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A new QRS complex detection based on wavelet transform

By

Khaled Daqrouq*

Ibrahim N. Abu-Isbeih*

Abstract:

In this paper a new QRS complex detection method is proposed based on wavelet transform (WT). Wavelet theory is inspired the development of a strong methodology for signal processing and can be used as a good tool for non-stationary electrocardiogram (ECG signal) detection. The new proposed method presents sharp results for ECG detection parameters where the fiducial points are easily detected. The obtained results show that the sensitivity of the proposed detector is 99.8% and that the specificity is 98.6%. The proposed detector used in this paper is tested using an original ECG signal data base.

Keywords:

ECG Signal, QRS detection and Wavelet transform

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* Department of Communication Engineering, Philadelphia University, Jordan

1. Introduction:

The wavelet functions (mother and its scaled version) are used as orthonormal functions for representing another functions in discrete wavelet transform (DWT) and continuous wavelet transform (CWT). Locating ECG parameters (fiducial points) like QRS complex, ST-segment, R-R interval, J point, iso-electric level, R peak and onset and offset of QRS complex and T wave have been very important for diagnosis many cardialogical diseases. The irregularity of ST-segment is considered electro-physiologically significant because it is an indicator of an imbalance myocardial oxygen supply and in myocardial ischemia or infarction. QRS complex and R-R interval have had very essential role in indicating and measuring heart rate variability.
As mentioned above, In ECG analysis the single most important feature is the QRS complex. Because all other features, like the P and T waves and the on- and offset of the QRS complex are defined relative to the QRS complex. The P and the T wave occur respectively before and after the QRS complex, without knowledge of the QRS location P and T waves are hard to distinguish from each other. Most QRS detectors can be divided in to two stages: a filtering stage and a decision stage. The filtering stage is used to emphasize the QRS complex and to reduce noise and the influence of the other waves in the ECG signal (P and T waves). Typically first a band pass filter is applied to the signal to reduce noise and to suppress P and T waves and then put through a non-linear stage to enhance the QRS complex. Then the QRS enhanced signal is thresholded and some decision logic is used for the final stage of detection. Wavelet transformation has proven to be a very efficient tool in the analysis of ECG
signals [11]. Its ability to automatically remove noise and to cancel out undesired phenomena such as baseline drift are a benefit over other techniques. In [12], a simple moving average-based computing method for real-time QRS detection is used. The numerical results indicated that the novel algorithm finally achieved about 99.5% of the detection rate for the standard database, and also, it could function reliably even under the condition of poor signal quality in the measured ECG data. In [13] a QRS complex detection algorithm that can be applied in various on-line ECG processing systems is presented. The algorithm is performed in two steps: first a wavelet transform filtering is applied to the signal, then QRS complex localization is performed using a maximum detection and peak classification algorithm. The algorithm has been tested in two phases. First the QRS detection in ECG registrations from the MIT-BIH database has been performed, which led to an average detection ratio of 99.5%. in [14] linear prediction coefficients of a forward linear predictor by minimizing the prediction error by a least-square approach is used. The residual error signal obtained after processing by the linear prediction algorithm is used to localize and to detect QRS complexes.
This paper presents CWT with Symmlets mother and father wavelets for detecting of QRS-complex. This transform is robust to noise because it divides the signal into

several bands of frequencies. Over more, Symmlets wavelet function has the following properties:

- Compactly supported wavelets with least asymmetry and highest number of vanishing moments for a given support width.
- Associated scaling filters are near linear-phase filters.
- Orthogonal and biorthogonal.
- Compact support.
- Near from Symmetry.

2. Wavelet Transform:

The orthonormal wavelet functions (bases) are analogous to trigonometric sine and cosine. These functions are fundamental functions for building the signals. As with sine and cosine, are oscillated about zero. However the oscillation for wavelets damp down fast to zero.

A. The Signal Approximation by Wavelets:

The $f(t)$ approximation by wavelet orthonormal bases can be defined as

$$f(t) = \sum_k s_{j,k}\Phi_{j,k}(t) + \sum_k d_{j,k}\Psi_{j,k}(t) + \sum_k d_{j-1,k}\Psi_{j-1,k}(t) + ... + \sum_k d_{1,k}\Psi_{1,k}(t) \tag{1}$$

where j is the scale, k the translation parameter, $s_{j,k}$, $d_{j,k}$ are the wavelet approximation coefficients and $\psi_{j,k}(t)$ and $\phi_{j,k}(t)$ are wavelet approximation functions. Wavelet functions have two forms: ψ is the mother of wavelets (wavelet function), and ϕ the father of wavelets (scaled function) shown in figure (1).

Roughly speaking, ψ (t) represents high frequency parts of the signal, and $\phi(t)$ represents smooth and low frequency parts of the signal [1,2]. The wavelet types, which generally used are: Haar, Daubechies, Symmlets and Coiflets. Functions $\psi_{j,k}(t)$ and $\phi_{j,k}(t)$ are scaled and translated version from ψ and ϕ [3,4]:

$$\psi_{j,k}(t) = 2^{-j/2}\,\psi\,(2^{-j}\,t-k) \tag{2}$$

$$\phi_{j,k}(t) = 2^{-j/2}\,\phi\,(2^{-j}\,t-k) \tag{3}$$

(*a*) (*b*)

Figure (1): *The scaled version (a) (father) of Symmlets. (b) Mother of Symmlets.*

B. Discrete Wavelet Transform:

The discrete wavelet transform (DWT) calculates the wavelet approximation coefficients. For example, for discrete and finite signal f= $(f_1,f_2,..., f_N)$, DWT calculates m coefficients vector w = $(w_1,w_2,...,w_m)$, which consists of wavelet approximation coefficients $s_{j,k}$ and $d_{j,k}$ j = 1, 2,..., J.
DWT in mathematical view is such multiplication:

$$W= W_* f \tag{4}$$

where W is a DWT matrix.
To calculate the wavelet approximation coefficients we apply known Mallat's algorithm (MA) shown in figure (2) [5]. This algorithm convolutes the signal with wavelet function and its scaled version as low pass and high pass (H, L), which are called quadrature mirror filters (QMF) [6,7] and applies decimation operation. By using Mallat's algorithm we decompose the original signal into subsignals (d_1, d_2, d_3..., d_j, s_j, where $d_j = (d_{j,1}, d_{j,2}, ... ,d_{j,N/2^j})$) and $s_j = (s_{j,1}, s_{j,2}, ..., s_{j,N/2^j})$), with different bands of signal frequency.
To understand Mallat's algorithm let's study its steps basing on the following program written by the authors in Matlab environment using wavelet toolbox:

```
% Mallat's algorithm for 3 levels
 [Lo_D,Hi_D] = wfilters('db1','d');
%level=1
f0L= conv(f0,Lo_D);
s1=dyaddown(f0L);
f0H= conv(f0,Hi_D);
d1=dyaddown(f0H);
%level=2
```

```
s1L= conv(s1,Lo_D);
s2=dyaddown(s1L);
s1H= conv(s1,Hi_D);
d2=dyaddown(s1H);
%level=3
s2L= conv(s2,Lo_D);
s3=dyaddown(s2L);
s2H= conv(s2,Hi_D);
D3=dyaddown(s2H)
```

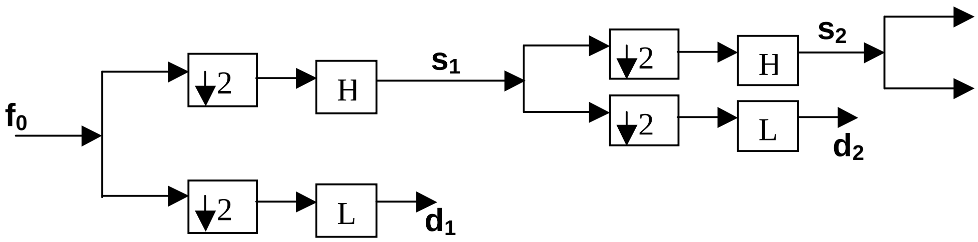

Figure (2): *Mallat's Algorithm, where f_0 is original signal and the arrow with number two means decimation*

3. New QRS Detector:

It was shown in [8] and [9] that the maximum of the absolute value of CWT using the mother wavelet as the first derivative of a smoothing function indicates the occurrence fast (sharp) signal variations like QRS complex. Author chooses function sym.8 form Symmlets wavelets shown in figure (1) to locate QRS complex by R wave peak location as the maximum of the square value of CWT. The presented detector can be divided into three stages as follows:

The first stage: The new detector is based on using the CWT with sym.8 and scale 2^3 (for sampling frequency f_s = 100 Hz and 2^{10} for f_s = 400 Hz), as a pass band filter (from 12 to 38 Hz), which permits the QRS complex frequency without P, T and noise frequencies shown in figure (3) and table (1). In [10] it was shown that the average spectral frequency of QRS complex from 6 to 30, and from 0 to 5 Hz artefact motion noises and from 5 to 10 Hz for P and T(Fig.4,5).

From figure (3) we can see that using the CWT with sym.8 and scale 2^3 is very suitable for QRS complex detection because:

The centre frequency at scale 2^3 is very suitable for QRS complex spectral frequency, which is about (17 Hz), it means R, and Q and S peaks have the same places as in original signal. T, P waves do not appear.

The very high frequency noise does not appear.

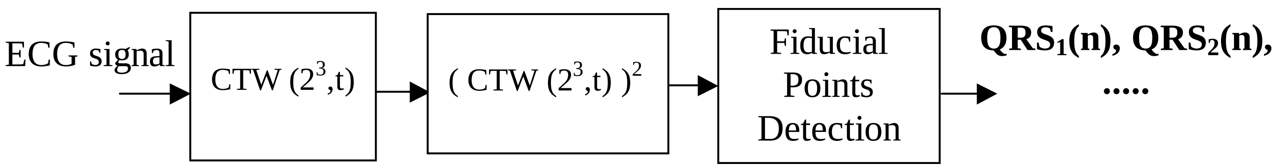

Figure (3): *The QRS complex detector*

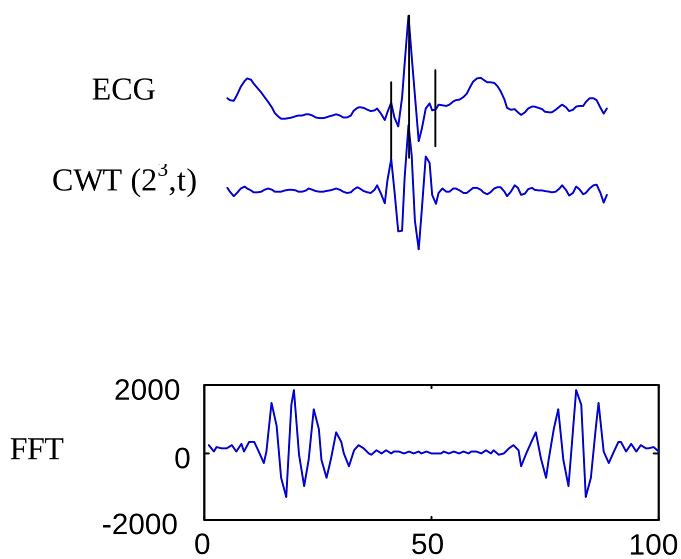

Figure (4): *CWT at scales 2^3 and FFT(d_3)*

Table (1): *The coefficients of low and high pass filters of sym.8 function*

L	0.0034 -0.0005 0.0317 0.0076 -0.1433 -0.0613 0.4814 0.7772 0.3644 -0.0519 - 0.0272 0.0491 0.0038 -0.0150 -0.0003 0.0019
H	-0.0019 -0.0003 0.0150 0.003 -0.0491 -0.0272 0.0519 0.3644 -0.7772 0.4814 0.0613 - 0.1433 -0.0076 0.0317 0.0005 -0.0034

The second stage: is to calculate square of coefficients $(CWT\ (2^3,t))^2$ in figure (4). Now it is very easy to detect threshold of QRS complex at CWT $(2^3,t)$; afterwards, detecting the maximum in every window, which includes QRS complex will indicate R peak (Fiducial point-FP).

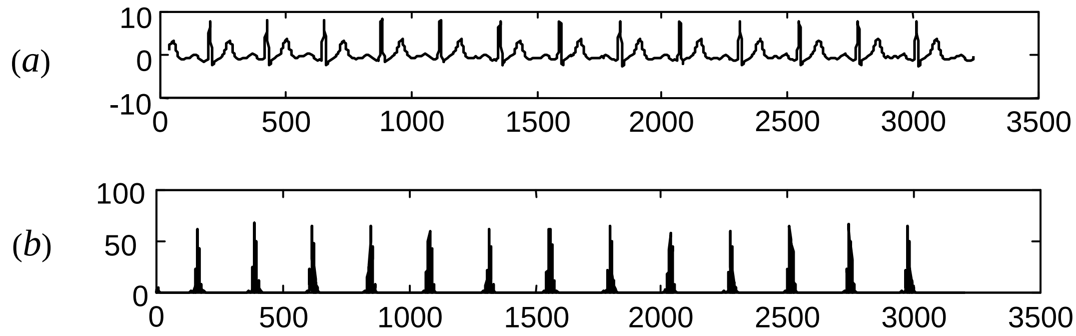

Figure (5): *(a) ECG signal (b) (CWT (23,t))2 signal*

The third stage: indicating all amplitudes higher than threshold B. B is indicated empirically equals to

$$L(i) > B*R \tag{5}$$

where L(i) is the vector of these amplitudes, i the index of amplitude in original signal, B is indicated empirically equals to 0.15 where the frequency of sampling is 100 Hz and 400 Hz, and R is max $(CWT\ (2^3,t))^2$).

The fourth stage: in this stage the QRS complex is located in the window (i=10:i+10) (where f_s is 100 Hz and (i=30:i+30) where f_s is 400 Hz) by indicating the fiducial point as maximum for each i in vector L(i)

$$FP(n)=\max(CWT(2^3,t))^2 \ , \qquad i-10 \geq i \leq i+10 \tag{6}$$

where n is the index of R peak in original signal.
To understand the detector let's study its stages basing on the following program written by author in Matlab environment using wavelet toolbox for fs =100 Hz:

```
% QRS complex detector
c0 = CWT(x,3,'sym8');
c=c0.^2;
L1=find(c>0.15*max(c));
```

```
for i=2:length(L1), l2(i-1)=find(c==max(c((L1(i-1)-10):(L1(i-1)+10))));
end
L4(1)=L3(1);
 j=2;
for i=2:length(L3)
if not (l3(i)==l4(j-1))
l4(j)=l3(i);
j=j+1;
end
end
```

commend c0 = CWT(x,3,'sym8'); calculates c0 as the CWT of x (ECG signal),
commend c=c0.^2; calculates square of c0, commend L1=find(c>0.15*max(c)); finds the indexes of amplitudes beggar than threshold B,
for i=2:length(L1), l2(i-1)=find(c==max(c((L1(i-1)-10):(L1(i-1)+10)))); this loop locates the index n of QRS complex in the window (i=10:i+10) by indicating the fiducial points as maximum for each and in vector L1(i),
the following procedure is used for getting L3(i) without repeating any elements.

```
L3(1)=L2(1);
 j=2;
for i=2:length(L2)
if not (l3(i)==l3(j-1))
l4(j)=l3(i);
j=j+1;
```

4. R-R Interval Detection:

The R-R interval detection is very important to measure heart rate and for heart rate variability diagnosing as shown in figure (6). This interval can be detected and measured after detecting FP of QRS complexes by:

$$\text{R-R} = \Delta T_{HR} = FP(i+1) - FP(i) \qquad (7)$$

where ΔT_{HR} is the time interval between two consecutive FP in seconds, FP(i) detects FP of QRS complex and FP(i+1) is the FP of next QRS complex. The heart rate is measured as:

$$HR = 60 / \Delta T_{HR} \qquad (8)$$

where HR is the heart rate in one minute. Up normal heart rate appears when
HR>100 beats/min (tachycardia): R-R<0.6 s, HR<60 beats/min (bradycardia): R-R>1 s.

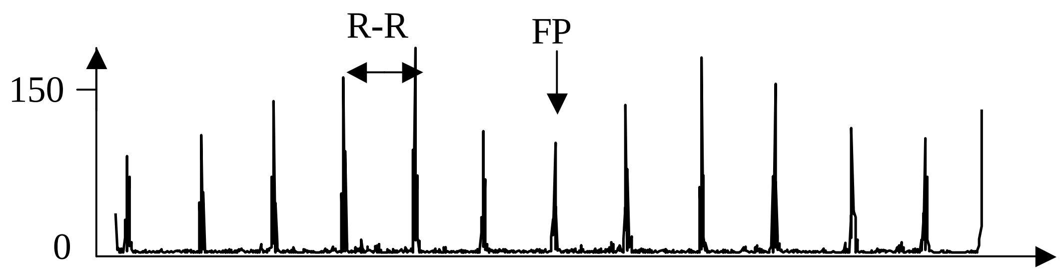

Figure (6): *R-R interval detection*

% Heart rate calculating program

```
 for i=2:length(l4)
 RR.(i-1)=l4(i)-l4(i-1);
Rr=rr>10;
RR=rr(Rr);RRmean=mean(RR);
HR=60/(RRmean/100);
 if HR>100
      HRD=('tachycardia');
elseif HR<60
     HRD=('bradycardia');
else
   HRD=('normal');
end
```

Loop for i=2:length(L3), rr(i-1)=l4(i)-l4(i-1); calculates rr as the R-R interval for all fiducial points in l4(i-1) vector,
commend HR=60/(RRmean/100); calculates heart rate for frequency sampling 100 Hz,
condition if, else if, else are used to write the result of heart rates diagnosing.

6. Conclusions:

QRS complex detection faces many problems like that the morphology of QRS depends on patient, the ECG leads and the change of impedance in the skin-electrode place. On another hand recording many another noises. But the successful detector should work despite of these difficulties
The first stage of the evaluation of presented detector is determining the errors. The errors detector are divided into two kinds:

- False positive: detector detects the QRS complex when it doesn't appear,
- False negative: detector doesn't detect the QRS complex when it appears,

The proposed detector is tested for 1001 QRS complexes of 30 several ECG signals each one has 1000 samples and sampling frequency 100 Hz and noticed that detector had FP at the beginning of signal when appeared some amplitudes before the first QRS complex as a result of cutting the signal. It determined:

FN = 1

FP = 7

The sensitivity of detector is

$$S1 = (([T] - [FN])/[T]) \cdot 100\% = 99.80\% \tag{9}$$

The specificity of detector is

$$S2 = (([T] - [FP])/[T]) \cdot 100\% = 98.60\% \tag{10}$$

where [T] is the number of QRS complexes for all base, [FN] is the number of false negative and [FP] is the number of false positive.

The presented QRS complex detector has been tested, also, for 1001 QRS complexes of several ECG signals of 3200 samples (8s) (for each one) and sampling frequency 400Hz, it has been determined the sensitivity S1 of detector equals to 100% and the specificity S2 equals to 99.70%.

The proposed detector used in this paper is tested for real ECG signal and the following results are concluded:

- The possibility of detection the QRS complex by CWT using wavelet function sym.8.
- The performance of the QRS complex detector presented in the thesis hasn't bean changed by adding muscle noise, even when SNR= -0.039 dB, because CWT is robust to noise and suitable for non-stationary ECG signal nature than averaging moving filter.

References:

[1]	I. Daubechies, *The orthonormal bases of compactly supported wavelets*, Comm. Pure Appl. Math. Vol.41, P. 909-996, 1988.
[2]	C. K Chui, *Wavelets: a tutorial in theory and application, Boston*.
[3]	V Nitish Guo Xon-rong, Ssun Yi-chun, F. Hanley, *Multiresolution wavelet analysis of evoked potential*, IEEE Transactions on Biomedical Engineering, Vol. 40, No. 11, November 1993.
[4]	S. G. Mallat, *Multifrequency channel decomposition of image and wavelet models*, IEEE Transactions, Acoustic Speech Signal Proc., Vol. 37, 1989.
[5]	J. Mallat, *A theory of multiresolution signal decomposition the wavelet representation*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, P. 674-693, July 1989.
[6]	Bruce, Andrew, *Applied Wavelet Analysis With S-plus*, New York: Springer-Verlag, XXI, 3385:IL., 1996.
[7]	J. Chen, I. Shuichi, *A wavelet Transform-Based ECG Compression Method Guaranteeing Desert Signal Quality*, IEEE Transactions on Biomedical Engineer*ing*, Vol. 45, No. 12, December 1993.
[8]	S. G. Mallat, S. Zhong, *Characterisation of signals from Multiscale edges*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 14, No. 7, P.710-732 July 1992.
[9]	S. G. Mallat, S. Zhong, *Compact image representation from Multiscale edges*, 3rd Conf. on Comput. Vision, 1990.
[10]	N. V. Thakor, J.G Webster, J. Tompkins, *Estimation QRS complex power spectra for design of QRS filter*, IEEE Transactions on Biomedical Engineering, Vol. 31, P.702-706, Nov., 1985.
[11]	Haddad, S.A.P., Houben, R., and Serdijn, W.A. (2004b). The history and development of pacemakers: an electronics perspective. Klinische Fysica, pp. 8–15.
[12]	S. Chen, H. Chen, H. Chan. A real-time QRS detection method based on moving-averaging incorporating with wavelet denoising. Computer Methods and Programs in Biomedicine, Volume 82, Issue 3, Pages 187-195
[13]	Quick QRS Complex Detection for On-Line ECG and Holter Systems L. Szilagyi; S.M. Szilagyi; A. Frigy; S.E. Laszlo; L.K. Gorog; Z. Benyo Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the Volume , Issue , 2005 Page(s):3906.
[14]	Z. E. Hadj Slimane a; F. Bereksi Reguig a a Laboratoire de Génie Biomedical (GBM), Département d'électronique Faculté des Sciences de l'Ingénieur, Université Abou Bekr Belkaid-Tlemcen. B.P.119, Tlemcen, Algeria