in Figure 1: baseline wander is corrected firstly, then ECG signals are decomposed to level 2 by lifting scheme constructing MDMM, finally we choose approximation component at level 2 as the pre-processing results and original data for QRS detection, because the root mean square is the least among level 1 to level 3 decomposition.

C. QRS Detection by Lifting scheme constructing MDMM

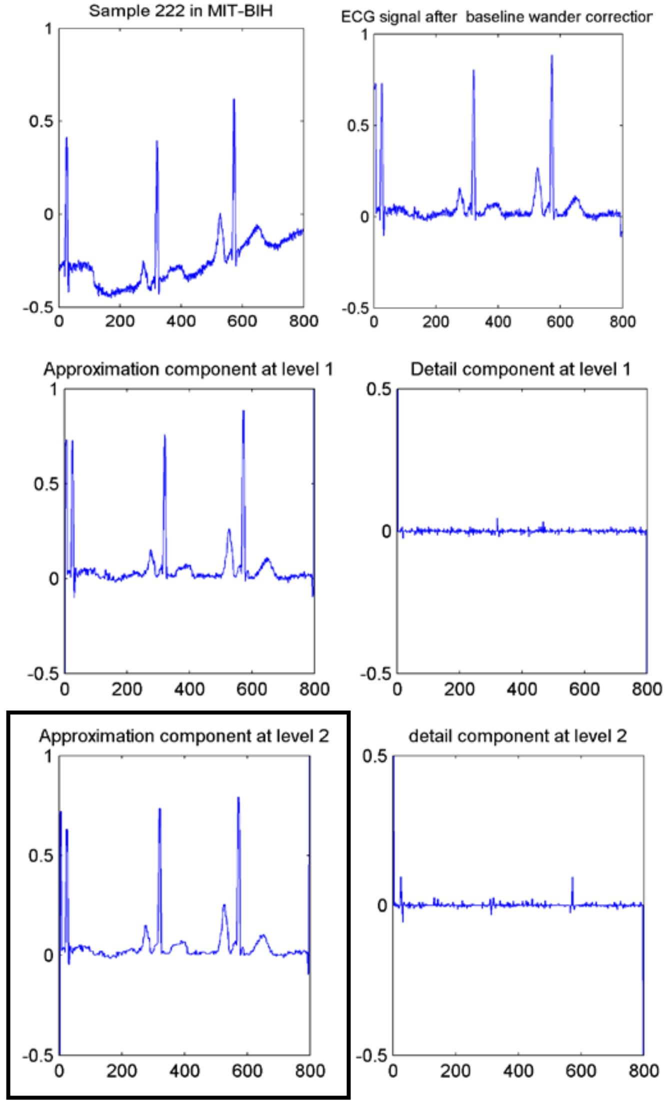

Figure 1. Sample 222 in MIT-BIH database. Preprocessing by LMW algorithm. Take Approximation component at level 2 as preprocessing results.

Algorithm

After ECG signal pre-processing,it becomes apt to detect QRS complex more easily. Then we considerdetecting QRS complex accurately by lifting scheme constructing MDMM with maximization operator (LMS algorithm for short). Let predicting operator is the difference between adjacent samples; and updating operator is the maximum of adjacent three samples, as describe in "(14)" and "(15)":

$$\pi(x_j)(n) = x_j(n) - x_j(n+1) \quad (14)$$

$$\lambda(y_j)(n) = \max(x_j(n-1), x_j(n), x_j(n+1)) \quad (15)$$

and ECG signals can be decomposed through "(3)-(8)". Furthermore, a search back method is encompassed in our proposed QRS detecting algorithm, which is called LM Algorithm for short and can be summarized by the application of the following steps, and the flow chart is illustrated inFigure 2:

1) Divide every 10 seconds ECG data as a segment. Set initial value of threshold as one-tenth the maximum of samples in the segment.

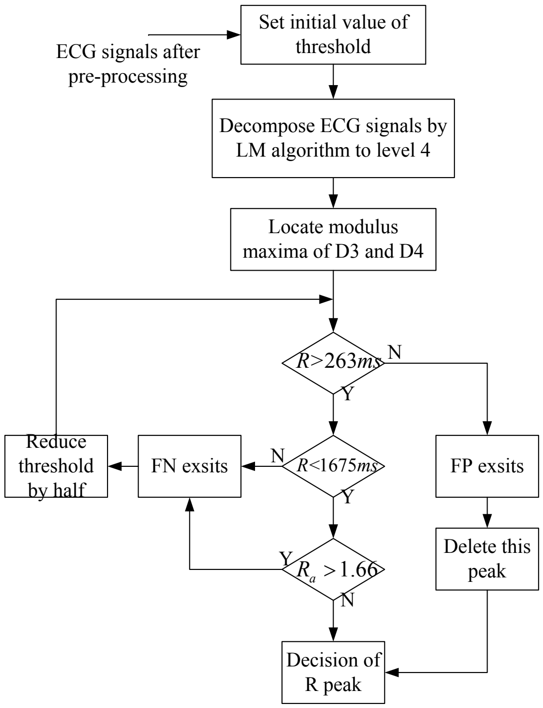

Figure 2. Flow chart of LMS Algorithm

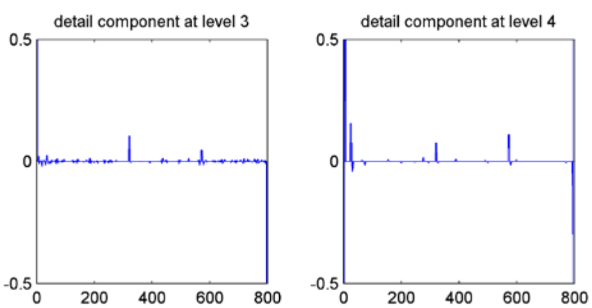

Figure 3. Detail components at level 3 and level 4

2) Decompose segment by using LM Algorithm up to level 4 (i.e. do twice lifting scheme constructing with maximization operator after pre-processing).

3) Locate modulus maxima of detail component at level 3 (D3) and detail component at level 4 (D4); D3 and D4 of Sample 222 is shown in Figure 3. Then do "OR" operation between D3 and D4 as the input to search back algorithm.

4) Define R is RR interval, and$aveR$is the average RR intervals of two preceding segments. It is critical for both medical staff and researchers to restrict R and $aveR$ in reasonable ranges. In [13], it presents that $R < 250ms$ is an important symbol of sudden death; and in [14], it is proved that only 5% of patients have $R > 1750ms$ occasionally. Therefore, we consider reasonable range is $250ms < R < 1750ms$. Because the sampling rate of MIT-BIH Arrhythmia Database is 360Hz, we set the limits of R are 263ms and 1675ms, which means if $R < 263ms$, there's a false peak (FP); if $R > 1675ms$, there's a leak detection (FN). Define $R_a = R/aveR$, if $R_a > 1.66$, we consider there's a FN. When there's a FP, the peak is deleted; when there's a FN, then the threshold is reduced by half and the search back algorithm is conducted one more time, until the values of R and R_a are reasonable and R peaks will be decided.

III. Results

LMS Algorithm is applied to 48 ECG signals in MIT-BIH Arrhythmia Database[15], which have been preprocessed by LMW Algorithm. Three initial evaluation index have been chosen: true positive (TP), false positive (FP), false negative (FN), which refer to the number of true beat detection, false beat detection and true beats that are failed to be detected. Meantime, overall performance has been evaluated through sensitivity (Se), positive prediction (+P) and detection error rate (Err), which are defined as follows,

$$Se = \frac{TP}{TP+\square\square} \times 100\% \quad (16)$$

$$+P = \frac{TP}{TP+FP} \times 100\% \quad (17)$$

$$Err = \frac{FP+FN}{RR\ Numbers} \times 100\% \quad (18)$$

where $RR\ Numbers$ denotes overall RR Numbers, i.e. heart beats in the sample. LMS Algorithm is compared with Method 1[16] based on sparse derivatives, Method 2 [17] based on positive and negative slope of QRS complex, Method 3 [18] based on wavelet transform, Method 4 [19] based on topological mapping. The performances of above algorithms for MIT-BIH Arrhythmia Database are shown in Table I.Compared with other algorithms, LMS Algorithm achieves better performance on all the evaluation indices. Not only the improving QRS detection method, but also the good pre-processing performance contributes to this priority. There are slightly different numbers of overall beats for different numbers. According to references [16,17,19], several segments in ECG data have been discarded because R peaks are unrecognizable even for physicians. The computational cost has been considered by the simulation time cost: Proposed method<Method 4< Method 3<Method 1<Method 2.

TABLE I. QRS detection performances applied to MIT-BIH Arrhythmia Database.

	Overall beats	*TP*	*FP*	*FN*	Se (%)	+P (%)	Err (%)
LMS (proposed)	109494	109396	115	98	99.91	99.89	0.19
Method 1 [16]	109452	109314	127	138	99.87	99.88	0.24
Method 2 [17]	109494	109241	393	253	99.77	99.63	0.59
Method 3 [18]	109428	109208	153	220	99.80	99.86	0.34
Method 4 [19]	109481	109146	137	335	99.69	99.88	0.43

IV. Discussion

LMS Algorithm achieves good performance in sensitivity; however, it is difficult to approach 100% for all the samples. It is mainly caused by sudden transform in waveform pattern, abnormal waveform, or severe interference. In the section, we will discuss specific condition that may lead to FP and FN.

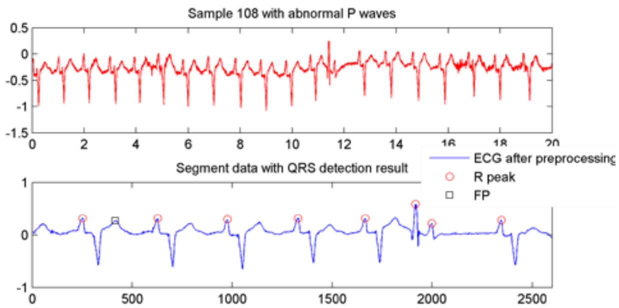

Figure 4. Sample 108 and segment data with QRS detection result

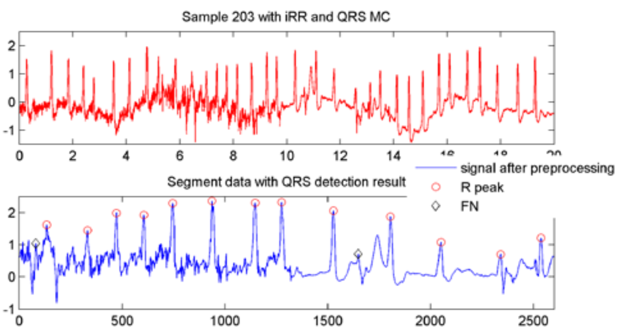

Figure 5. Sample 203 and segment data with QRS detection result

Figure 4 shows Sample 108 with abnormal P waves. Generally, high P waves do not cause false detection (FP); but when RR intervals become longer suddenly and high P waves exist, it is possible to cause FP, as samples between 400 and 500. On the other hand, for samples around 2000, two adjacent R peaks are very close, $RR = 230ms, R_a \approx 1.724$. Therefore, if there's no search back process, a FN will definitely occur.

Figure 5 shows Sample 203 with irregular RR intervals (iRR) and QRS morphological changes (QRS MC). Obviously, irregular RR intervals and noise interference are the reason that causes the first FN, and amplitude changes rapidly causes the second FN.

High P waves, irregular RR intervals, Changing R peaks and noise are the main reasons that cause FP and FN. Also, there're other factors which can also found in the database, such as high R peaks with change in RR interval and so on, but we will not discuss themin detail in this paper.

V. Conclusion

This paper proposed a novel QRS complex detection method based on lifting scheme constructing mathematical morphology basing multi-resolution decomposition. Cooperating with good performance pre-processing and effective search back strategy, this method achieved good performances as applied to MIT-BIH Arrhythmia Database, and possessed certain robustness to abnormal ECG signals. Furthermore, the calculation complexity was much lower than methods based on wavelet or other multi-resolution decomposition methods. Therefore, it can be adopted by mobile medical devices using in Telemedicine system as part of auto-diagnosis or compressing and transmission design.

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