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Selection of Wavelets for Evaluating SNR, PRD and CR of ECG Signal

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***Abstract*— This paper presents a technique used to choose optimal wavelets for electrocardiogram (ECG) signal. Various criteria were used to evaluate the fidelity of the reconstruction. The Percent Root Difference (PRD) has been widely used in the literature as the principal error criterion. During the process of recording, the ECG wave suffers from several noise and interferences. These signals have been filtered using by various wavelet filters. The use of filters improves signal quality. In this paper, three more criteria are used namely signal to noise ratio, percent root difference (PRD without mean and PRD with mean) and compression ratio (CR). The best results have been obtained with the Sym20 dictionary.**

***Index Terms*— QRS Complex, ECG, Wavelet, Signal to Noise ratio, Percent Root Difference, Compression Ratio.**

I. INTRODUCTION

Electrocardiogram (ECG) provides representation of the electrical activity of the heart over time and is probably the single most useful indicator of cardiac function. The ECG waveform is recorded from the body surface using the surface electrodes and an ECG monitoring system.ECG processing is a diagnosis for detecting abnormalities in the heart functioning [1,13].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 a trial contraction, the QRS complex corresponds to the current that causes contraction of the left and right ventricles, the T wave represents the depolarization 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 of these waves as well as the QT interval and PR interval are meaningful parameters in the screening and diagnosis of cardiovascular diseases [1].
ECG data increases with increase of number of channels, sampling rate, sample resolution, recording time etc. With the sampling rate of 360 Hz, 11 bits/sample data resolution, a 24-h record requires about 43 Mbytes per channel [2, 3].

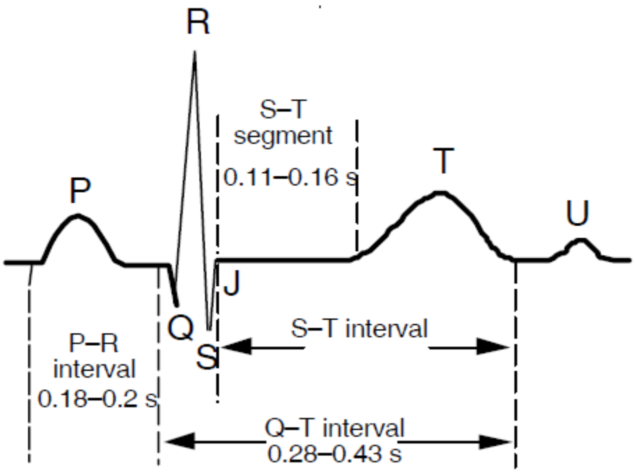

Fig.1 ECG Signal [1]

Modern ECG monitors offer multiple filters for signal processing. The most common settings are monitor mode and diagnostic mode. 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 50/60 Hz power line noise. In diagnostic mode, the low frequency

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(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 analysis of ECG signal application is 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. Most of the time the desired ECG signals are either corrupted or embedded in noises. Problems can be solved by Wavelet analysis.
This paper is organized as follows: In Section II, wavelet transform is presented. The various steps used in SNR, PRD and CR are shown in Section III. Error criterion and distortion methods are presented in Section IV. Result and discussion are shown in Section V. Finally, a conclusion is drawn in Section V.

A. Wavelet Transform

The WT is designed to address the problem of non-stationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis [5, 6, 7, 8, 11,12].
The WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT) is defined by

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi^{*}_{a,b}(t)dt \qquad (1)$$

Where *x(t)* represents the analyzed signal, *a* and *b* represent the scaling factor (dilatation/compression coefficient) and translation along the time axis (shifting coefficient), respectively, and the superscript asterisk denotes the complex conjugation. $\psi_{a,b}(\cdot)$ is obtained by scaling the wavelet at time *b* and scale *a*:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \qquad (2)$$

Where $\psi(t)$ represents the wavelet [5,6,15].
Continuous, in the context of the WT, implies that the scaling and translation parameters *a* and *b* change continuously. However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore discrete wavelet transform (DWT) is often used. The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The procedure of multiresolution decomposition of a signal $x[n]$ is schematically shown in Fig. 1. Each stage of this scheme consists of two digital filters and two down samplers by 2. The first filter, $g[\cdot]$ is the discrete mother wavelet, high-pass in nature, and the second, $h[\cdot]$ is its mirror version, low-pass in nature. The down sampled outputs of first high-pass and low-pass filters provide the detail, $D1$ and the approximation, $A1$, respectively. The first approximation, $A1$ is further decomposed and this process is continued as shown in Fig. 2. All wavelet transforms can be specified in terms of a low-pass filter *h*, which satisfies the standard quadrature mirror filter condition:

$$H(Z)H(Z^{-1}) + H(-Z)H(-Z^{-1}) = 1 \qquad (3)$$

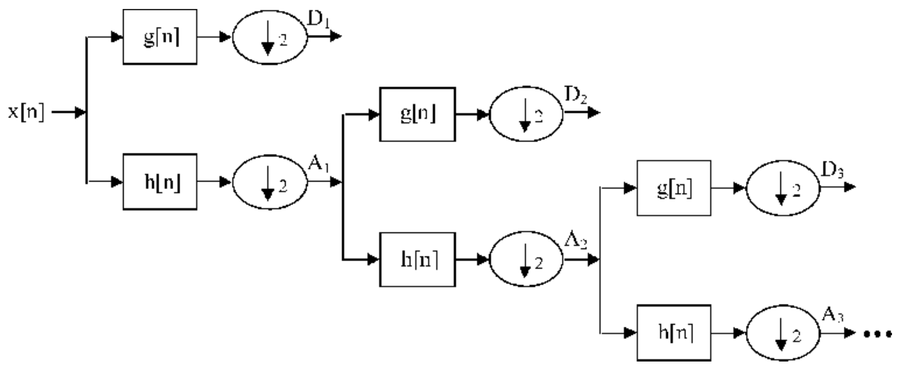

Fig.2 Sub band Decomposition Of Discrete Wavelet Transform Implementation; G[N] Is The High-Pass Filter, H[N] Is The Low-Pass Filter.

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Where $H(z)$ denotes the z-transform of the filter h. Its complementary high-pass filter can be defined as

$$G(Z) = ZH(-Z^{-1}) \qquad (4)$$

A sequence of filters with increasing length (indexed by i) can be obtained:

$$H_{i+1}(Z) = H\left(Z^{2^i}\right) H_i(Z),$$

$$G_{i+1}(Z) = G\left(Z^{2^i}\right) H_i(Z) \qquad i = 0, \ldots \ldots, I-1 \qquad (5)$$

With the initial condition $H0(z) = 1$. It is expressed as a two-scale relation in time domain

$$h_{i+1}(k) = [h]_{\uparrow 2^i} * h_i(k), \;\; g_{i+1}(k) = [hg]_{\uparrow 2^i} * h_i(k) \qquad (6)$$

$$h_{i+1}(k) = [h]_{\uparrow 2^i} * h_i(k)$$

$$g_{i+1}(k) = [hg]_{\uparrow 2^i} * h_i(k)$$

Where the subscript $[\cdot]_{\uparrow m}$ indicates the up-sampling by a factor of m and k is the equally sampled discrete time. The normalized wavelet and scale basis functions $\phi_{i,l}(k)$, $\psi_{i,l}(k)$ can be defined as

$$\varphi_{i,l}(k) = 2^{i/2}\; h_i\left(k - 2^i l\right), \psi_{i,l}(k) = 2^{i/2}\; g_i\left(k - 2^i l\right) \qquad (7)$$

Where the factor $2^{i/2}$ is an inner product normalization, i and l are the scale parameter and the translation parameter, respectively. The DWT decomposition can be described as

$$a_{(i)}(l) = x(k) * \varphi_{i,l}(k), \;\; d_{(i)}(l) = x(k) * \psi_{i,l}(k) \qquad (8)$$

Where $a_{(i)}(l)$ and $d_{(i)}(l)$ are the approximation coefficients and the detail coefficients at resolution i, respectively [6,7]. The concept of being able to decompose a signal totally and then perfectly reconstruct the signal again is practical, but it is not particularly useful by itself. In order to make use of this tool it is necessary to manipulate the wavelet coefficients to identify characteristics of the signal that were not apparent from the original time domain signal.

II. ANALYSIS METHOD

The various steps used in SNR, PRD and CR are discussed below.

A. Database

The first step in ECG signal processing is to obtain it from MIT-BIH Arrhythmia database, available online [4]. Various ECG signal records are used for experiments and algorithm is tested from each record 100,101,102,105,110,113,117,119,205,209 and 210. The database is sampled at 360Hz and the resolution of each sample is 11 bits/sample over a 10mV range. To obtained wavelet analysis, use Matlab program which contains a very good "wavelet Toolbox". Fig. 3 shows Symlet 20 wavelet filter.

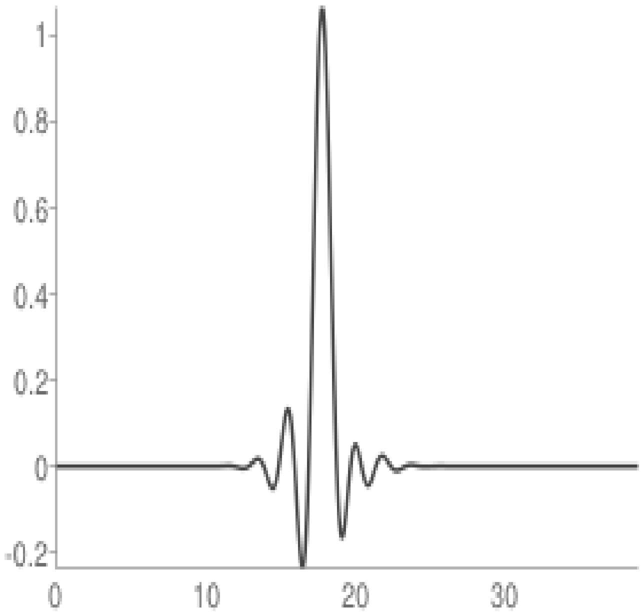

Fig.3. Sym 20 Wavelet Filter

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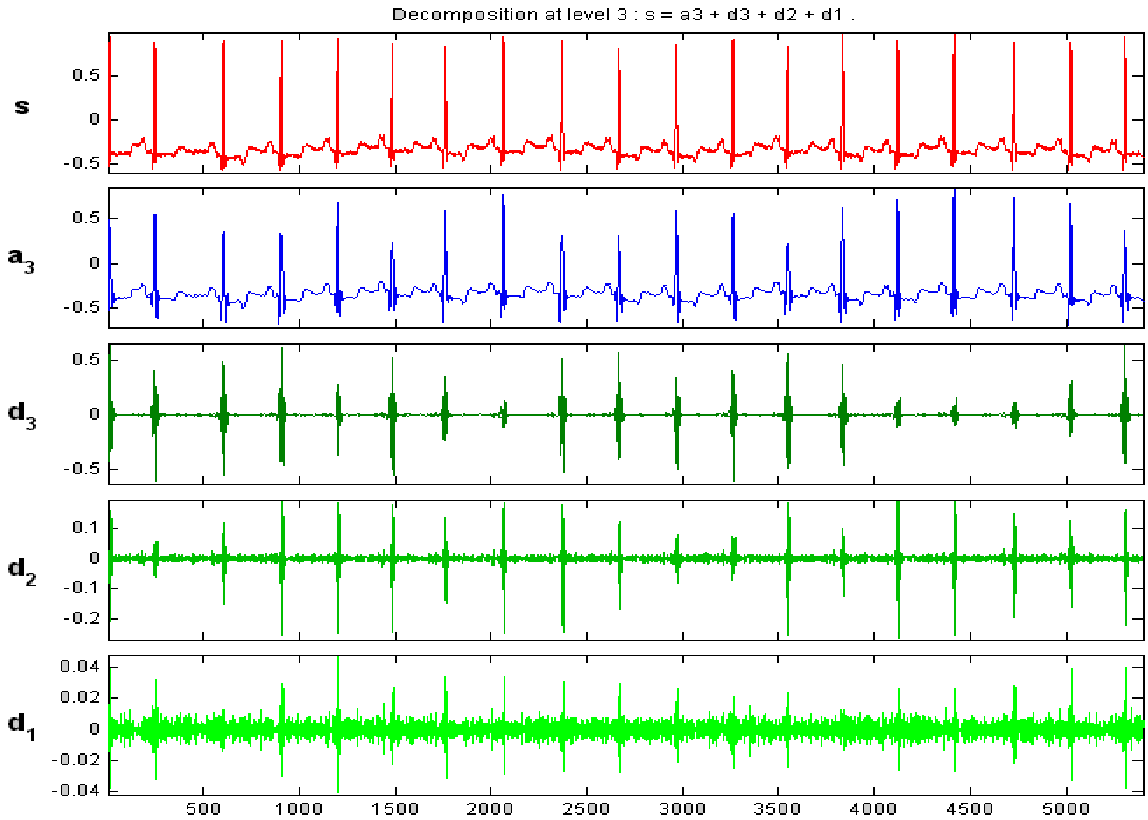

Fig.4 ECG signals decomposition using sym20 Wavelet for 117 [14]

Fig.4 shows the ECG signal decomposition using sym 20 wavelet filters for 117 records. This decomposition is a three level with detailed and approximation information of the signal.

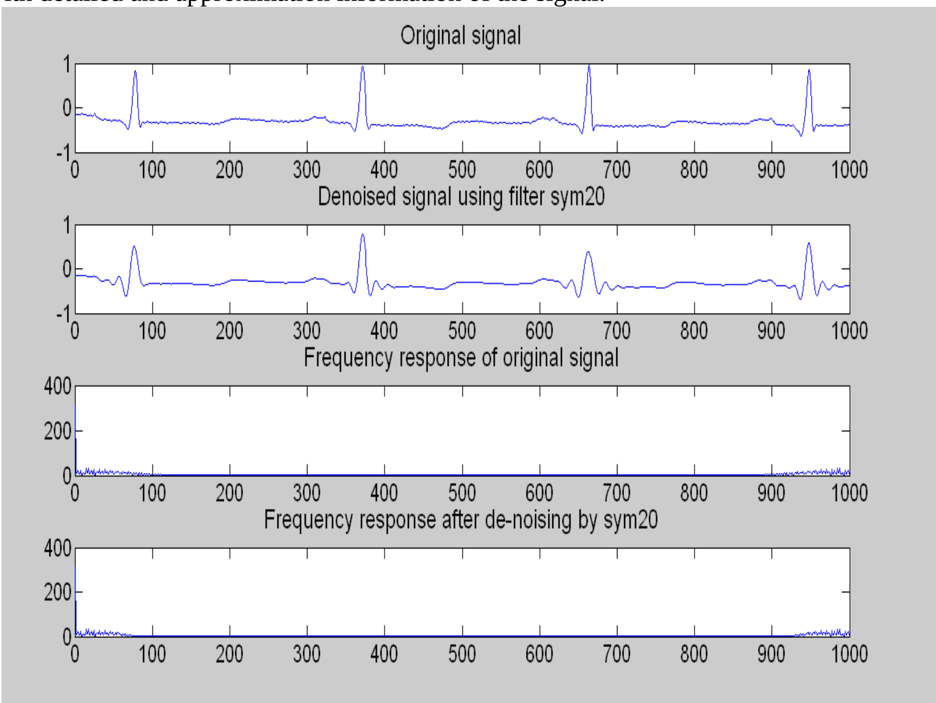

Fig.5 (a) Original Signal,(b) Denoised Signal Using Sym20,(c) Frequency Response of Original Signal (d) Frequency Response after Denoising by Sym20

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Fig.5 shows the original signal of record 117 and frequency response of the signal.

III. MEASURES OF PERFORMANCE

Error criterion and Distortion Methods:

1) Percent Root Mean Square Difference: PRD

One of the most difficult problems in ECG compression applications and reconstruction is defining the error criterion. The purpose of the compression system is to remove redundancy and irrelevant information. Consequently the error criterion has to be defined so that it will measure the ability of the reconstructed signal to preserve the relevant information. Since ECG signals generally are compressed with lossy compression algorithms, a way of quantifying the difference between the original and the reconstructed signal, often called distortion. The most prominently used distortion measure is the Percent Root mean square Difference (PRD) that is given by

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}[x[n] - \hat{x}[n]]^2}{\sum_{n=1}^{N}[x[n]]^2}} \times 100 \qquad (9)$$

Where x[n] and $\hat{x}$[n] are the original and reconstructed signals of length N, respectively. The PRD indicates reconstruction fidelity by point wise comparison with the original data.

Another definition of error measure called PRD1, is same as PRD but it subtracts the average value of the signal from the signal in the denominator and is given by

$$PRD1 = \sqrt{\frac{\sum_{n=1}^{N}[x[n] - \hat{x}[n]]^2}{\sum_{n=1}^{N}[x[n] - \bar{x}]^2}} \times 100 \qquad (10)$$

$\bar{x}$ is the average value of the signal.

PRD provides a numerical measure of the residual root mean square (rms) error.

2) Signal to Noise Ratio: SNR

Basically signal to noise ratio (SNR) is an engineering term for the power ratio between a signal and noise. It is expressed in terms of the logarithmic decibel scale.

$$SNR = 10 \log_{10}\left(\frac{E_{signal}}{E_{noise}}\right)^2$$

$$SNR = 20 \log_{10}\left(\frac{E_{signal}}{E_{noise}}\right)^2 \qquad (11)$$

Where E_{signal}: Root mean square amplitude of the signal

E_{noise}: Root mean square amplitude of the noise

3) Compression Ratio: CR

The compression ratio (CR) is defined as the ratio of the number of bits representing the original signal to the number of bits required to store the compressed signal. All data compression algorithm, used to minimize data storage by eliminating the redundancy wherever possible to increase the compression ratio. Compressed data must also represent the data with better fidelity while achieving high compression ratio[9,10,12].

$$CR = \frac{B_{original}}{B_{compressed}} \qquad (13)$$

Where $B_{original}$- Bit rate of the original signal

$B_{compressed}$- Bit rate of the compressed signal

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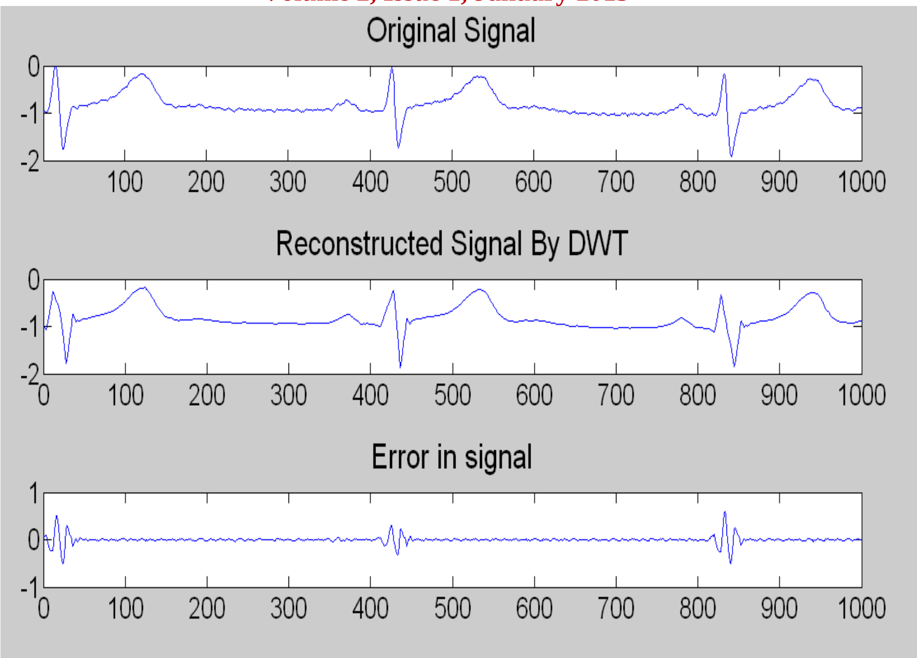

Fig 6 Original ECG signal, reconstructed signal and Error signal using sym20 wavelet for 117

Fig.6 shows original signal, reconstructed signal using by DWT and error signal which is from original signal (record 117).

IV. RESULT AND DISCUSSION

To measure the performance for different compression methods, the distortion between original signal and reconstructed signal is measured by PRD. As PRD measure is very sensitive to the DC level of the original signal, a second definition of the PRD1 that overcomes this problem is sometimes used. Finally, the percent root mean square distortion (PRD) and signal to noise ratio (SNR) are calculated to verify the improvement of the reconstruction signal. While in case different wavelet filter, the compression ratio (CR) are 4.79,4.78,4.81,4.87,4.82,4.68,4.73,4.83,4.98,4.65,4.75,4.80,4.86.Therefore,the transforms can be effectively used for ECG signal compression while preserving necessary clinical information. From Table1, it can be seen that the minimum PRD and maximum SNR values are obtained from sym20 wavelet filter.

Table1.Different Parameters for Various Wavelet Filters

Wavelet Filter	SNR	PRD (normal)	PRD (mean)	CR
db1	27.0005	0.2592	0.5117	4.79
db3	31.2242	0.2099	0.4143	4.78
db10	30.6355	0.2162	0.4267	4.81
db40	32.0040	0.2019	0.3984	4.87
coif1	29.5717	0.228	0.45	4.77
coif3	31.7021	0.2049	0.4045	4.82
sym2	26.9990	0.2593	0.5117	4.68
sym5	29.9524	0.2237	0.4415	4.73
sym10	30.3267	0.2195	0.4333	4.83
sym20	**32.2486**	**0.1994**	**0.3936**	**4.98**
demy	32.0773	0.2011	0.3970	4.65
bior1.1	27.0005	0.2592	0.5117	4.75
bior2.4	31.1820	0.2103	0.4152	4.80
bior3.7	31.8545	0.2034	0.4014	4.86

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Fig.7 shows SNR values of various wavelet filters.
Fig 8 shows PRD (Normal) values of various wavelet filters.
Fig 9 shows PRD (Mean) values of various wavelet filters.
Fig 10 shows CR values of various wavelet filters.

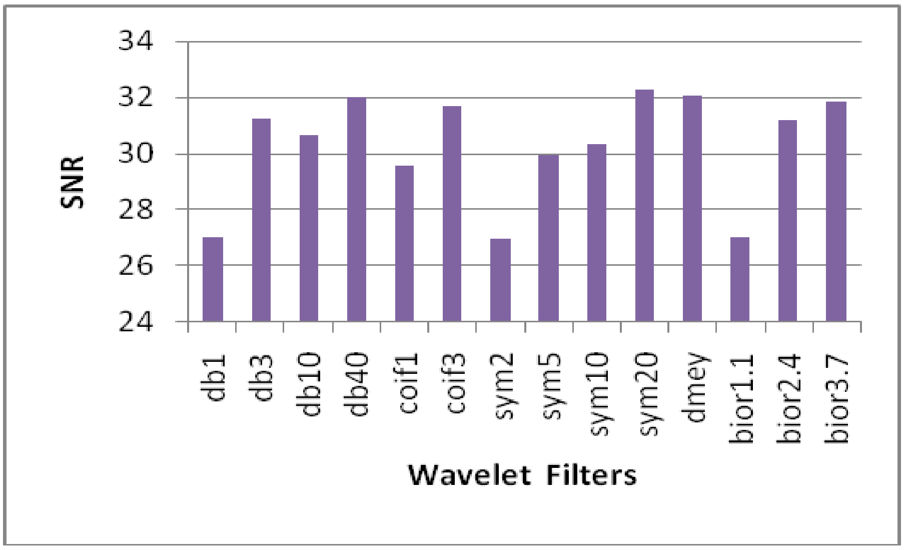

Fig 7. Plot of Signal to Noise ratio with various wavelet filters

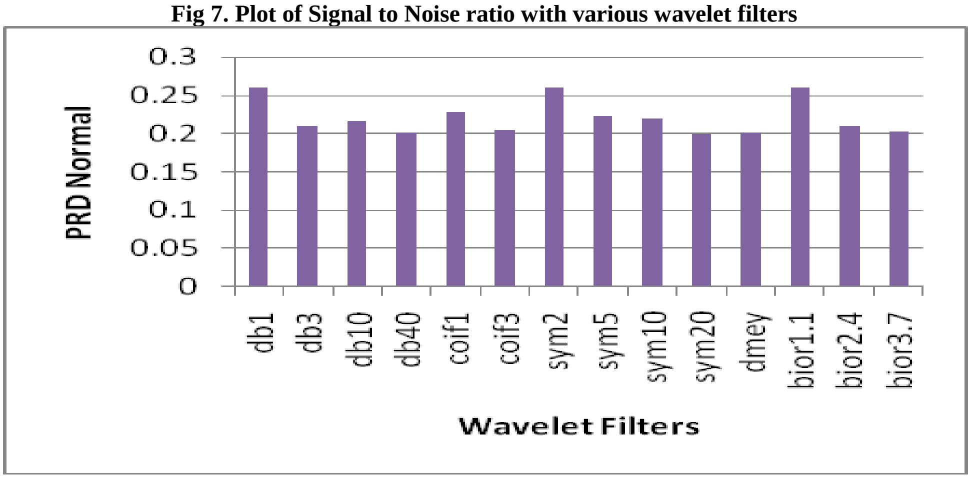

Fig 8. Plot of PRD with various wavelet filters

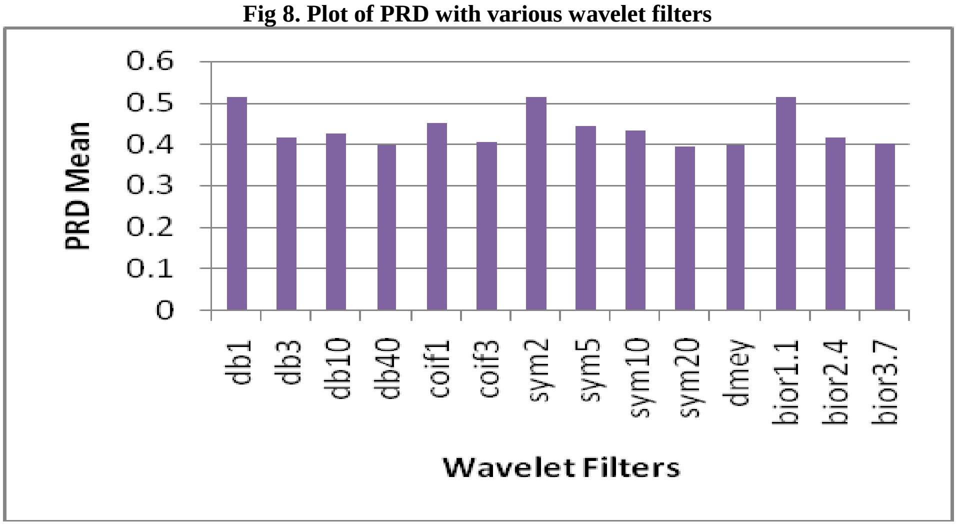

Fig 9 . Plot of PRD(Mean) with various wavelet filters

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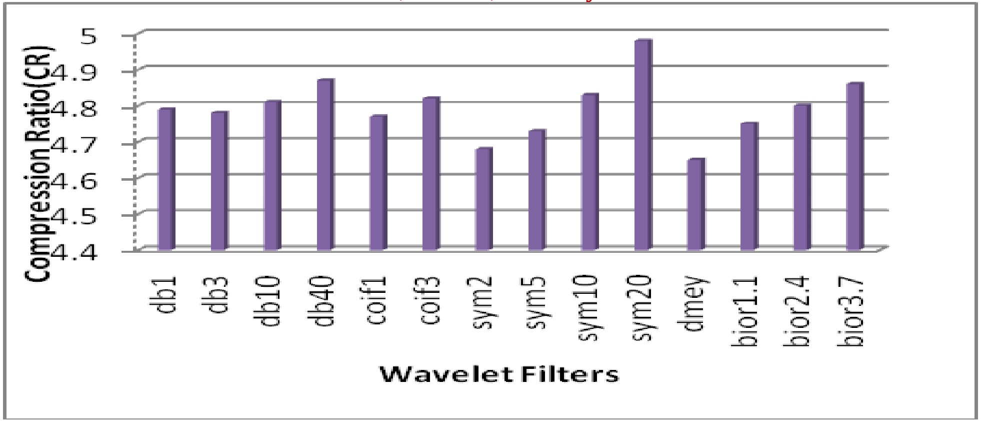

Fig 10 Plot of CR with various wavelet filters

V. CONCLUSION

The advantage of wavelet method is possibly receive good quality signal beat to beat analysis and possibility to have high quality signal while averaging technique is impossible, as causing morphology distortion of ECG Signal. The selected basis function has been found to be optimal not only in terms of SNR, but also it preserves PRD and CR of the ECG signal which contains valuable physiological information for analysis purpose. The conclusion can be drawn from the study of test results of SNR, PRD and CR have shown the best performance of Sym20 wavelet filter compared to other wavelet filters.

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