QRS Complex extraction from ECG signal using Discrete Wavelet Transform

Sergio R. Espinal, BIOM5101 Biological Signals, Fall 2014

Department of Electronics, Carleton University
Ottawa, ON. Canada

***Abstract*— This paper presents a method of filtering the noise from the real ECG signal and detection of QRS complex, based on Discrete Wavelet Transform. Wavelets provide temporal and spectral information simultaneously, offering flexibility with a choice of wavelet functions with different properties. The sample used was the record 118e00 from the MIT-BIH Noise Stress Test Database.**

I. INTRODUCTION

The electrocardiogram (ECG) signal is the electrical interpretation of the heart activity. The signal is composed of a set of well defined- successive – waves denoted as: P, Q, R, S and T waves. The ECG signal is often corrupted by several sources of noise, called artifacts. Artifacts are signals that are not "heart-made". Some of the artifacts (noise) that can be present in the signal are: 50/60 Hz frequency interference from power line, Electrode motion artefact, Baseline wander/drift due to breathing of subject (lower than 1Hz), and Muscle artifact (EMG). This noise reduces the quality and useful information of the ECG signal for diagnosis purposes. To obtain a useful signal, like the QRS complex, the contaminated ECG will be decomposed, denoised and reconstructed employing Discrete Wavelet Transform.

II. DISCRETE WAVELET TRANSFORM

The method proposed for denoising is the Discrete Wavelet Transform [2]. It is based on the STFT, and the Continuous Wavelet Transform. The DWT uses a window function called wavelet to evaluate the frequency components at different time slots (intervals) and see if they are present in that time frame. By this, it is possible to locate

The DWT employs a dyadic scaling (1), in which the signal is divided by a factor of 2 using low-pass and high-pass filters (wavelets). Also, the translation and scaling of the window are done by a factor of 2, easy for computers to evaluate. This accounts for discretising the signal.

$$\psi_{i,k}(t) = \frac{1}{\sqrt{2^i}} \cdot \psi(2^{-i} \cdot t - k) \quad (1)$$

In Eq. (1), i represents the scaling parameter, and k the translation parameter. $1/\sqrt{2^i}$ is the normalization parameter, and it is used to normalize the wavelet to have "unit energy".

Each scaling indicates a new level, and for every level the previous signal is being decimated by a factor of 2, and the new signal will have half the size of the previous signal, employing the wavelet transform. The result is half the data output (at each level) compared to the Continuous Wavelet Transform, and a better frequency resolution compared to the Short-Time Fourier Transform due the window scaling.

The wavelet selected was the Coiflet 4 which offers a good correlation with the "desired" output signal. The entire process is divided into 4 stages: decomposition, denoising, reconstruction and QRS complex detection.

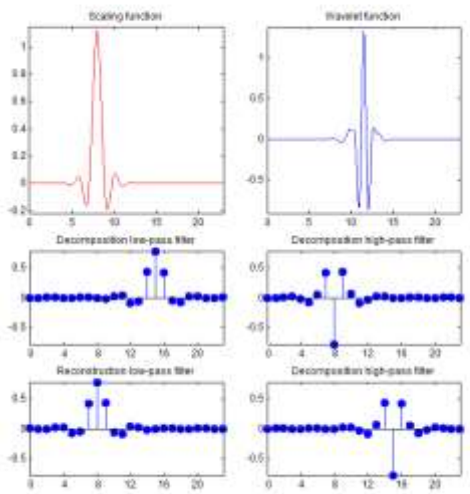

Fig.1 Coiflets 4 wavelet.

III. DECOMPOSITION

The original input signal $x(n)$, located at level $i = 0$, will be convolved with a decomposition scaling function (which acts as a low-pass filter) and downsampled by a ratio of 2 in order to obtain a vector of approximation coefficients at level $i = 1$. This output signal, called c_1, represents a scaled (half) version of the previous stage signal c_0 (which is the same as $x(n)$).

At the same time, $x(n)$ will be convolved with a decomposition wavelet function (which acts as a high-pass filter) and downsampled by a ratio of 2 in order to obtain a vector of detail coefficients at level $i = 1$. This vector, called d_1, contains the "details" (higher frequency components) of the previous stage signal c_0.

By shifting two spaces the wavelet function for every increasing position k, is the same as performing an overall downsampling by a power of 2. The $c_i(k)$ coefficient vector will have half the number of samples of $c_{i-1}(n)$.

The Average Approximation Coefficients at position k for level i are calculated by (2):

$$c_i(k) = 2^{-\frac{i}{2}} \sum_{n=0}^{M} p(n-2k) c_{i-1}(n) \quad (2)$$

The Wavelet Transform Coefficients at position k for level i are calculated by (3):

$$d_i(k) = 2^{-\frac{i}{2}} \sum_{n=0}^{M} q(n-2k) c_{i-1}(n) \quad (3)$$

Here, k is the translation parameter of the window and also indicates the index of the coefficient being calculated. i is the current decomposition level, and goes from 0 up to $\log_2(N)$, where N is the number of samples the original signal.

The value of n goes from 0 up to M, which is the number of samples of the previous stage coefficient vector c_{i-1}. $p(n)$ is the scaling decomposition function, and $q(n)$ is the wavelet decomposition function.

The value of the coefficients will be high if the signal and the wavelet have a good correlation; if they do not correlate well, the value may be low or zero.

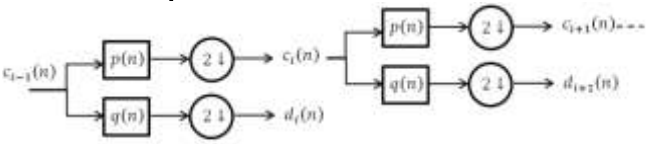

Fig. 2 Filter bank tree of decomposition.

IV. DENOISING

The objective of the wavelet based denoising process is to estimate the signal of interest $s(i)$ from the composite one $f(i)$ by discarding the corrupted noise $e(i)$:

$$f(i) = s(i) + e(i) \quad (4)$$

The underlying model for the noisy signal is the superposition of the signal of interest and a Gaussian zero mean white noise with a variance of σ^2. The threshold value is computed according to the model of the signal of interest to be estimated, and the corrupted noise. Donoho and Jonhstone proposed the universal "VisuShrink" threshold [1] [3], given by:

$$T = \sigma \cdot \sqrt{2 \cdot \log(M)} \quad (5)$$

$$\sigma = \frac{Median(|d_i|)}{0.6745} \quad (6)$$

Where M is the size of the current detail coefficients' vector d_i at scale level i. $Median(|d_{i,k}|)$ is the median value of the absolute value of the vector d_i. There are two algorithms of thresholding: Hard and Soft thresholding algorithms. For this purpose, the hard thresholding will be used. The denoising is done by making the detail coefficients (on each scale) equal to zero that are less than a threshold value.

$$d_{i,k} = \begin{cases} |d_{i,k}| & \geq T \\ 0 & < T \end{cases} \quad (7)$$

V. RECONSTRUCTION

The reconstruction (synthesis) process is similar to decomposition. Assuming that level $i = 0$ is the highest scale level, and level $i = j$ is the lowest, the approximation coefficients' vector at the "lowest scale level" is convolved with a reconstruction scaling wavelet (low-pass filter) and then is upsampled by 2. Upsampling the signal is doubling the number of samples of it by adding a zero in between each sample, laying these zeros at odd index positions. The detail coefficients' vector at the same scale level is convolved with a reconstruction detail wavelet (high-pass filter) and then is upsampled by 2. Finally, the two vectors are added together. The outcome is the approximation coefficients' vector for the upper level.

$$c_{i-1}(n) = 2^{-\frac{i}{2}} \sum_{k=0}^{M} p(n-2k) c_i(n) + 2^{-\frac{i}{2}} \sum_{k=0}^{M} q(n-2k) d_i(n) \quad (8)$$

Here, k is the index of the transform coefficients at the scale level i. The approximation coefficient being computed will have double the size of the previous approximation before the upsampling. n represents the index of the slot for the coefficient being calculated.

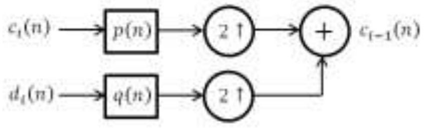

Fig. 3 Filter bank tree for reconstruction.

VI. QRS COMPLEX DETECTION

The QRS complex is found by first locating the R-peaks (representing the maximum peaks on the plot) and the S-peaks (minimum peaks), which are more-or-less evenly separated. Locating the Q-peaks is a bit harder, because it is not the minimum peak of the plot, but it is for a determined interval.

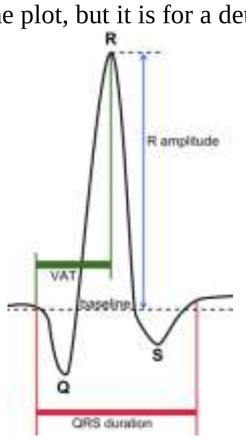

Fig.4 Schematic representation of a QRS complex[7].

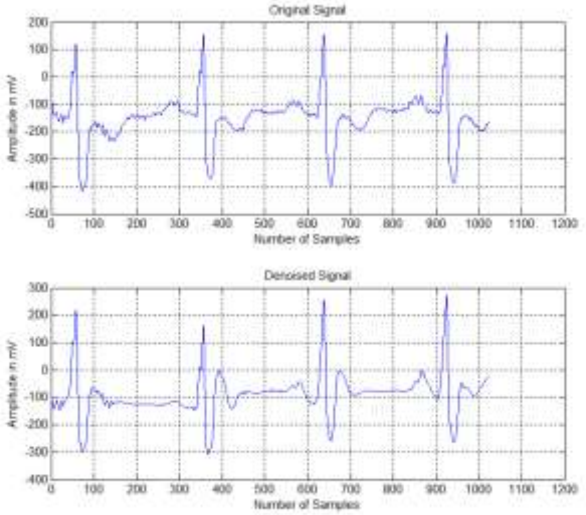

Fig 5 Plot of the original signal, denoised signal, of the "118e00" record.

The plot on Fig. 5 shows that the R-peaks are separated roughly by equal amount of samples: 250 samples. Also the peaks have almost the same amplitude of 100 mV.

Using Matlab, the function "findpeaks" was implemented using the previous information, which saves the index of the peak value(s) of the signal, as in [5], and then mark the points on the plot. Same process for locating the S-peaks, only that the signal used was an inverted signal, which favoured the function.

For the Q-peak, a vector of samples was extracted from the "inverted signal" starting from the index R-peak of a QRS complex and ending 35 points in back direction. This vector represents Ventricular Activation Time (VAT), and is the interval between the ending of the P-peak and the R-peak. Using the function "findpeaks", the index of the Q-peak was located on the VAT vector. The value of this index was added with the length of the VAT vector, and the result was subtracted from the R-peak index, yielding the location index on the ECG plot. The QRS complex interval was marked on the plot.

VII. RESULTS

The record used for evaluation was the record "118e00" from the MIT-BIH Noise Stress Test Database [6]. The duration of the signal was of 1 minute, with 21600 samples. The signal was increased up to 32768 samples by padding zeros at the end of the signal so it could have a size multiple of 2 to ease the calculations.

After the signal was decomposed using a coif4 wavelet, denoised and reconstructed, it was plotted for only 1024 samples for simple purposes. The plot is shown on Fig. 6, where the marks indicate the location of the QRS peaks using the algorithm proposed.

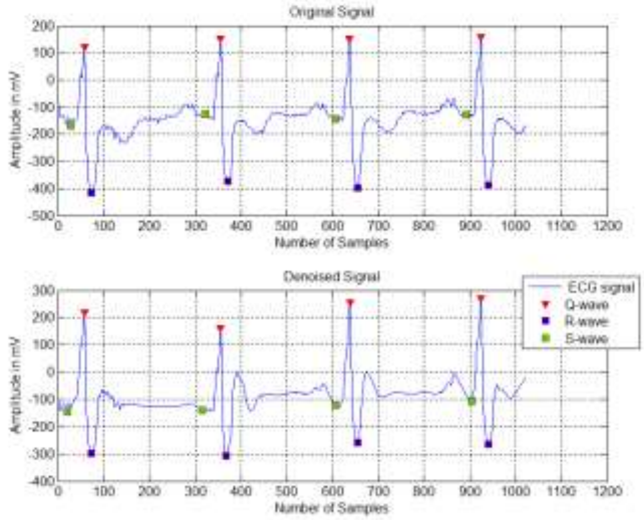

Fig. 6 Plot of the original signal, denoised signal, and QRS complex marking of the "118e00" record.

As seen on Fig. 6, the noise filtering made the signal "smoother", but still it presents some ripples where the Q-peak is located. These ripples make difficult localizing the Q- or S- peak for the QRS complex detection.

VIII. CONCLUSION

The DWT denoising and the algorithm for detecting the QRS complex gave acceptable results for one sample, using the coif4 wavelet. By acceptable means that it is not robust enough, in comparison to other advanced algorithms that can filter the signal better (like having an adaptive threshold) and have a better ways for QRS complex detection.

REFERENCES

[1] S.A. Chouakri, F Bereksi-Reguig, S Ahmaïdi, O. Fokapu "Wavelet Denoising of the Electrocardiogram Signal Based on the Corrupted Noise Estimation". *Computers in Cardiology 2005;* 32:1021−1024

[2] Alexander D. Poularikas . *The Transforms and Applications Handbook*: 3rd ed. Boca Raton, FL. CRC Press LLC, 2000.

[3] David L. Donoho. "De-noising by Soft-Thresholding". *IEEE Transactions on Information Theory, Vol. 41, No. 3. May 1995*.

[4] H. A. N. Dinh, D. K. Kumar, N. D. Pah and P. Burton "Wavelets for QRS Detection". *Engineering in Medicine and Biology Society, 2001.* Proceedings of the 23rd Annual International Conference of the IEEE (Volume:2). 2001.

[5] MathWorks. Peak Analysis. [Online]. Available: http://www.mathworks.com/help/signal/examples/peak-analysis.html

[6] The MIT-BIH Noise Stress Test Database. [Online]. Available: http://www.physionet.org/physiobank/database/nstdb/

[7] QRS Complex. [Online]. Available: http://en.wikipedia.org/wiki/QRS_complex