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WAVELET TRANSFORM BASED ECG SIGNAL ANALYSIS

Zoltán Germán-Salló[1]

Abstract - The Electrocardiogram (ECG) is the most important biosignal used by cardiologists for diagnoses purposes, which provides key information about the electrical activity of the heart. Detection of abnormalities in ECG signal is a critical step in health care. This paper briefly introduces theory of wavelet transform and shows a few promising applications in ECG signal processing, as noise suppression , baseline wandering removal, ECG characteristic points detection. Wavelets provide efficient localization in both time and frequency (or scale) due to the multiresolution analysis (provided by the wavelet basis).

Key words: Wavelet Transform, multiresolution analysis, wavelet decomposition, ECG signal processing, QRS detection

I. INTRODUCTION

The goal of wavelet research is to create a set of basis functions and transforms that can give an efficient and useful description of a signal (or function). Wavelets provide efficient localization in both time and frequency (or scale). Wavelet based analysis of an ECG signal is an exciting new tool for both scientists and engineers. The discretized wavelet analysis fits naturally with the digital computer with its basis functions defined by summations not integrals or derivatives. Unlike most traditional expansion systems, the basis functions of the wavelet analysis are not solutions of differential equations.To analyze any finite energy signal $f(t)\in \mathbf{L}^2(R)$, the continous wavelet transform (CWT) uses the dilation and translation of a single wavelet function $\psi(t)$ called mother wavelet [3]. The continous wavelet transform $(W_\psi f)(s,\tau)$ of the signal $f(t)\in \mathbf{L}^2(\mathbf{R})$ [1] is defined as:

$$(W_\psi f)(s,\tau)=\int_{-\infty}^{+\infty} f(t)\cdot\frac{1}{\sqrt{s}}\cdot\overline{\psi\left(\frac{t-\tau}{s}\right)}\cdot dt \quad (1)$$

where, we have used $\overline{\psi}$ to denote the complex conjugate of ψ. The function $\psi\in \mathbf{L}^2(R)$ is an oscillatory function with zero mean. This last condition allows for the inversion of the wavelet transform. In particular the function $f(t)\in \mathbf{L}^2(R)$ can be recovered from its transform $(W_\psi f)(s,\tau)$ by the inverse formula:

$$f(t)=C_\psi^{-1}\int_0^{+\infty}\int_{\mathbf{R}}\tau^{-2}(W_\psi f)(s,\tau)\cdot\psi\left(\frac{t-\tau}{s}\right)\cdot ds\cdot d\tau \quad (2)$$

Since the scale factor s is proportional to the inverse of the frequency ω, the value $(W_\psi f)(s_0,\tau_0)$ exhibits the frequency content of $f(t)$ in a frequency interval centered around $\omega_0 = s_0^{-1}$ at the time interval centered around $t=\tau_0$. The continous wavelet transform maps a signal of one independent variable t of two independent variables s,τ. The scale factor and/or the translation parameter can be discretized. The usual choice is to follow a dyadic grid $(s_j,\tau_{j,k})$ on the time-scale plane with $s_j = 2^j$ and $\tau_{j,k} = k\cdot 2^j$ The transform is then called the dyadic discrete wavelet transform:

$$(W_\psi f)(2^j,k2^j)=< f(t),\psi_{j,k}(t)> \quad (3)$$

where $<\bullet,\bullet>$ denotes the inner product in $\mathbf{L}^2(\mathbf{R})$. The dyadic sampling is a very natural choice for computers.We can construct functions [11]:

$$\left\{\psi_{j,k}(t)=\frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k\cdot 2^j}{2^j}\right)\right\}_{(j,k)\in\mathbf{Z}^2} \quad (4)$$

to form an orthonormal basis for signal representations. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components [3]. For discrete-time signals, the dyadic discrete wavelet transform (DWT) is equivalent, according to Mallat's algorithm [1] to an octave filter bank, and can be implemented as a cascade of identical cells (low-pas and high-pass finite impulse response (FIR) filters). These filters split the signal's bandwidth to half. Using downsamplers after each filter, the redundancy of the signal representation can be removed. This is called the wavelet decomposition tree.

1 "Petru Maior" University Tg-Mureş,
str. Nicolae Iorga nr 1 e-mail:zgerman@upm.ro

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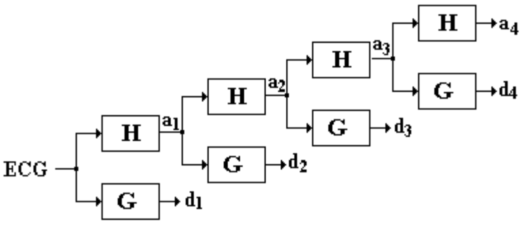

Fig.1 Wavelet decomposition tree

II. THE MAIN ECG SIGNAL PARAMETERS

The electrocardiogram, is a time-varying signal that measures the electrical activity (on the surface of the human body) of the heart. Each heartbeat is a complex of distinct cardiological events, represented by distinct features in the ECG waveform. These features represent either depolarization (electrical discharging) or repolarization (electrical recharging) of the muscle cells in particular regions of the heart. Figure 2 shows a (human) ECG waveform and the associated parameters (features)

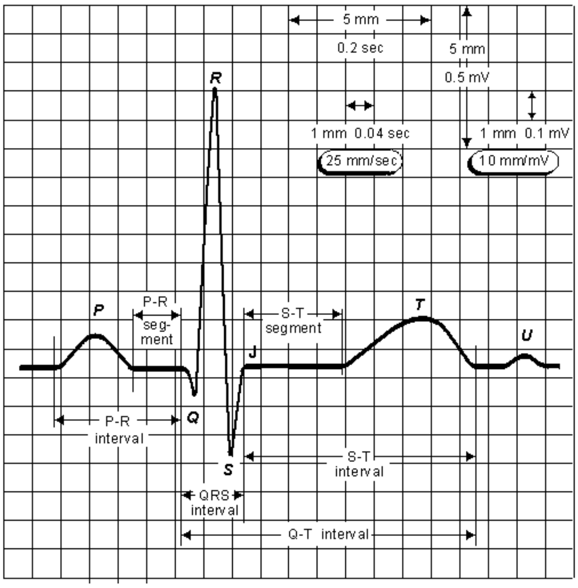

Fig 2. The most important parameters of an ECG signal

The standard parameters of the ECG waveform are the P wave, the QRS complex and the T wave. But most of information lies around the R peak. Additionally a small U wave (with an uncertain origin) is ocassionally present. The cardiac cycle begins with the P wave, which corresponds to the period of atrial depolarization in the heart. This is followed by the QRS complex, which is usually the most relevant (recognizable) feature of an ECG waveform.

The QRS complex corresponds to the period of ventricular depolarization. The start and end points of the QRS complex are referred to as Q and J (or very often S) points. The T wave follows the QRS complex and corresponds to the period of ventricular repolarization. The end point of the T wave represents the end of the cardiac cycle (presuming the absence of U wave). The durations (time between the onset and offset) of particular parameters of the ECG (referred as an time interval) is of great importance since it provides a measure of the state of the heart and can show the presence of cerTain cardiological conditions. In practice, interval measurements, wave interpretations are carried out manually by ECG specialists.

III. MATERIALS AND METHODS

In all applications were used signals from MIT-BIH database with annotations from specialists (cardiologists), all methods were developed under Matlab (and Wavelet Toolbox). At first, the signals from database were filtered, denoised and after that baseline variation was removed, using wavelet approximation. The main idea of wavelet analysis is to find a function (a basis function) which properties are appropiate to the analysed signal, to obtain maximum of information with less coefficients. In this work, biorthogonal wavelet were used, because after many experiments they gave the best results in signal reconstruction from approximation coefficients [5,12]. These wavelets have a minimum number of sign changes which simplify the steps in the parameter estimation algorithm. The next figure presents how the wavelet analysis based feature extraction is carried out .

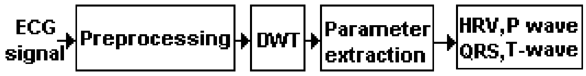

Fig.3. Wavelet analysis based feature extraction

At first, in the preprocessing stage, the signals from database are filtered, denoised and baseline wander removed, using wavelet approximation. The basic denoising concept is to decompose the signal at different scales (the largest quantity of information about noise is contained by the first scales detail coefficients [4]), to threshold the detail coefficients and after that to reconstruct the signal, using the original approximation coefficients and the modified detail coefficients.

Fig.4. Wavelet decomposition based denoising

The first step in the baseline wandering removal is to identify the low frequency (large scale) components in the ECG signal. The typical baseline variation means 15 percent of peak-to-peak ECG amplitude variation of 0.15 to 0.3 Hz. This variation can be identified as the 8th level approximation for a signal sampled with 128 Hz

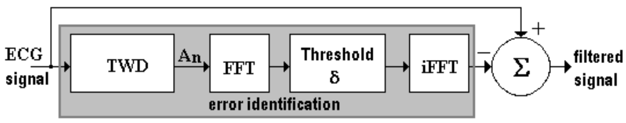

Fig.5 Wavelet decomposition, spectral thrasholding for baseline wander removal

The proposed algorithm (baseline variation identified as the lowest frequency component) was experimented on test signals (weighted sum of sinusoidal functions). The lowest frequency components were identified and extracted from the original signal [6]. Figure 6 shows this procedure in the frequency domain.

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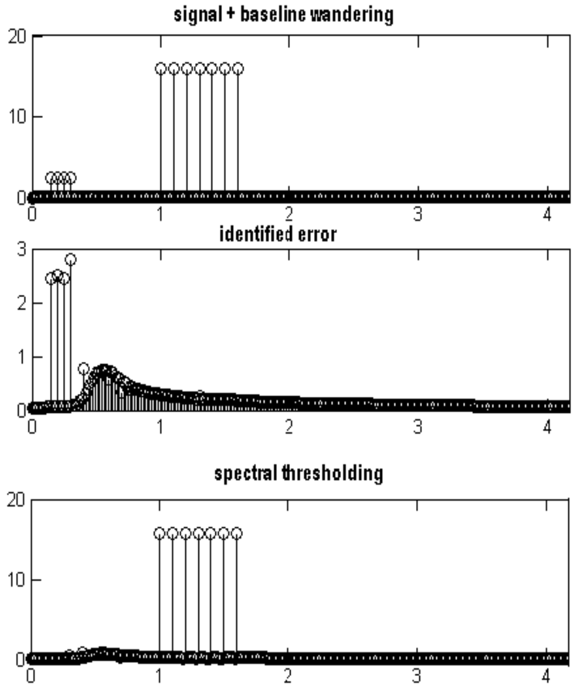

Fig.6. Identification of baseline variation

This algorithm applied to real ECG signals gave good results. Results can be seen below:

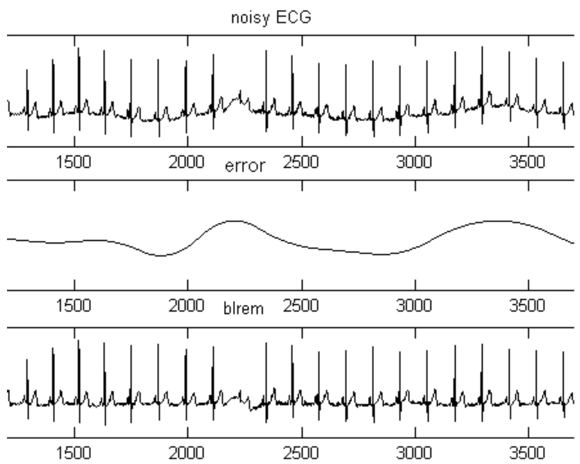

Fig.7. Results obtained in baseline wandering removal

The main advantage of this algorithm is, that it can be applied again to the already filtered signal.
In the processing stage, the main ECG signal parameters are identified, following the algorithm presented below:
Steps:
1.The segment of ECG signal considered for analysis consists of 60 s (meaning 7680, 128 Hz sample rate)
2.A 4 level wavelet decomposition performed, using biorthogonal wavelet functions (the reconstruction and decomposition filters are implemented as quadrature mirror filter of FIR type)
3.Determination of the R wave location (as local maxima) on first level approximation (first scale) Additionally, in this step the maxima can be identified as zero crossing points of the first derivative. An adaptive threshold is used (related to the maximum and mean values of the signal), to find the points over this value. After that, the R peaks are selected.
4.Determination of R-R intervals, as R-R distances
5.Determination of Q, S points as the first zero crossing or local minimum point before and after R wave. QRS complex's area can be calculated from the Q-S duration and the value of the R peak .
6.Elimination of the QRS complex from the signal to obtain the other parameters
7.Determination of the P wave location (as maxima) (scales3,4) (the same procedure as in step 2), and the P-Q distance
8.Elimination of the P wave from the signal (same as 5)
9.Determination of the T wave location (as the remained maxima) (scales 3,4) and S-T segments durations

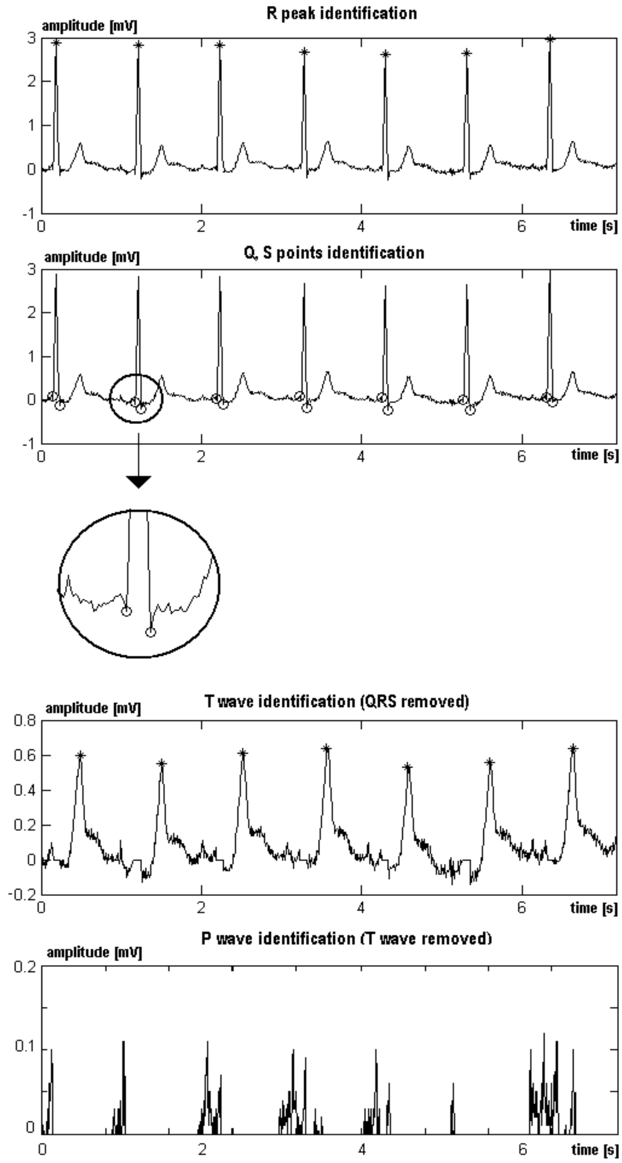

figure 8. Characteristic points detections

IV. RESULTS

This algorithm leads us to determine the main parameters of an ECG signals.Were used over 27 files from the MIT-BIH database (free available on the Internet for algorithm test purposes), signals containing normal sinus rythms and signals with abnormalities in order to find the main parameters. The results obtained (processing mainly ECG signals from normal sinus database) were compared with

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annotated files from ECG databases, and gave very promising results: R wave detection around 98%, QRS complex detection over 95%, T wave detection/localization 88%, P wave detection/ localization 88%.

Table 1

action	results
R peak identification	98,2 %
QRS complex extraction	95,4 %
T wave identification	89,5 %
P wave identification	88,2 %

V.CONCLUSIONS

The present study is based on biorthogonal wavelets. It has been shown [2] that these wavelets are ideally suited for the purpose since they excite the various morphologies of the ECG signals at different scales. With the multiscale feature of WT's, the QRS complex can be distinguished from P or T waves, noise, baseline drift, and artifacts [5]. Various morphologies are excited better at different scales. From these scales various segments, time widths as signal parameters can be determined more accurately.
As a further work, an artificial neuronal network will be implemented (trained with a set of normal sinus beats) for ECG events analysis and abnormalities detection.

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