ECG SIGNALS PROCESSING USING WAVELETS

Gordan Cornelia, Reiz Romulus
University of Oradea: Electronics Department, Faculty of Electrical Engineering and Information Technology,
Oradea, Romania
e-mail: cgordan@uoradea.ro

***Abstract* - Biomedical signals like heart wave tend to be nonstationary. To analyze this kind of signals wavelet transforms are a powerful tool. In this paper we make use of wavelets to filter and analyze noisy ECG signals. We use wavelets to detect the positions of the occurrence of the QRS complex during the period of analysis.**

I. INTRODUCTION

An electrocardiogram (ECG or EKG, abbreviated from the German Elektrokardiogramm) is a graphic produced by an electrocardiograph, which records the electrical activity of the heart over time. The signal is constructed by measuring electrical potentials between various points of the body using a galvanometer. Understanding the various waves and normal vectors of depolarization and repolarization is very important to obtain useful diagnostic information. ECG signals have a wide array of applications throughout the medical field in determining whether the heart is functioning properly or suffering from any abnormalities.

ECG analysis is the gold standard for the evaluation of cardiac arrhythmias, it guides therapy and risk stratification for patients with suspected acute myocardial infarction. The baseline voltage of the electrocardiogram is known as the isoelectric line. A typical ECG tracing of a normal heartbeat (or cardiac cycle) consists of a P wave, a QRS complex and a T wave. A small U wave is normally visible in 50 to 75% of ECGs.[7]

Fig.1 shows an example of a normal ECG trace, which consists of a P wave, a QRS complex and a T wave. The small U wave may also be sometimes visible, but is neglected in this work for its inconsistency. The P wave is the electrical signature of the current that causes atrial contraction; the QRS complex corresponds to the current that causes contraction of the left and right ventricles; the T wave represents the repolarization of the ventricles; and the U wave, although not always visible, is considered to be a representation of the papillary muscles or Purkinje fibers. The presence or lack of presence of these waves as well as the QT interval and PR interval are meaningful parameters in the screening and diagnosis of cardiovascular diseases.

Modern ECG monitors offer multiple filters for signal processing. The most common settings are monitor mode and diagnostic mode.

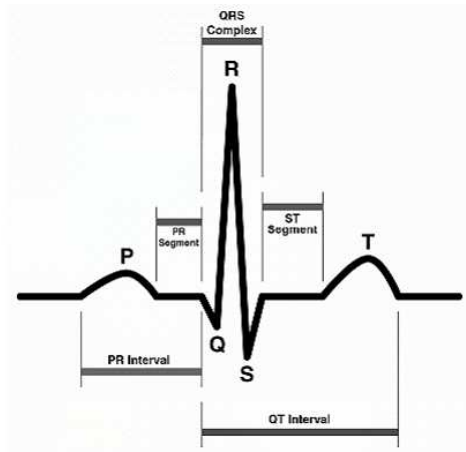

Figure 1. The ECG signal

In monitor mode, the low frequency filter (also called the high-pass filter because signals above the threshold are allowed to pass) is set at either 0.5 Hz or 1 Hz and the high frequency filter (also called the low-pass filter because signals below the threshold are allowed to pass) is set at 40 Hz. This limits artifact for routine cardiac rhythm monitoring. The low frequency (high-pass) filter helps reduce wandering baseline and the high frequency (low pass) filter helps reduce 60 Hz power line noise. In diagnostic mode, the low frequency (high pass) filter is set at 0.05 Hz, which allows accurate ST segments to be recorded. The high frequency (low pass) filter is set to 40, 100, or 150 Hz. Consequently, the monitor mode ECG display is more filtered than diagnostic mode, because its bandpass is narrower.

The objective to analyze accurately an ECG signal is especially important in this application where the feature extraction of the ECG signals is to locate the interested characteristic points that can be used to detect possible cardiovascular abnormalities. The topic is further complicated, since most of the time the desired ECG signals are either corrupted or embedded in noises. The answer to all of these problems is wavelet analysis.

Wavelet theory provides a unified framework for a number of techniques, which had been developed independently for various signal-processing applications. For example, multiresolution signal processing used in computer vision; subband coding, developed for speech and image compression; and wavelet series expansions, developed in applied mathematics, have been recently recognized as different views of a single theory. In fact, wavelet theory covers quite a large area. It treats both the continuous and the discrete time cases. It provides very general techniques that can be applied to many tasks in signal processing and therefore has numerous potential applications.

In particular the "wavelet" transform (WT) is of interest for the analysis of non-stationary signals, because it provides an alternative to the classical Short-Time Fourier Transform (STFT) or Gabor transform. The basic difference is as follows: in contrast with the STFT, which uses a single analysis window, the WT uses short windows at high frequencies and long windows at low frequencies. The WT is also related to time-frequency analysis based on Wigner-Ville distribution.

For some applications it is desirable to see the WT as signal decomposition into a set of basis functions called wavelets. They are obtained from a single prototype wavelet by dilations and contractions as well as shifts. The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function or alternatively as shown in the following equation:

$$\mathrm{CWT}(a,\tau)=\frac{1}{\sqrt{a}}\int s(t)\,\psi\left(\frac{t-\tau}{a}\right)dt \quad (1)$$

In this equation, the parameter “a” is the scaling factor that stretches or compresses the function. The parameter τ is the translation factor that shifts the mother wavelet along the axis. The parameter s(t) is an integrable signal whose sum is to be multiplied by the translated mother wavelet. And finally, the mother wavelet is denoted by $\psi(t)$, which is a function of the scaling and translation factors just as the result of the continuous wavelet is, the wider is the basis function transformation CWT.

It is often desirable to work with discretized signals. By switching into the discrete domain, it is possible to not only save a fair amount of work, but also by choosing carefully of the scales and positions based on powers of two, receive results that are just as accurate. This is called the discrete wavelet transform (DWT) as defined as:

$$\mathrm{DWT}(m,n)=2^{-\frac{m}{2}}\sum_{k} s(k)\,\psi\left(2^{-m}k-n\right) \quad (2)$$

Often, Discrete Wavelet Transform is also referred to as decomposition by wavelet filter banks. This is because DWT uses two filters, a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into different scales. The output coefficients of the LPF are called approximations while the output coefficients of the HPF are called details. The approximations of the signal are what define its identity while the details only imparts nuance. Furthermore, the decomposition process is iterative. The approximation signal may be passed down to be decomposed again by breaking the signal into many levels of lower resolution components. This is called multiple-level decomposition and may be represented in a wavelet decomposition tree. Only the last level of approximation is save among all levels of details, which provides sufficient data to fully reconstruct the original signal using complementary filters.

The automatic detection of ECG wave is an important topic, especially for extended recordings, because it provides many clinical insights can be derived from the information found in the intervals and amplitudes defined by the significant points. The performance of such automatic systems relies heavily on the accuracy and reliability in the detection of the QRS complex, which is necessary to determine the heart rate, and as reference for beat alignments. As shown above, the QRS complex is the most characteristic waveform of the signal with higher amplitudes. It may be used as references for the detection of other waves, such as the P and T complexes, which are also useful at times. The feature extraction methods applied in this thesis focuses on the detection of the QRS complex and characteristic points in addition to attempting to locate the associated P and T waves if there are any. Wavelet transform is a perceived as a very promising technique for this type of applications because it is localized in both the frequency and time domain. It may be used to distinguish ECG waves from serious noise, artifacts, and baseline drift. Wavelet transformation represents the temporal features of a signal at different resolution providing better analysis of ECG signals, which is characterized by cyclic occurring patterns at difference frequencies. The wavelet transformation is not difficult to apply as a mathematical tool for decomposing signals. The real difficulty comes at choosing a mother wavelet that optimally fits the signal depending on the application and the signal itself. Discrete wavelet transform has its natural advantages when applied towards ECG analysis. Conventionally, ECG feature extraction is preceded by a bandpass or a matched filter to suppress the P and T waves and noises before sending the signal for characteristic detection. By using discrete wavelet transform, frequency domain filtering is implicitly performed, making the system robust and allowing the direct application over raw ECG signals. Again, this is made possible due to the nature of the discrete wavelet transform. Discrete wavelet transform is also referred to as decomposition by wavelet filter banks.

II. ANALYSIS METHOD

The ECG signal that is used in the paper is part of the MIT-BIH Arrhythmia Database, available online [2]. The recordings downloadable from there were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. To obtain our wavelet analysis, we used the Matlab program, which contains a very good “wavelet toolbox”.

First the considered signal was decomposed using a three level wavelet decomposition. One of the key criteria of a good mother wavelet is its ability to fully reconstruct the signal from the wavelet decompositions. We used in our analysis the Daubechies db1 and db3 wavelets, the symlet sym2 and the first order coiflet coif1 wavelets. Fig. 2 shows the Daubechies db3 wavelet’s waveform.

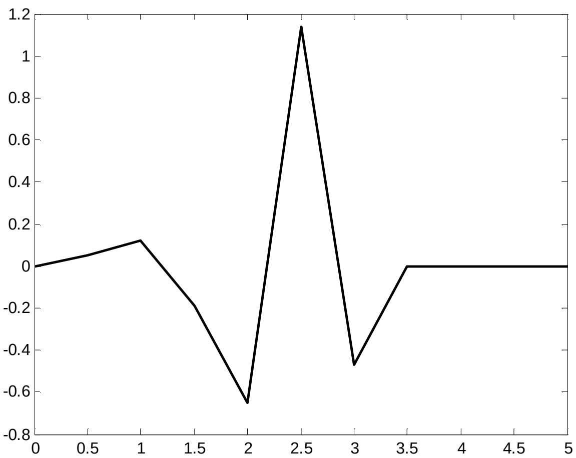

Figure 2. The Daubechies db3 wavelet

In Fig. 3 is presented a 3-level signal decomposition of a sample ECG waveform using the db3 wavelet.

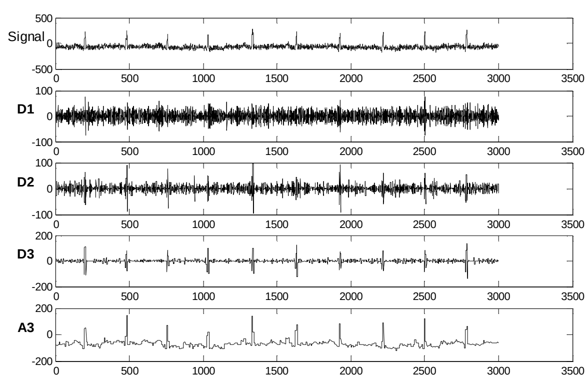

Figure 3. ECG signal decomposition using db1 wavelet

The high frequency components of the ECG signal decreases as lower details are removed from the original signal. As the lower details are removed, the signal becomes smoother and the noises on the T and P waves disappears since noises are marked by high frequency components picked up along the ways of transmission. This is the contribution of the discrete wavelet transform where noise filtration is performed implicitly. In Fig.4 is presented the ECG signal before and after noise removal.

The detection of the QRS complex is the last step of feature extraction. The R peaks have the largest amplitudes among all the waves, making them the easiest way to detect and good reference points for future detections.

The signal was processed using the wavelets up to 3 levels. However for the detection of the QRS complex, only details up to level 2 were kept and all the rest removed. This procedure removed lower frequencies considering QRS waves have comparatively higher frequency than other waves.

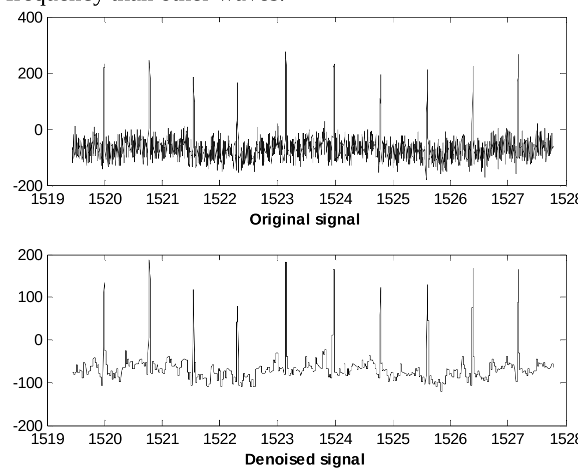

Figure 4. Removing background noise from the ECG signal

The attained data is then squared to stress the signal. A threshold equals to 30% of the maximum value is sub-sequentially applied to set a practical lower limit to help to remove the unrelated noisy peaks. At this point, the data set is ready for peak detection through a very simple search algorithm that produces very accurate results. In Fig. 5 is presented the ECG signal and the extracted peaks corresponding to the QRS complex.

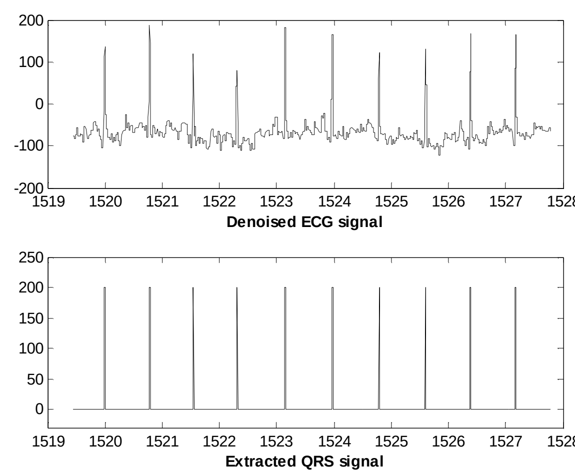

Figure 5. QRS detection from ECG signal

The results obtained with the proposed wavelets using several different noise levels that covered the ECG signal are presented in Table 1.

It can be noticed that the best results are obtained with the db3 wavelet, and the worst ones with the sym wavelet.

The good results obtained with the db3 wavelet are caused by the resemblance that exist between this wavelet and the actual ECG signal.

TABLE 1

Wavelet	SNR[dB]	QRS detected	Erors [%]
Db1	10	170	0
	5	163	4
	3	150	12
DB3	10	170	0
	5	170	0
	3	166	2
Coif	10	170	0
	5	165	3
	3	157	8
Sym	10	170	0
	5	149	12
	3	143	16

III. CONCLUSIONS

In this work we pointed out the advantage of using wavelet transform associated with a noise thresholding strategy. Further, the possibility of detecting positions of QRS complexes in ECG signals is investigated and a simple detection algorithm is proposed. Through wavelet thresholding all relevant noise are removed of the signal, allowing the utilization of simple detection logic for the QRS detection. The main advantage of this kind of detection is less time consuming analysis for long time ECG signal.

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