ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 2, Issue 3, May 2013

QRS Complex Detection using Wavelet Transform

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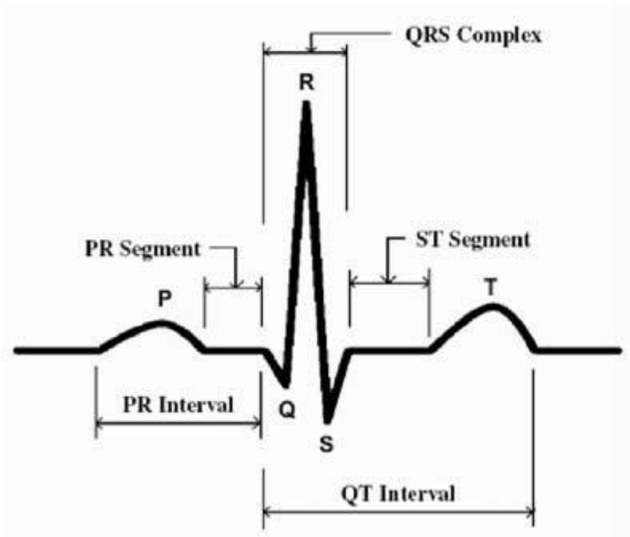
Abstract*— In recent years, ECG signal plays an important role in the primary diagnosis, prognosis and survival analysis of heart diseases. In this project a new approach based on the threshold value of ECG signal determination is proposed using Wavelet Transform coefficients. Electrocardiography has had a profound influence on the practice of medicine. The electrocardiogram signal contains an important amount of information that can be exploited in different manners. The ECG signal allows for the analysis of anatomic and physiologic aspects of the whole cardiac muscle. Different ECG signals are used to verify the proposed method using SCILAB software. In the first step an attempt is made to generate ECG waveforms by developing a suitable SCILAB toolbox and in the second step, using wavelet transform, the ECG signal is denoised by removing the corresponding wavelet coefficients at higher scales. Then QRS complexes will be detected and each complex will be used to find the peaks of the individual waves like P and T, and also their deviations.

Index Terms—**Electrocardiogram, QRS complex, SCILAB, wavelet transform.**

I. INTRODUCTION

E.C.G stands for Electrocardiogram and represents the electrophysiology of the heart. Cardiac electrophysiology is the science of the mechanisms, functions, and performance of the electrical activities of specific regions of the heart. ECG signals are oscillatory and periodic in nature. A complete ECG beat is shown in Fig.1. It can be seen from Fig. 1 that the ECG beat has a distinct, characteristic shape. ECG is a very important biological signal to diagnose cardiac arrhythmia. Usually ECG signals are subjected to contamination by various noises. The sources of noise may be either cardiac or extra cardiac. Reduction or disappearance of the isoelectric interval, prolonged repolarization and a trial flutter are responsible for cardiac noise, whereas respiration, changes of electrode position, muscle contraction, and power line interference cause extra cardiac noise [2].A typical ECG signal is shown.



Noise contamination of the ECG such as baseline wander, power line interference and muscle activities can pollute the ECG and reduce the clinical value of an ECG signal. Thus, filtering of the ECG signal is a necessary pre-processing step to conserve the useful information and to remove such noises. 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

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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. 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 band pass 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.

II. WAVELET TRANSFORM

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; sub band 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

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

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

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

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

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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 band pass 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.

III. ANALYSIS METHOD

The ECG signal that is used in the paper is part of the MIT-BIH Arrhythmia Database, available online [7]. 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 SCILAB program and developed a" Wavelet Toolbox".

De-noising of ECG signal is performed using Daubechies wavelet transform (Db4) to obtain the noise free ECG signal. Fig.2 shows the simulated result of the Daubechies algorithm (Db4). The Daubechies wavelet transforms results shows less distortion in original signal

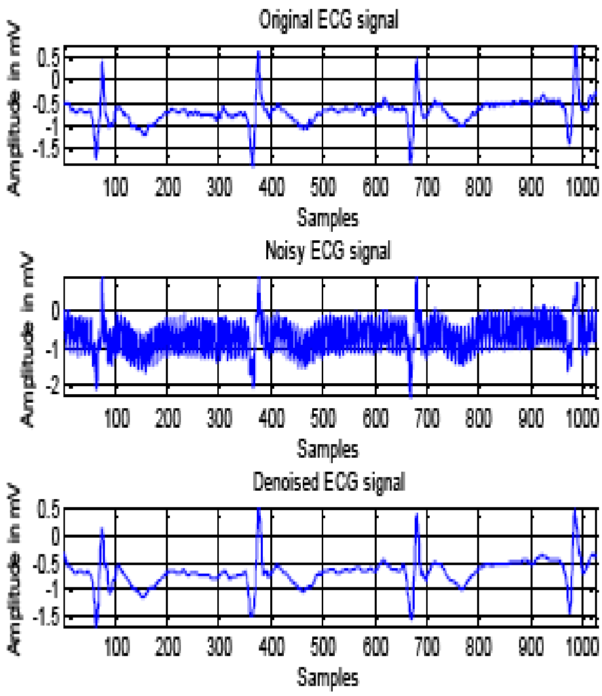

Fig.2 Denoising of ECG signal using Db4 wavelet Transform

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IV. DETECTION OF R PEAK AND QRS

In order to detect the peaks, specific details of the signal are selected. The detection of R peak is the first step of feature extraction. The R peak in the signal has the largest amplitude among all the waves compared to other peaks. A normal QRS complex indicates that the electrical impulse has progressed normally from the bundle of His to the Purkinje network through the right and left bundle branches and that normal depolarization of the right and left ventricles has occurred. Most of the energy of the QRS complex lies between 3 Hz and 40 Hz. The 3-dB frequencies of the Fourier Transform of the wavelets indicate that most of the energy of the QRS complex lies between scales of 23 and 24, with the largest at 24. The energy decreases if the scale is larger than 24. The energy of motion artifacts and baseline wander increases for scales greater than 25. Therefore, we choose to use characteristic scales of 21 to 24 for the wavelet. The detection of the QRS complex is based on modulus maxima of the Wavelet Transform. This is because modulus maxima and zero crossings of the Wavelet Transform correspond to the sharp edges in the signal. Therefore detection rule has been applied to the Wavelet Transform of the ECG signal. The Q and S point occurs about the R Peak with in 0.1second. The left point denoted the Q point and the right one denotes the S point. Calculating the distance from zero point or close to zero of left side of R Peak within the threshold limit denotes Q point. Similarly the right side denotes the S point. QRS width is calculated from the onset and the offset of the QRS complex. The onset is the beginning of the Q wave and the offset is the ending of the S wave. Normally, the onset of the QRS complex contains the high-frequency components, which are detected at finer scales. To identify the onset and offset of the wave, the wave is made to zero base. The onset is the beginning and the offset is the ending of the first modulus maxima pair. Once this QRS complex is located the next step is to determine the onset and offset points for each QRS complex and to identify the component waves of the QRS complex.

V. CONCLUSION

Filtering is an important step in the processing of the ECG signal. The proposed work shows the effect of the wavelet thresholding on the quality reconstruction of an ECG signal. 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.

REFERENCES

[1] Rafael C. Gonzalez, Richard E. woods, Steven L. Eddins, “Digital Image Processing using Matlab”, 2nd Edition, Pearson Prentice Hall, and ISBN 81-7758-898-2.

[2] Leslie Cromwell, Fred J. Weibell, Erich A. Pfeiffer, Biomedical Instrumentation and Measurements, 2nd Edition, Pearson Prentice Hall, ISBN 81-317-0315-0.

[3] Rangaraj M. Rangayyan, Biomedical Signal Analysis, IEEE Press, Wiley-Interscience, ISBN 9814-12-611-X .

[4] William F. Ganong, Review of Medical Physiology, Prentice-Hall International Inc., ISBN 0-8385-8235-4.

[5] P. Karthikeyan, M. Murugappan, and S.Yaacob” ECG Signal Denoising Using Wavelet Thresholding Techniques in Human Stress Assessment” Volume 4, Number 2, July 2012.

[6] Lukáš CHMELKA,” Denoising ECG signals using Wavelet Transform”, Dept. of Biomedical Engineering, FEEC, BUT, research plan No. J22/98:262200011.

[7] MIT-BIH Arrhythmia Database, www.physionet.org.

[8] http://en.wikipedia.org/wiki/Electrocardiogra-phy.

[9] http://en.wikipedia.org/wiki/Scilab