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ECG signal denoising using Wavelet transform.

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ABSTRACT

We proposed the detection of QRS complexes of ECG signals using Pan-Tompkins and wavelet transform based algorithms. The electro cardiogram 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 from MIT/BIH Arrhythmia data base are used to verify the various algorithms using MATLAB software. Wavelet based algorithm presented for signal de-noising and detection of QRS complexes meanwhile better results are obtained for ECG signals by the wavelet based algorithm. In the wavelet based algorithm, the ECG signal has been de-noised by removing the corresponding wavelet coefficients at higher scales. Then QRS complexes are detected and each complex is used to find the peaks of the individual waves like P and T, and also their deviations.

Keywords: QRS complex, ECG, Arrhythmia, Wavelet.

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INTRODUCTION

An ECG is simply a representation of the electrical activity of the heart muscle as it changes with time, usually printed on paper for easier analysis. Like other muscles, cardiac muscle contracts in response to electrical *depolarisation* of the muscle cells. It is the sum of this electrical activity, when amplified and recorded for just a few seconds that we know as an ECG. The first electrical signal on a normal ECG originates from the atria and is known as the **P wave**. Although there is usually only one P wave in most leads of an ECG, the P wave is in fact the sum of the electrical signals from the two atria, which are usually superimposed. There is then a short, physiological delay as the atrioventricular (AV) node slows the electrical depolarisation before it proceeds to the ventricles. This delay is responsible for the PR interval, a short period where no electrical activity is seen on the ECG, represented by a straight horizontal or 'isoelectric' line. Depolarisation of the ventricles results in usually the largest part of the ECG signal (because of the greater muscle mass in the ventricles) and this is known as the **QRS complex**.

The Q wave is the first initial downward or 'negative' deflection. The R wave is then the next upward deflection (provided it crosses the isoelectric line and becomes 'positive').The S wave is then the next deflection downwards, provided it crosses the isoelectric line to become briefly negative before returning to the isoelectric baseline. In the case of the ventricles, there is also an electrical signal reflecting repolarisation of the myocardium. This is shown as the **ST segment** and the **T wave**. The ST segment is normally isoelectric, and the T wave in most leads is an upright deflection of variable amplitude and duration.

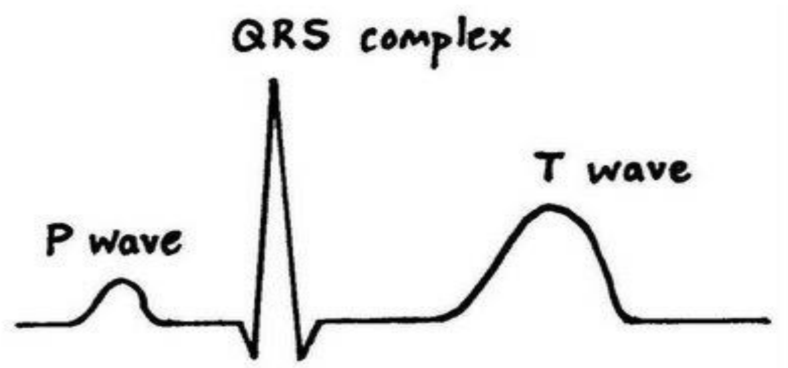

Figure 1 The major waves of a single normal ECG pattern

The recording of an ECG on standard paper allows the time taken for the various phases of electrical depolarisation to be measured, usually in milliseconds. There is a recognised normal range for such intervals.

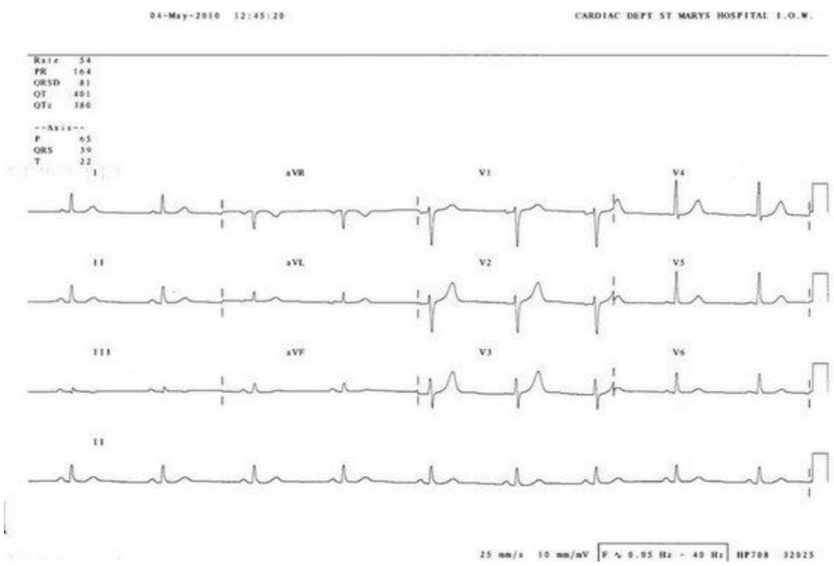

Figure 2: Example of a normal 12 lead ECG

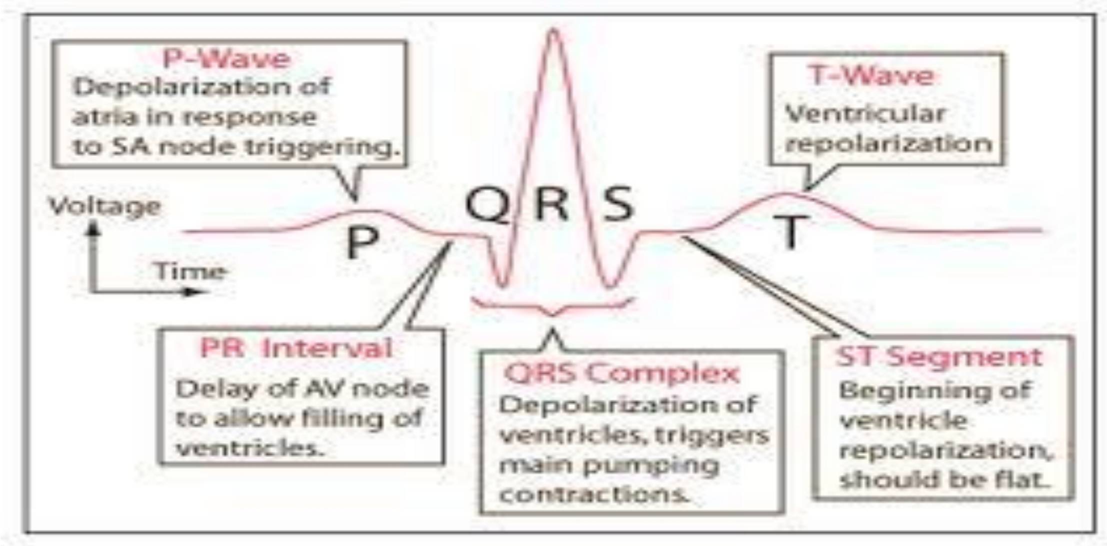

Figure 3: PQRST WAVE

PR interval (measured from the beginning of the P wave to the first deflection of the QRS complex). Normal range 120 – 200 ms (3 – 5 small squares on ECG paper).

QRS duration (measured from first deflection of QRS complex to end of QRS complex at isoelectric line). Normal range up to 120 ms (3 small squares on ECG paper).**QT interval** (measured from first deflection of QRS complex to end of T wave at isoelectric line). Normal range up to 440 ms (though varies with heart rate and may be slightly longer in females)

Heart rate estimation from ECG

Standard ECG paper allows an approximate estimation of the heart rate (HR) from an ECG recording. Each second of time is represented by 250 mm (5 large squares) along the horizontal axis. So if the number of large squares between each QRS complex is:

5 - the HR is 60 beats per minute.
3 - the HR is 100 per minute.
2 - the HR is 150 per minute.

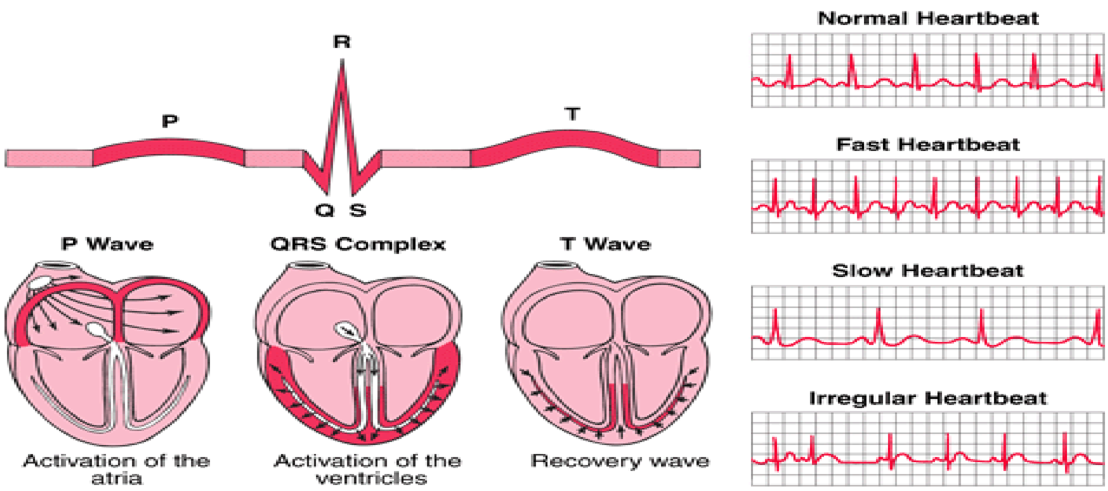

Figure 4: PQRST wave Vs Heart Beat

The ECG is nothing but the recording of the heart's electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders. The time domain method of ECG signal analysis is not always sufficient to study all the features of ECG signals. So, the frequency representation of a signal is required.

To accomplish this, FFT (Fast Fourier Transform) technique can be applied. But the unavoidable limitation of this FFT is that the technique failed to provide the information regarding the exact location of frequency components in time. As the frequency content of the ECG varies in time, the need for an accurate description of the ECG frequency contents according to their location in time is essential. This justifies the use of time frequency representation in quantitative electrocardiology. The immediate tool available for this purpose is the Short Term Fourier Transform (STFT). But the major draw-back of this STFT is that its time frequency precision is not optimal. Hence we opt a more suitable technique to overcome this drawback. Among the various time frequency transformations the wavelet transformation is found to be simple and more valuable. Hence in this work, for denoising wavelets are used and QRS detectors accuracy using is tested with the data available from online database .

The wavelet transformation is based on a set of analyzing wavelets allowing the decomposition of ECG signal in a set of coefficients. Each analyzing wavelet has its own time duration, time location and frequency band. The wavelet coefficient resulting from the wavelet transformation corresponds to a measurement of the ECG components in this time segment and frequency band. Electrocardiography has a basic role in cardiology since it consists of effective, simple, noninvasive, low-cost procedures for the diagnosis of cardiovascular disorders that have a high epidemiological incidence and are very relevant for their impact on patient life and social costs.

The ECG as shown in Figure 5 records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Any ECG gives two kinds of information. One, the duration of the electrical wave crossing the heart which in turn decides whether the electrical activity is normal or slow or irregular and the second is the amount of electrical activity passing through the heart muscle which enables to find whether the parts of the heart are too large or overworked.

Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mV. The ECG signal is characterized by five peaks and valleys labeled by the letters P, Q, R, S, T. In some cases we also use another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T- and P waves

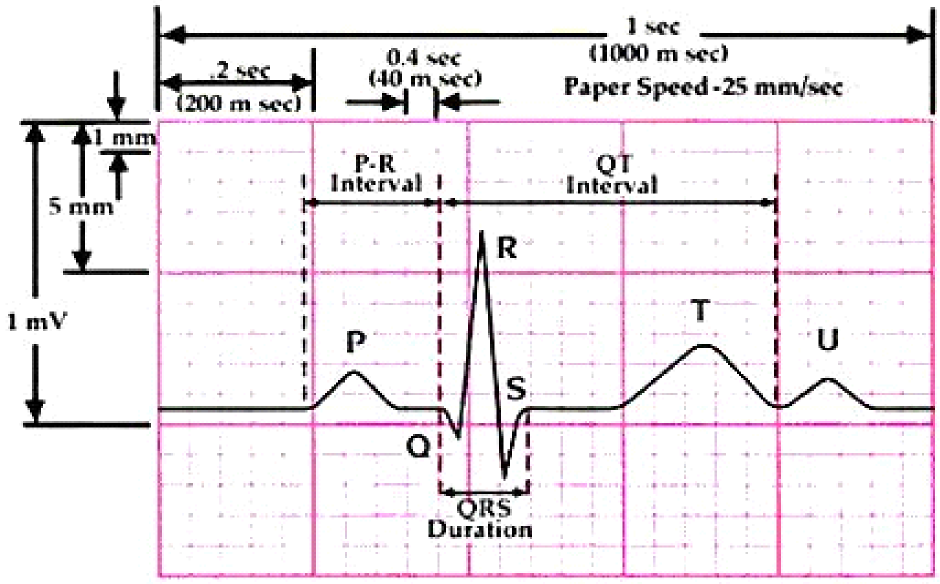

Figure 5: A typical cardiac waveform

The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The QRS complex is the most striking waveform within the ECG. Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart.

Due to its characteristic shape it serves as the basis for the automated determination of the heart rate, as an entry point for classification schemes of the cardiac cycle, and often it is also used in ECG data compression algorithms. In that sense, QRS detection provides the fundamentals for almost all automated ECG analysis algorithms. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment *etc.* can be performed.

Software QRS detection has been a research topic for more than 30 years. The evolution of these algorithms clearly reflects the great advances in computer technology. Whereas in the early years the computational load determined the complexity and therefore the performance of the algorithms, nowadays the detection performance is the major development objective.

The computational load becomes less and less important. The only exception from this trend is probably the development of QRS detection algorithms for battery-driven devices. Within the last decade, many new approaches to QRS detection have been proposed by Rosaria Silipo and Carlo Marchesi (1998), by V.X. Afonso, W.J. Tompkins (1999); for example, algorithms from the field of artificial neural networks, genetic algorithms, wavelet transforms, filter banks as well as heuristic methods mostly based on nonlinear transforms.

Power spectrum of ECG

The power spectrum of the ECG signal can provide useful information about the QRS complex. This section reiterates the notion of the power spectrum presented earlier, but also gives an interpretation of the power spectrum of the QRS complex. The power spectrum (based on the FFT) of a set of 512 sample points that contain approximately two heartbeats results in a series of coefficients with a maximal value near a frequency corresponding to the heart rate. The heart rate can be determined by multiplying together the normalized frequency and the sampling frequency. We can also get useful information about the frequency spectrum of the QRS and is subject to physiological variations due to the patient and to corruption due to noise. Since the QRS complexes have a time-varying morphology, they are not always the strongest signal component in an ECG signal. Therefore, P-waves or T-waves with characteristics similar to that of the QRS complex, as well as spikes from high frequency pacemakers can compromise the detection of the QRS complex. In addition, there are many sources of noise in a clinical environment that can degrade the ECG signal. These include power line interference, muscle contraction noise, poor electrode contact, patient movement, and baseline wandering due to respiration. Therefore, QRS detectors must be invariant to different noise sources and should be able to detect QRS complexes even when the morphology of the ECG signal is varying with respect to time. Most of the current QRS detectors can be divided into two stages as shown in Figure 6 a preprocessor stage to emphasize the QRS complex and a decision stage to threshold the QRS enhanced signal.

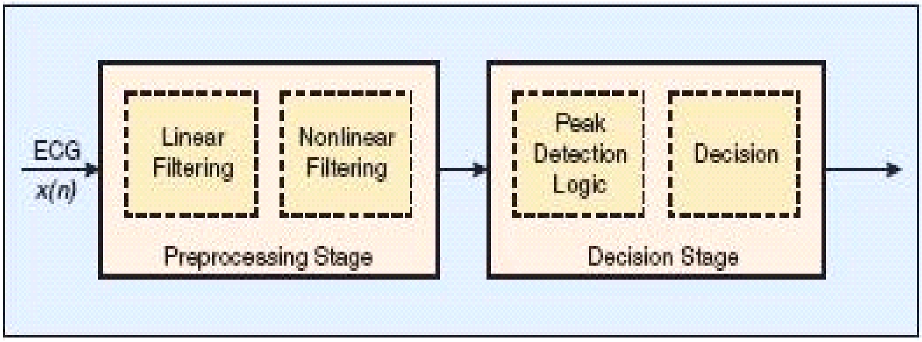

Figure 6: Common Structure of the QRS Detectors

Typically, the preprocessor stage consists of both linear and nonlinear filtering of the ECG.

Wavelet transform

A wavelet is simply a small wave which has energy concentrated in time to give a tool for the analysis of transient, non stationary or time-varying phenomena such as a wave shown in Figure 7.

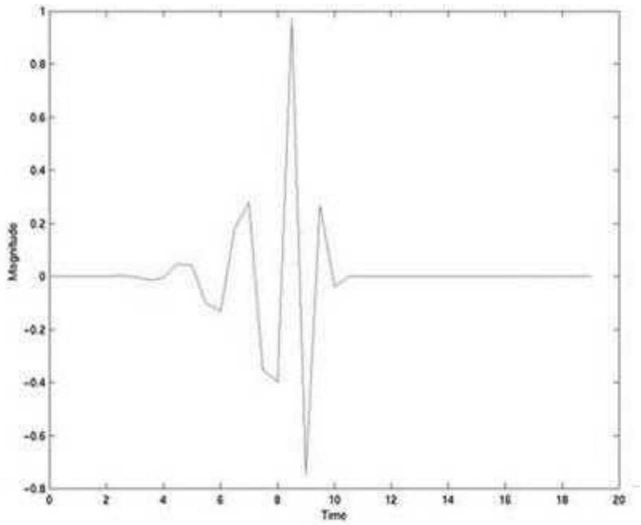

Figure 7: Wavelet function.

A signal as the function of f(t), can often be better analyzed and expressed as a linear decomposition of the sums: products of the coefficient and function. In the Fourier series, one uses sine and cosine functions as orthogonal basis functions. But in the wavelet expansion, the two-parameter system is constructed such that one has a double sum and the coefficients with two indices. The set of coefficients are called the Discrete Wavelet Transform (DWT) of f(t). Namely called a wavelet series expansion which maps a function of a continuous variable into a sequence of coefficients much of the same way as Fourier series dose with the main useful four properties. The representation of singularities, the representation of local basis functions to make the algorithms adaptive in-homogeneities of the functions, also they have the unconditional basis property for a variety of function classes to provide a wide range of information about the signal. They can represent smooth functions. The wavelet transform, the original signal (1-D, 2-D, 3-D) is transformed using predefined wavelets. The wavelets are orthogonal, orthonormal, or biorthogonal, scalar or multiwavelets. In discrete case, the wavelet transform is modified to a filter bank tree using the Decomposition/ reconstruction given in Figure 8.

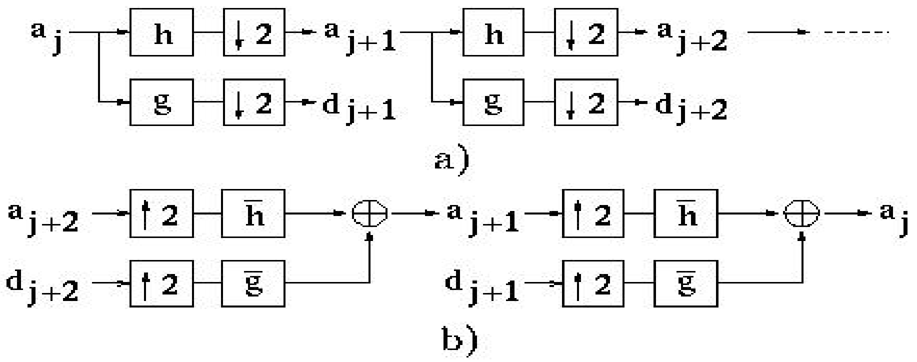

Figure 8: Filter bank tree of a) Decomposition and b) Reconstruction

The wavelet transform is a convolution of the wavelet function $\psi(t)$ with the signal $x(t)$. Orthonormal dyadic discrete wavelets are associated with scaling functions $\varphi(t)$.

The scaling function can be convolved with the signal to produce approximation coefficients S.

In the present work, Daubechies wavelet is chosen although the Daubechies algorithm is conceptually more complex and has a slightly complicated computations, yet this algorithm picks up minute detail that is missed by other wavelet algorithms, like Haar wavelet algorithm. Even if a signal is not represented well by one member of the Daubechies family, it may still be efficiently represented by another.

The wavelet based algorithm has been implemented using MATLAB software. MATLAB is a high performance; interactive system which allows to solve many technical computing problems. The MATLAB software package is provided with wavelet tool box. It is a collection of functions built on the MATLAB technical computing environment. It provides tools for the analysis and synthesis of signals and images using wavelets and wavelet packets within the MATLAB domain.

RESULTS AND DISCUSSION

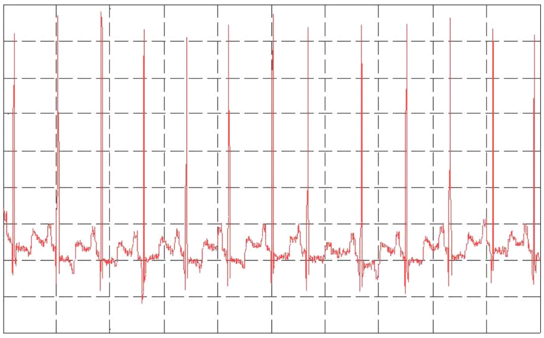

Figure 9: The ECG record 100.dat of 10 sec duration

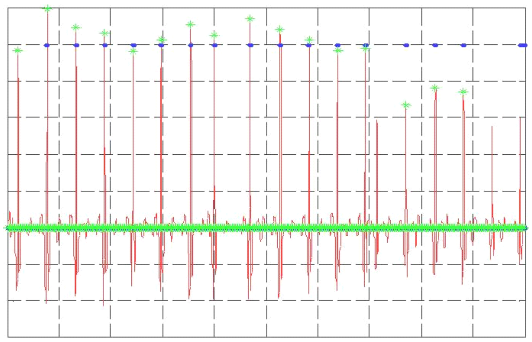

Figure 10: ECG record 100.dat with QRS Complex detection

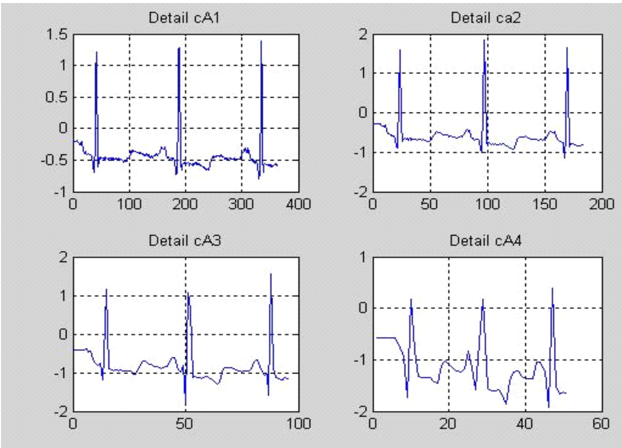

Figure 11: ECG record 100.dat with QRS Complex detection

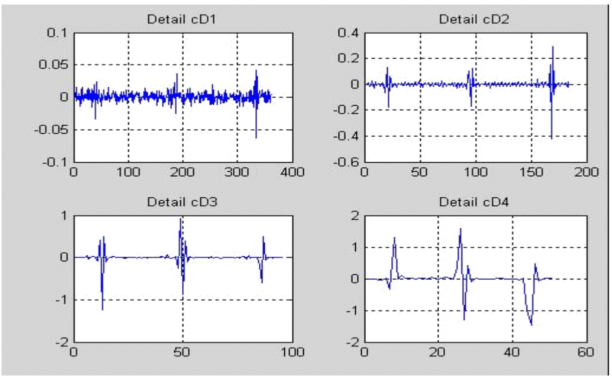

Figure 12: Details cD1 to cD4

Table I. Results of testing by using 46 sets of ECG record files in MIT-BIH database

Record	Total Beats	FP*	FN†	Accuracy‡
100	2272	0	0	100%
101	1870	6	1	100%
102	2187	63	63	94%
103	2083	0	1	100%
104	2322	135	42	92%
105	1959	170	783	51%
106	1927	20	120	93%
107	2135	39	41	96%
109	2452	78	158	90%
111	2123	6	7	99%
112	2556	18	1	99%
113	1794	0	0	100%
114	1878	2	3	100%
115	1953	0	0	100%
116	2390	13	35	98%
117	1537	4	2	100%
118	2291	16	13	99%
119	1987	5	5	99%
121	1862	3	4	100%
122	2476	1	1	100%
123	1518	0	0	100%
124	1605	14	28	97%
200	2593	22	30	98%
201	1933	173	240	79%
202	2123	6	19	99%
203	2839	284	425	75%
205	2652	0	4	100%
207	2072	210	470	67%
208	2919	48	84	95%
209	3008	9	5	100%
210	2551	61	160	91%
212	2749	2	1	100%
213	3243	32	39	98%
214	2261	26	26	98%
215	3365	6	4	100%
217	2210	14	12	99%
219	2148	2	141	93%
220	2048	0	0	100%
221	2413	0	14	99%
222	2486	49	46	96%
223	2563	37	79	95%
228	2034	82	101	91%
230	2256	1	1	100%
231	1571	0	2	100%
232	1806	35	9	98%
234	2752	0	1	100%
			Average	95%

*FP: Number of false detections when there exist no beats but detected as "beats exist"

†FN: Number of false detections when there exist beats but detected as "beats does not exist"

‡Accuracy = 1- (FP+FN)/(Total Beats)

FUTURE WORK

Since the application of wavelet transformation in electrocardiology is relatively new field of research, many methodological aspects (Choice of the mother wavelet, values of the scale parameters) of the wavelet technique will require further investigations in order to improve the clinical usefulness of this novel signal processing technique. Simultaneously diagnostic and prognostic significance of wavelet techniques in various fields of electro cardiology needs to be established in large clinical studies.

CONCLUSION

In the present work, Daubechies wavelet is chosen although the Daubechies algorithm is conceptually more complex and has a slightly complicated computations, yet this algorithm picks up minute detail that is missed by other wavelet algorithms, like Haar wavelet algorithm. Even if a signal is not represented well by one member of the Daubechies family, it may still be efficiently represented by another.

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