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Comparative Analysis of Wavelet Basis Functions for ECG Signal Compression through Compressive Sensing

Akanksha Mishra, Falgun Thakkar, Chintan Modi and Rahul Kher

Abstract— Compressed Sensing (CS) is a novel approach of reconstructing a sparse signal much below the significant Nyquist rate of sampling. Due to the fact that ECG signals can be well approximated by the few linear combinations of wavelet basis, this work introduces a comparison of the reconstructed 10 ECG signals based on different wavelet families, by evaluating the performance measures as *MSE* (Mean Square Error), *PSNR* (Peak Signal To Noise Ratio), *PRD* (Percentage Root Mean Square Difference) and *CoC* (Correlation Coefficient). Reconstruction of the ECG signal is a linear optimization process which consider the sparsity in the wavelet domain, perceived by the fact that higher the sparsity, more better the recovery. *L1* minimization is used as the recovery algorithm. The reconstruction results are comprehensively analyzed for three compression ratios, i.e. 2:1, 4:1 and 6:1. The results indicate that reverse biorthogonal wavelet family can give better results for all CRs compared to other families.

Index Terms— Compressive Sensing, Wavelet Transform, Sparsity, Incoherence and *L1* Minimization

I. INTRODUCTION

EFFICIENT compression of the ECG signal is very important for: 1) storing the large amount of data, particularly the long term/ ambulatory ECG data, and 2) transmission over the digital telecommunication network and telephone line [1]. As an example, about 43 Mbytes per channel is needed for 24-h recording of ECG signal with 360Hz sampling rate and 11bits/sample data resolution. For storing and transmitting of these data, better compression is the obligatory step which can reduce the computational cost. There are two major categories [10] in which data

compression is divided: 1) direct method, where actual signal samples are analyzed, 2) wavelet transform based method where first signal transform is taken and then spectral and energy distribution of energy is done. Up till now, it was the well known fact by Shannon-Nyquist theorem that in order to reconstruct the compressed signal exactly as that of the original signal, we must sample the signal at a rate at least twice of its bandwidth.

Traditionally, in data acquisition systems, central role is the transform coding, that is: 1) *N*-sample signal *x* is acquired, 2) transform coefficients are computed by $s = \Psi^T X$, 3) largest coefficients *K* are considered and smallest (*N-K*) coefficients are discarded, 4) Finally, largest coefficients are located and *K* values are encoded. Surprisingly, this sampling and then compressing process suffers from three inherent inefficiencies which are: 1) even if the desired *K* has to be small, initial number of samples *N* is large enough, 2) transformation has to be performed on all *N* number of samples, 3) an overhead is introduced by encoding locations of the large coefficients.

CS theory [5] is a useful tool for eliminating these inefficiency, because 1) it offers simpler hardware implementation for encoder, as it transforms its computational burden from encoder to decoder, 2) no need to encode the location of the largest coefficients in the wavelet domain, 3) its ability to reconstruct the signal from significantly fewer data samples compared to conventional Nyquist sampling theory. It is a novel technique which suggests random acquisition of the non adaptive linear projection at lower than the Nyquist rate, which preserves the signal structure. By using an Optimization problem the signal is reconstructed [4].

The ECG signal can be represented in different sparsity levels in different respective wavelet families. Wavelet transform are the best way to represent the signal as it can decompose the signal into number of sub band signals which consists of different spatial resolution, frequency and directional characteristics. CS has been used recently for rapid magnetic resonance imaging [6] and for electroencephalogram signals [7]. In recent work, CS is implemented on three cardiac signals named as ballistocardiogram, electrocardiogram and Photoplethysmogram, and reconstructed by TwIST algorithm [8]. Many authors have applied DWT in compressed sensing. In [11] Daubechies-4 wavelet is used. Haar and Daubechies-8 wavelet are implemented in [12]. In [13] Daubechies-6 and curvelet transform is used. Haar wavelet in CS is used in [14].

Akanksha Mishra is a PG student at Department of Electronics & Communication Engg of G H Patel College of Engg & Tech, Vallabh Vidyanagar, India (e-mail: akankshamishra33@yahoo.in).

Falgun Thakkar is with Department of Electronics & Communication Engg of G H Patel College of Engg & Tech, Vallabh Vidyanagar, India as Assistant Professor (e-mail: falgungcet@gmail.com).

Chintan Modi is with Department of Electronics & Communication Engg of G H Patel College of Engg & Tech, Vallabh Vidyanagar, India as Professor & Head (e-mail: chintankmodi@yahoo.com).

Rahul Kher is with Department of Electronics & Communication Engg of G H Patel College of Engg & Tech, Vallabh Vidyanagar, India as Associate Professor (phone: +91 2692 231651 Ext. 236; fax: : +91 2692 236896; e-mail: rahul2777@yahoo.com).

But the question is which wavelet is the best one to create sparsity?

In this work, evaluation of the performance of the ECG signal is done based on the different wavelet families and consequently an attempt to select the better wavelet transform is made for three compression ratios (CRs) i.e. 2:1, 4:1, 6:1. Performance is analyzed by comparing *MSE*, *PSNR*, *PRD* and *CoC* values. The performance of the signal in terms of quality of reconstruction is evaluated using the MIT-BIH arrhythmia [9]. L1 minimization is used for reconstruction purpose as it is less combinatorial in nature. The organization of the paper is as follows. In the following Section, basics of Compressive Sensing is discussed, in Section III, background of Wavelet transform is discussed, Section IV consists of methodology used in this paper, Section V contains results and in Section VI the paper is concluded.

II. BASICS OF COMPRESSIVE SENSING

The ability of the compressive sensing is due to the way it samples the signal in the random manner. At the time of acquiring process simultaneously compression is done and signal is recovered by convex optimization problem. On the basis of a) sparsity in wavelet domain, b) compressibility of the signal, c) reconstruction algorithm selected, d) random sampling (choice of measurement matrix), and compressive sensing is done. The size of the measurement matrix ($M \times N$) depends upon the sparsity level K of the signal. The measurement vectors length is also determined by the K sparsity in the signal x . CS can sample the signal by much lesser measurements than those required by the Nyquist sampling theorem. Two major concepts are: Sparsity and Incoherence, which includes sparse representation, random measurements taken and signal recovery via ℓ_1 minimization. Candes, Romberg et al. (2006) [1] proposed that the measurement matrix should have at least $2K$ rows as a sufficient condition and measurement matrix to be Gaussian as the necessary condition. Optimum reconstruction is guaranteed by $M > K \ll N$ using $M > 3K$.

To explain this, consider to recover a non sparse signal $x \in R^N$ which can be transformed by $N \times N$ matrix as:

$$x = \sum_{i=1}^N \alpha_i s_i = \Psi s \quad (1)$$

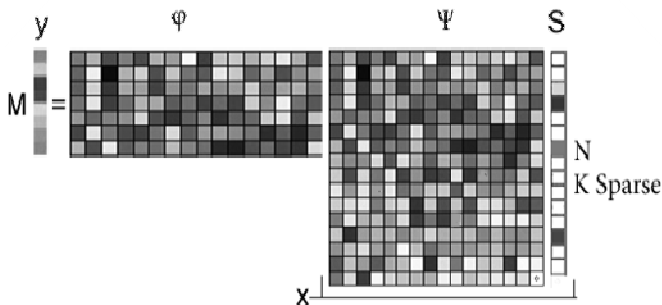


Fig . 1. Compressive sensing measurement process with random Gaussian measurement matrix ϕ

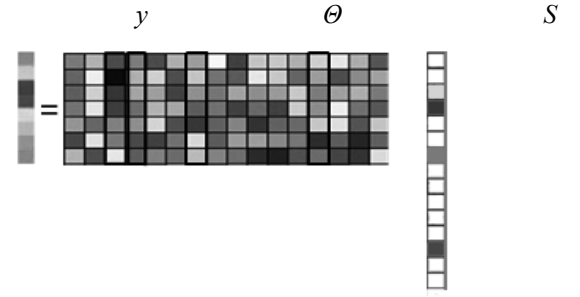


Fig. 2. Measurement vector, y , is the linear combination of respective columns

Where x and S represents $N \times 1$ column vector. S denotes transformed coefficients

$$s_i = \langle x, \Psi_i \rangle \quad (2)$$

To compress the signal x , take Φ with $M \times N$ matrix with $M \ll N$ by which we get M non adaptive sensing measurements y as:

$$y = \phi x = \phi \Psi s = \Theta s \quad (3)$$

As shown in Fig. 2 multiplication of the column vector ϕ_i with the column vector x , is the value of the measurement y and $M > 2K$. The vector of coefficients S is sparse at $k=4$. In Fig3, $\Theta = \Phi \Psi$ measurement process, measurement vector y is the linear combination of respective columns. There are four columns that correspond to nonzero $s(i)$ coefficients. The y vector and encoding basis is used for reconstruction process to recover the original signal x . As at the compression side undetermined system is created due to which infinite many solution of y will be formed. But during reconstruction unique solution will be calculated due to minimization step.

$$y = \phi x^* \quad (4)$$

The minimization is obtained as the result of the following norms:

L0 norm of vector x :

$$\|x\|_0 = \sum_{i=1}^N |x(i)|_0 \quad (5)$$

L1 norm of vector x :

$$\|x\|_1 = \sum_{i=1}^N |x(i)|_1 \quad (6)$$

L2 norm of vector x :

$$\|x\|_2 = \sqrt{\sum_{i=1}^N |x(i)|^2} \quad (7)$$

Among these, L1 minimization [4] is a convex optimization problem which reduces to linear problem also known as basis pursuit. K sparse signal is obtained by using Gaussian measurements.

$$s^* = \arg \min \|s'\|_1 \quad \text{such that} \quad \Theta s' = y \quad (8)$$

Aim is to find the smallest L1 norm among the all possible solution. Where, s^* is a solution vector, s^l is denomination for all possible solution vector x .

III. WAVELET TRANSFORM: AS A TOOL FOR SPARSITY

A. Introduction

Wavelets are used as transform basis in wavelet transform. By scaling and translating one single function Ψ Wavelet functions are generated.

$$\Psi_{a,b}(t) = 1/\sqrt{a}\Psi((t-b)/a) \quad (9)$$

$\Psi(t)$ which is mother wavelet has to be zero integral. $\int \Psi(t)dt = 0$. For $a < 1$, they are high frequency wavelets or correspond to narrow width and for $a > 1$, they are low frequency wavelets or corresponds to wider width. The idea behind the wavelet transform theory is to represent any function f as a linear superposition of wavelets. By superposition, f is decomposed to different scale levels, which can be further decomposed to the levels with their adapted resolution. Function f can be written as a sum of wavelets $\Psi_{m,n}(t)$ over m and n which leads to discrete wavelet transform

$$f(t) = \sum C_{m,n} \Psi_{m,n}(t) \quad (10)$$

The Wavelet transform is an invertible linear operator, which maps a signal to a sparse vector i.e to a vector which has only few large components. It has received a great amount of attention because of its straightforward implementation and good localization properties in time and frequency domain. With only few transformed coefficients most energy of the signal can be captured. Incoherence is the vital requirement between the basis functions of the transform and the domain in which the measurements are acquired. Initially the signal is converted to the Wavelet domain to get the sparse representation.

B. 1-D Signal Compression Using Wavelet Transform

On 1D finite signals Compressive sensing can be applied. Here, a real valued, finite length, one dimensional, discrete time signal has been considered of ECG. The function x which is being expanded is discrete, in which resulting coefficients are obtained by Discrete Wavelet Transform (DWT) by the use of wavelet Basis function Ψ . Wavelet transform in time and frequency domains has good localization properties, easy implementation, efficiency, and good energy compaction ability. The original signal is normalized to $[0, 1]$ and DWT is then performed for sparse representation. After Wavelet transform most of the coefficients are sparse which consist of major information of the original signal. Signal is recovered in time domain by taking into consideration the sparsity level for different transforms by minimizing the dot product of estimated signal and wavelet coefficients.

C. Sparse signals

The ‘‘sparse’’ is a term that explains that the signal has more number of zero values than the nonzero values. Nonzero values are represented by the spikes in the signal with indeterminate distances. When we say ‘‘sparse’’, it means that, magnitude sorted transform coefficients decay rapidly. Consequently, we can say that the signal is compressible. Fig1 shows an example of the sparse signal. Here there are few spikes which represent nonzero values and flat portions that represent zero values.

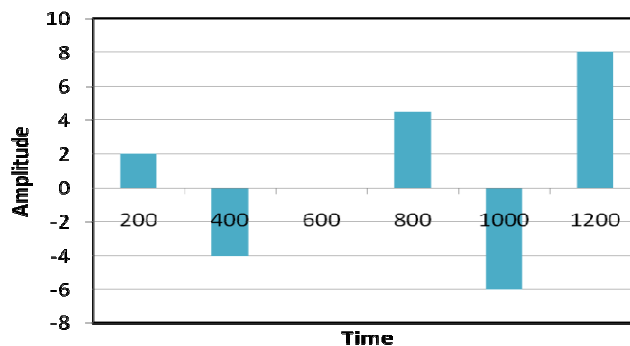


Fig. 3. Sparse Signal Example

D. Selecting Appropriate Wavelet Basis for ECG Signal Compression

DWT can be represented as a matrix form with columns denoting to orthonormal scaling and wavelet basis vector. Daubechies wavelets are extension of Haar. They are those functions which qualify as orthonormal wavelets, but lacks desirable symmetry properties. Two different wavelet basis are used by Biorthogonal wavelets $\Psi(x)$ and $\bar{\Psi}(x)$. One is for analysis (decomposition) and other is for synthesis (reconstruction). That is:

$$\langle \Psi_{j,k}, \bar{\Psi}_{l,m} \rangle = \delta_{j,l} \delta_{k,m} \quad (11)$$

Then we have

$$c_{j,k} = \langle f(x), \bar{\Psi}_{j,k}(x) \rangle \text{ and } d_{j,k} = \langle f(x), \Psi_{j,k}(x) \rangle \quad (12)$$

for the decomposition and

$$f(x) = \sum_{j,k} c_{j,k} \bar{\Psi}_{j,k}(x) = \sum_{j,k} d_{j,k} \Psi_{j,k}(x) \quad (13)$$

for the reconstruction. In frequency domain the two Scaling functions are given by

$$\Phi(2s) = \prod_{n=0}^{\infty} \bar{H}_0(s/2^n) \text{ and } \bar{\Phi}(2s) = \prod_{n=0}^{\infty} H_0(s/2^n) \quad (14)$$

and the wavelets are

$$\bar{\Psi}(2s) = \prod_{n=0}^{\infty} H_0(s/2^n) \text{ and}$$

$$\Psi(x) = \sqrt{2} \sum_n \tilde{h}_1(n+1) \tilde{\phi}(2x-n) \quad (15)$$

Where,

$$\sum_n h_0(n) = \sum_n \tilde{h}_0(n) = \sqrt{2} \quad \text{and} \quad \sum_n h_1(n) = \sum_n \tilde{h}_1(n) = 0 \quad (16)$$

IV. DESCRIPTION OF ALGORITHM

From the incomplete measurements successful recovery of the signal mainly depends upon three factors: 1) the way “sampling” is done (e.g., uniform or non-uniform, in the spatial domain or in the frequency domain), 2) with respect to some prescribed transform how the signal is “compressible”, 3) the measurement and sparsity domains are “mutually incoherent” upto how much extent. Perceived by the fact that greater the information, higher is the number of the samples and much better should be the compression. The methodology followed is as shown in Fig. 4 which starts with the analysis of the signal, searching for the operation and finally achieve for the sparse representation. Signal is represented by discrete wavelet coefficients which are obtained by scaling and translating process. Each and every coefficient at any particular scale is related to the other two coefficients at immediate lower scale. The final wavelet coefficients set which is obtained provides alternative representation of the original signal which is less redundant and well suited for compression. Most of the coefficients in the higher frequency bands are either zero or close to zero. Then the measurement matrix is applied to the signal and measurement vector is created. CVX [3] reconstruction tool is used for the reconstruction process. It is done in the signal domain by minimizing the dot product of estimated signal and wavelet coefficients. ECG signals 1-10 represents to records 100,101,102,103,104,105,106,107,118, 119 ECG signals taken from MIT-BIH [9] arrhythmia with 1024 point length.

The *MSE* for measuring the performance is stated as:

$$MSE = (\sum (f - fp)^2) / N \quad (17)$$

Where, f is original signal, fp is reconstructed signal, N is total signal length. The *PSNR* calculated for the comparison of ECG signal is:

$$PSNR = 10 \log_{10} (M^2 / MSE) \quad (18)$$

Where, M is maximum value from the original ECG signal.

The Compression ratio used is:

$$CR = \text{length}(f) / \text{length}(fp) \quad (19)$$

PRD is Percentage root mean square difference which is computed as follows

$$PRD = \sqrt{MSE / (\sum f^2)} \times 100 \quad (20)$$

Where, f is original signal.

For respective compression ratio we have evaluated the ECG signal for *MSE*, *PSNR*, *PRD* and *CoC* values. For highest value of the *PSNR*, the *PRD* value should be minimum. Eventually the *CoC* value for that ECG signal should tends to 1 more sharply. *CoC* is computed as

$$CoC = \frac{(\sum (f \times fp) \times N) - (\sum f - \sum fp)}{\sqrt{((N \times \sum f^2) - \sum f^2) \times ((N \times \sum fp^2) - \sum fp^2)}} \quad (21)$$

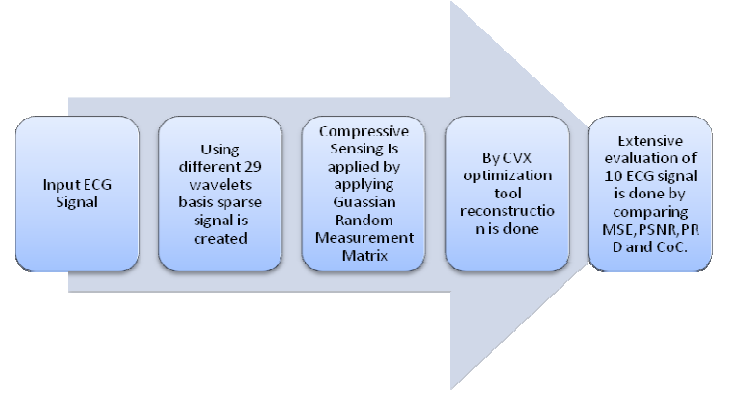


Fig. 4. Methodology for evaluating ECG signal in different wavelet domain

Number of compressive samples is arbitrarily chosen by the Gaussian sensing matrix to be reconstructed effectively. 1024*1024 sparse wavelet coefficients are created. Cvx optimal value for the 2:1CR is stated to be 5592.31 iterations occurred by CVX is counted to be 20. The length of the data or size of matrix should be the power of two. Depth of the transformation ranges from 1 to $\log(N)$, where N denotes the length of data. For computing the solution of the reconstruction process the time required by L1 minimization is measured by performing the simulation in an Intel®Core™ i3-2100CPU at 3.10GHz Processor, with 4 GB RAM, equipped with Windows7 and MATLAB which is 3.7646 ± 3.8954 s for ECG signal.

V. RESULTS AND DISCUSSION

Various wavelets namely Coiflets, Daubichies, Symlets, Biorthogonal, Reverse biorthogonal etc. have been studied and used to compress the cardiac signals [16]. As shown in Table 1, the most preferable wavelet transforms for efficient reconstruction of the signal based on 10 different ECG signals has been evaluated for three different CR 2:1,4:1,6:1. *MSE*, *PSNR*, *PRD* and *CoC* values of all signals are computed and by comparing the performance values dominant wavelet basis is decided. For compression ratio 2:1 for most of the ECG signals *rbio* 3.9 is dominant. It creates the highest sparsity which is being utilized at the time of reconstruction for finding the sparsest signal from infinite many solutions of original signal. By comparing the performance parameters for 10 ECG signals we observed as shown in Table 2, *MSE* values 1.43, 2.12, 1.58 and 1.65 for ECG6, ECG7, ECG8 and ECG10 signals, respectively at reverse biorthogonal basis (*rbio*3.9), is

minimum compared to other basis. Mean square error for four signals out of 10 signals is minimum for rbio3.9 wavelet family. Next, preferable basis can be rbio3.7 as for ECG1 and ECG5 mean square error is minimum. PSNR values as shown in Table 3, for these four signals are 58.88db, 56.51db, 58.89db, 57.52db which proves that peak signal to noise ratio is dominant for rbio3.9 basis. Noise content is very less in the reconstructed signal. Similarly, as shown in Table 4, there correlation coefficient (CoC) values are 0.999786, 0.999648, 0.99996 and 0.999736. As most of the values are close to 1 it gives an idea of strong correlation between original and reconstructed signal. PRD values as shown in Table 5 for these signals are .01% which shows the lowest rate distortion among others. The worst basis for 2:1 CR is bior3.1 (biorthogonal 3.1) as all the four performance parameters are minimum for this wavelet family for 10 different ECG signals.

For compression ratio 4:1, as shown in Table 6, MSE values 7.26, 6.88, 7.84, 6.49 of ECG1, ECG2, ECG3 and ECG5 signals are minimum for rbio3.7 which proves this wavelet suitable for 4:1 CR. During L1 minimization lowest error is indicated by rbio3.7 basis which creates more number of zeros at the reconstruction step. Consequently, PSNR values for these signals as shown in Table 7 are 44.24db, 45.00db, 43.60db and 45.29db. Similarly, CoC values as shown in Table 8, for these signals are 0.987475, 0.99113, 0.993406, 0.994642. The values close to 1 proves this wavelet as the most favorable one. Second favorable one for 4:1 CR is rbio3.9 as out of 10 ECG signals three ECG signals are sparse under this wavelet family. PRD values, as shown in Table 9, are .03% for ECG1, ECG2 and ECG5. Whereas it is .04% for ECG5 signal. The worst basis for 4:1 CR is again bior3.1 as mainly its PRD values lies between 0.22% to 0.48%, which proves to be the greatest distortion. For 6:1 CR, again rbio3.9 is the most occurring wavelet family which gives the highest sparsest representation of the signal and reconstruct with much less error among others. It leads the role against its counterparts. Mean square error (MSE) as shown in Table 10, for ECG1, ECG5 and ECG8 signals are 18.74, 21.85, and 43.29 respectively. For, three signals the reconstruction error is the lowest for rbio3.9. PSNR values as shown in Table 11, for these signals are 36.00db, 34.74db, and 30.14db respectively. CoC values as shown in Table 12, for these signals are 0.91018, 0.936612, and 0.969895. PRD values as shown in Table 13 for these signals are 0.09%, 0.10% and 0.19% respectively. The two wavelets which can be considered as the second most dominant one are the rbio3.7 and rbio3.3 as there reconstruction error is lower after rbio3.9 basis. Bior3.1 again proves to be the worst basis.

To compare the original and reconstructed signals of 2:1 compression ratio by rbio3.9 of ECG104 record, are shown in Fig 5. Both the signals are exactly the same as the sparse signal detected by the reconstruction algorithm for reverse biorthogonal wavelet basis function is efficient in comparison to other basis. It is difficult to see the differences between the two signals. Similarly to compare the performance of rbio3.7 for 4:1 CR both the original and reconstructed signal is shown in Fig.6. By minimizing the dot product wavelet basis function of rbio3.7 and estimated signal with the help of CVX

optimization toolbox this wavelet family proves to be the best. Low decomposition coefficients of the particular wavelets are used to create a wavelet matrix which is later used at the reconstruction step. Again for the 6:1 CR original and reconstructed signals are shown in Fig 7. In case of Daubechies (db) for each signal the best Daubechies is selected for the comparison with different wavelets. From db2 to db8, db4 is selected for 2:1 CR. For 4:1 CR, db8 comes out to be the most promising one. For 6:1 db4 again proves to be the most preferable one.

VI. CONCLUSION

In this paper, we test the quality of reconstructed ECG signals by using 29 wavelets for three different compression ratios. Simulations show that random measurements of the ECG signal in wavelet domain gives us the plausible methodology for compressing the signal. With the help of performance measures such as *MSE*, *PSNR*, *PRD* and *CoC* we found that for 2:1 compression ratio rbio3.9 is the best basis as it creates more sparsity for most of the ECG signals. As we increase the CR to 4:1 we observed again rbio3.7 is the more efficient one as its PSNR values are the highest among its counterparts. For 6:1 CR rbio3.9 is the again best choice and consequently rbio3.7 and rbio3.3 is the second better choice. For all the three CR's bior3.1 is the worst among different wavelet families. In future, we intend to explore the use of other transforms like Curvelet and Ridgelet transform in order to generate sparsity in ECG signal.

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TABLE I
MSE VALUES OF 10 ECG SIGNALS FOR CR = 2:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	3.50	3.95	4.967	4.97	8.47	6.38	12.49	17.58	13.28	7.42
db	2.43	2.46	3.507	3.57	2.85	6.36	9.95	3.95	12.90	4.31
coif	2.39	2.50	3.886	1.73	3.68	3.11	3.79	3.28	9.82	4.02
sym	2.85	2.47	2.794	1.81	2.48	3.11	4.79	4.50	8.35	2.58
bior1.1	2.97	5.97	2.794	7.29	6.67	8.19	8.70	14.71	13.41	7.62
bior2.2	6.47	5.68	4.305	4.18	6.03	7.51	8.29	8.32	14.04	6.07
bior2.4	6.21	4.32	5.965	2.40	4.27	3.73	5.74	9.35	19.88	5.18
bior2.6	5.30	7.75	6.917	4.40	3.53	4.91	6.61	7.19	17.85	5.57
bior2.8	4.90	4.63	5.658	3.59	4.31	5.04	6.53	5.81	13.68	3.77
bior3.1	9.65	25.90	19.1	16.79	32.60	29.98	32.97	57.65	28.92	20.10
bior3.3	11.19	10.02	13.21	11.49	7.01	12.04	12.19	16.25	20.85	16.26
bior4.4	4.47	2.79	4.531	2.76	2.46	3.27	4.98	6.08	10.01	5.56
bior5.5	2.61	1.91	3.099	1.59	1.91	2.49	3.41	3.90	7.72	3.31
bior6.8	3.81	3.03	4.016	2.22	3.13	4.28	4.81	3.49	11.11	3.15
rbio1.1	3.18	5.64	6.147	5.06	8.78	6.24	8.15	16.40	13.70	7.15
rbio1.3	3.78	5.00	5.877	4.96	7.10	7.54	9.03	19.76	14.19	7.31
rbio1.5	2.89	3.89	5.4	4.72	5.51	8.48	8.48	17.45	11.60	8.28
rbio2.2	2.13	2.39	2.871	1.67	1.99	2.27	3.44	3.29	7.53	3.01
rbio2.4	2.36	2.47	2.817	2.10	2.68	1.97	3.32	3.28	8.43	2.99
rbio2.6	2.29	2.33	2.204	1.87	2.36	2.11	3.33	3.55	8.34	2.95
rbio2.8	1.93	2.27	2.032	2.00	1.77	2.48	3.74	4.65	7.02	2.21
rbio3.1	1.69	1.74	1.255	1.10	1.34	1.87	2.23	2.12	5.09	1.75
rbio3.3	1.48	1.54	1.835	1.19	1.62	1.68	2.30	2.05	6.30	2.20
rbio3.5	1.85	1.90	1.627	1.21	1.64	1.77	2.62	1.92	4.91	1.88
rbio3.7	1.36	1.55	1.547	1.32	1.32	2.00	2.47	1.91	5.34	2.12
rbio3.9	1.57	1.73	1.548	1.51	1.53	1.43	2.12	1.58	6.38	1.65
rbio4.4	2.97	3.46	3.837	2.31	2.73	2.55	4.01	2.98	9.73	3.73
rbio5.5	5.12	5.75	10.9	2.90	3.96	3.71	6.97	4.94	14.85	6.24
rbio6.8	2.63	2.46	2.571	1.43	2.98	2.02	3.25	2.84	10.77	4.02

TABLE II
PSNR VALUES OF 10 ECG SIGNALS FOR CR 2:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	50.57	49.83	47.56	48.89	42.97	45.86	41.09	37.97	38.35	44.48
db	53.75	53.94	50.58	51.77	52.43	45.89	43.07	50.94	38.60	49.19
coif	53.87	53.81	49.69	58.09	50.21	52.10	51.44	52.56	40.97	49.79
sym	52.38	53.91	52.56	57.68	53.64	52.10	49.43	49.80	42.38	53.63
bior1.1	51.99	46.24	52.56	45.57	45.05	43.69	44.23	39.51	38.27	44.24
bior2.2	45.24	46.66	48.80	50.41	45.92	44.45	44.66	44.46	37.87	46.21
bior2.4	45.60	49.04	45.97	55.22	48.93	50.53	47.85	43.45	34.85	47.60
bior2.6	46.98	43.97	44.68	49.94	50.57	48.14	46.62	45.73	35.78	46.97
bior2.8	47.65	48.45	46.43	51.72	48.84	47.92	46.72	47.58	38.09	50.36
bior3.1	41.76	33.49	35.86	38.32	31.27	32.43	32.66	27.65	31.59	35.82
bior3.3	40.48	41.74	39.07	41.62	44.62	40.35	41.30	38.65	34.43	37.66
bior4.4	48.44	52.84	48.36	54.01	53.72	51.68	49.08	47.19	40.81	46.98
bior5.5	53.11	56.13	51.66	58.80	55.91	54.05	52.38	51.04	43.07	51.49
bior6.8	49.83	52.14	49.41	55.90	51.62	49.34	49.38	52.01	39.90	51.93
rbio1.1	51.41	46.73	45.71	48.73	42.66	46.06	44.80	38.57	38.08	44.79
rbio1.3	49.92	47.77	46.10	48.91	44.51	44.42	43.91	36.95	37.78	44.60
rbio1.5	52.24	49.95	46.83	49.34	46.71	43.39	44.46	38.03	39.53	43.52
rbio2.2	54.88	54.18	52.32	58.36	55.54	54.85	52.30	52.53	43.27	52.30
rbio2.4	54.00	53.90	52.49	56.39	52.96	56.05	52.61	52.54	42.29	52.38
rbio2.6	54.24	54.42	54.62	57.37	54.09	55.47	52.58	51.87	42.39	52.50
rbio2.8	55.76	54.62	55.32	56.79	56.55	54.06	51.57	49.52	43.89	54.98
rbio3.1	56.91	56.96	59.51	61.99	58.99	56.53	56.04	56.33	46.87	57.01
rbio3.3	58.08	58.03	56.21	61.33	57.36	57.45	55.79	56.63	44.83	55.05
rbio3.5	56.13	56.19	57.26	61.13	57.23	56.98	54.64	57.19	46.99	56.41
rbio3.7	58.79	57.95	57.69	60.44	59.15	55.95	55.17	57.25	46.26	55.34
rbio3.9	57.57	57.02	57.69	59.22	57.86	58.88	56.51	58.89	44.72	57.52
rbio4.4	52.02	50.99	49.80	55.57	52.82	53.81	50.97	53.39	41.05	50.45
rbio5.5	47.28	46.57	40.73	53.57	49.57	50.58	46.16	48.99	37.38	45.97
rbio6.8	53.05	53.93	53.28	59.73	52.04	55.84	52.78	53.79	40.17	49.79

TABLE III
CoC VALUES OF 10 ECG SIGNALS FOR CR = 2:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	0.9971	0.9971	0.9955	0.9971	0.9910	0.9958	0.9893	0.9951	0.9855	0.9949
Db	0.9986	0.9989	0.9977	0.9985	0.9990	0.9957	0.9925	0.9998	0.9869	0.9983
coif	0.9986	0.9988	0.9972	0.9996	0.9983	0.9990	0.9989	0.9998	0.9924	0.9985
Sym	0.9981	0.9988	0.9985	0.9996	0.9992	0.9990	0.9983	0.9997	0.9943	0.9994
bior1.1	0.9979	0.9930	0.9985	0.9937	0.9943	0.9931	0.9941	0.9965	0.9855	0.9946
bior2.2	0.9898	0.9940	0.9965	0.9979	0.9957	0.9941	0.9947	0.9990	0.9838	0.9965
bior2.4	0.9908	0.9964	0.9933	0.9993	0.9977	0.9985	0.9977	0.9986	0.9694	0.9975
bior2.6	0.9933	0.9884	0.9912	0.9977	0.9985	0.9975	0.9967	0.9992	0.9750	0.9973
bior2.8	0.9940	0.9958	0.9940	0.9985	0.9976	0.9973	0.9966	0.9995	0.9846	0.9987
bior3.1	0.9763	0.8581	0.9274	0.9635	0.8576	0.8992	0.9157	0.9435	0.9297	0.9600
bior3.3	0.9694	0.9798	0.9665	0.9836	0.9938	0.9848	0.9884	0.9959	0.9647	0.9761
bior4.4	0.9953	0.9985	0.9962	0.9991	0.9993	0.9989	0.9981	0.9994	0.9919	0.9972
bior5.5	0.9984	0.9993	0.9983	0.9997	0.9995	0.9994	0.9991	0.9998	0.9953	0.9990
bior6.8	0.9965	0.9982	0.9970	0.9994	0.9988	0.9980	0.9982	0.9998	0.9900	0.9991
rbio1.1	0.9975	0.9940	0.9933	0.9969	0.9907	0.9959	0.9952	0.9958	0.9850	0.9954
rbio1.3	0.9969	0.9954	0.9936	0.9970	0.9938	0.9946	0.9937	0.9937	0.9836	0.9950
rbio1.5	0.9980	0.9972	0.9950	0.9973	0.9960	0.9927	0.9947	0.9950	0.9892	0.9934
rbio2.2	0.9998	0.9989	0.9986	0.9997	0.9995	0.9994	0.9991	0.9998	0.9955	0.9991
rbio2.4	0.9987	0.9988	0.9986	0.9995	0.9991	0.9996	0.9992	0.9998	0.9946	0.9992
rbio2.6	0.9987	0.9990	0.9991	0.9996	0.9993	0.9995	0.9991	0.9998	0.9946	0.9992
rbio2.8	0.9991	0.9990	0.9992	0.9995	0.9996	0.9993	0.9989	0.9997	0.9961	0.9995
rbio3.1	0.9993	0.9994	0.9997	0.9999	0.9998	0.9996	0.9996	0.9999	0.9980	0.9997
rbio3.3	0.9995	0.9996	0.9994	0.9998	0.9997	0.9997	0.9996	0.9999	0.9969	0.9995
rbio3.5	0.9992	0.9993	0.9995	0.9998	0.9997	0.9997	0.9995	0.9999	0.9981	0.9997
rbio3.7	0.9995	0.9995	0.9995	0.9998	0.9998	0.9996	0.9995	0.9999	0.9977	0.9996
rbio3.9	0.9994	0.9994	0.9996	0.9997	0.9997	0.9998	0.9996	1.0000	0.9968	0.9997
rbio4.4	0.9979	0.9977	0.9974	0.9994	0.9991	0.9993	0.9988	0.9999	0.9927	0.9988
rbio5.5	0.9938	0.9935	0.9780	0.9990	0.9980	0.9986	0.9964	0.9996	0.9819	0.9965
rbio6.8	0.9983	0.9989	0.9988	0.9998	0.9989	0.9996	0.9992	0.9999	0.9906	0.9985

TABLE IV
PRD VALUES OF 10 ECG SIGNALS FOR CR = 2:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	0.02%	0.02%	0.02%	0.02%	0.04%	0.03%	0.06%	0.08%	0.07%	0.03%
db	0.01%	0.01%	0.02%	0.02%	0.01%	0.03%	0.04%	0.02%	0.07%	0.02%
coif	0.01%	0.01%	0.02%	0.01%	0.02%	0.01%	0.02%	0.01%	0.05%	0.02%
sym	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.02%	0.02%	0.05%	0.01%
bior1.1	0.01%	0.03%	0.01%	0.03%	0.03%	0.04%	0.04%	0.06%	0.07%	0.03%
bior2.2	0.03%	0.03%	0.02%	0.02%	0.03%	0.03%	0.04%	0.04%	0.08%	0.03%
bior2.4	0.03%	0.02%	0.03%	0.01%	0.02%	0.02%	0.03%	0.04%	0.11%	0.02%
bior2.6	0.02%	0.04%	0.03%	0.02%	0.02%	0.02%	0.03%	0.03%	0.10%	0.02%
bior2.8	0.02%	0.02%	0.03%	0.02%	0.02%	0.02%	0.03%	0.03%	0.07%	0.02%
bior3.1	0.04%	0.12%	0.09%	0.08%	0.15%	0.14%	0.15%	0.25%	0.16%	0.09%
bior3.3	0.05%	0.05%	0.06%	0.05%	0.03%	0.05%	0.05%	0.07%	0.11%	0.07%
bior4.4	0.02%	0.01%	0.02%	0.01%	0.01%	0.01%	0.02%	0.03%	0.05%	0.02%
bior5.5	0.01%	0.								

TABLE V
MSE VALUES OF 10 ECG SIGNALS FOR CR = 4:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	12.56	18.32	22.42	18.23	29.54	20.38	31.44	69.22	38.73	31.92
db	21.30	20.19	22.95	25.94	29.07	21.67	28.42	63.02	33.23	36.47
coif	19.77	16.43	21.26	17.91	21.87	18.35	16.72	39.92	31.39	25.53
sym	28.48	19.90	23.84	10.56	16.52	17.75	13.65	52.61	37.30	26.08
bior1.1	14.01	14.65	18.58	25.23	27.30	27.00	26.77	73.35	34.29	22.71
bior2.2	30.57	25.76	30.59	28.46	39.39	32.64	28.95	67.73	60.58	41.21
bior2.4	24.67	28.78	32.37	33.31	32.04	31.78	34.09	64.07	39.71	51.94
bior2.6	22.96	29.66	23.10	27.83	36.68	24.78	45.97	59.50	58.65	42.19
bior2.8	14.32	33.70	25.60	33.86	25.60	36.01	30.05	0.94	40.55	36.60
bior3.1	47.20	59.05	63.55	55.05	71.93	78.66	76.67	109.27	76.55	61.20
bior3.3	40.54	40.42	35.56	41.67	41.24	47.01	65.50	81.17	59.29	59.10
bior4.4	23.53	23.04	21.25	17.94	15.00	19.60	18.71	43.63	37.23	30.67
bior5.5	11.68	13.50	16.37	12.34	10.43	17.78	12.34	24.43	25.82	25.33
bior6.8	17.62	20.20	24.42	19.04	31.41	21.01	16.46	46.53	32.57	21.04
rbio1.1	16.55	15.49	19.19	17.26	25.65	26.16	55.39	60.50	32.59	20.10
rbio1.3	15.28	15.26	15.21	20.66	29.88	23.86	32.79	47.11	27.98	24.79
rbio1.5	12.28	21.35	17.51	15.84	22.23	31.17	37.58	46.98	36.88	23.21
rbio2.2	7.85	9.77	9.44	13.38	15.83	13.55	23.82	34.61	25.28	20.27
rbio2.4	10.86	9.59	8.89	13.14	19.86	14.85	17.30	33.80	32.40	19.16
rbio2.6	10.73	9.17	11.74	9.69	19.59	15.53	11.42	32.35	33.99	15.78
rbio2.8	8.82	16.25	11.83	10.65	17.43	14.44	15.92	33.14	20.89	10.59
rbio3.1	9.70	15.13	9.99	13.29	15.07	14.79	13.26	34.84	20.71	11.69
rbio3.3	14.33	13.31	13.45	5.42	8.94	10.35	8.78	16.98	12.91	11.86
rbio3.5	9.04	20.24	9.31	8.56	6.54	11.79	6.82	14.55	19.20	11.20
rbio3.7	7.26	6.88	7.84	5.64	6.49	12.94	9.13	21.60	23.05	9.42
rbio3.9	8.55	9.44	8.36	4.70	10.16	9.05	12.74	24.69	28.07	9.14
rbio4.4	16.63	10.51	18.68	24.13	23.58	28.01	19.77	39.56	26.54	13.98
rbio5.5	30.05	33.53	33.76	37.97	22.42	57.78	38.37	84.42	58.62	54.81
rbio6.8	23.27	19.11	14.65	17.87	19.98	20.96	18.40	39.23	27.99	12.49

TABLE VII
CoC VALUES OF 10 ECG SIGNALS FOR = 4:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	0.9651	0.9318	0.9018	0.9602	0.8886	0.9563	0.9274	0.9243	0.8750	0.9100
db	0.8840	0.9141	0.8933	0.9103	0.8861	0.9500	0.9355	0.9371	0.9064	0.8814
coif	0.8975	0.9453	0.9167	0.9621	0.9424	0.9635	0.9782	0.9740	0.9172	0.9387
sym	0.7697	0.9187	0.8851	0.9877	0.9638	0.9699	0.9867	0.9540	0.8780	0.9380
bior1.1	0.9533	0.9586	0.9401	0.9197	0.9040	0.9189	0.9443	0.9084	0.8999	0.9498
bior2.2	0.7349	0.8575	0.8006	0.8991	0.7719	0.8816	0.9315	0.9256	0.6588	0.8215
bior2.4	0.8332	0.8177	0.7715	0.8488	0.8719	0.8891	0.9075	0.9337	0.8606	0.6969
bior2.6	0.8583	0.8041	0.8940	0.8997	0.8050	0.9314	0.8164	0.9411	0.6702	0.8096
bior2.8	0.9477	0.7385	0.8642	0.8458	0.9134	0.8518	0.9248	0.9430	0.8540	0.8606
bior3.1	0.4551	0.3969	0.2930	0.6397	0.3653	0.3318	0.4971	0.7801	0.5640	0.6290
bior3.3	0.5303	0.6237	0.7275	0.7478	0.7486	0.7265	0.5963	0.8849	0.6702	0.6097
bior4.4	0.8533	0.8902	0.9139	0.9609	0.9709	0.9598	0.9733	0.9688	0.8804	0.9100
bior5.5	0.9661	0.9639	0.9494	0.9826	0.9863	0.9693	0.9883	0.9910	0.9458	0.9385
bior6.8	0.9255	0.9187	0.8797	0.9549	0.8656	0.9574	0.9798	0.9695	0.9117	0.9568
rbio1.1	0.9321	0.9541	0.9339	0.9640	0.9133	0.9283	0.7355	0.9440	0.9099	0.9632
rbio1.3	0.9451	0.9560	0.9584	0.9492	0.8802	0.9387	0.9131	0.9640	0.9341	0.9401
rbio1.5	0.9669	0.9052	0.9403	0.9687	0.9343	0.8904	0.8895	0.9630	0.8880	0.9481
rbio2.2	0.9851	0.9828	0.9847	0.9795	0.9680	0.9804	0.9618	0.9814	0.9495	0.9633
rbio2.4	0.9745	0.9830	0.9850	0.9794	0.9484	0.9783	0.9787	0.9814	0.9105	0.9674
rbio2.6	0.9717	0.9841	0.9770	0.9895	0.9528	0.9757	0.9897	0.9835	0.9017	0.9781
rbio2.8	0.9817	0.9496	0.9734	0.9862	0.9602	0.9778	0.9805	0.9828	0.9656	0.9897
rbio3.1	0.9794	0.9573	0.9821	0.9787	0.9734	0.9782	0.9872	0.9809	0.9674	0.9880
rbio3.3	0.9511	0.9678	0.9680	0.9968	0.9896	0.9888	0.9945	0.9956	0.9868	0.9872
rbio3.5	0.9810	0.9179	0.9883	0.9910	0.9946	0.9862	0.9965	0.9969	0.9701	0.9892
rbio3.7	0.9875	0.9911	0.9934	0.9964	0.9946	0.9832	0.9935	0.9925	0.9561	0.9917
rbio3.9	0.9831	0.9844	0.9871	0.9973	0.9886	0.9923	0.9876	0.9907	0.9368	0.9928
rbio4.4	0.9314	0.9793	0.9331	0.9290	0.9298	0.9146	0.9693	0.9766	0.9402	0.9825
rbio5.5	0.7511	0.7435	0.7674	0.8029	0.9316	0.5986	0.8739	0.8748	0.6880	0.6643
rbio6.8	0.8540	0.9310	0.9594	0.9614	0.9489	0.9510	0.9738	0.9763	0.9346	0.9855

TABLE VI
PSNR VALUES OF 10 ECG SIGNALS FOR CR = 4:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	39.48	36.49	34.47	37.61	32.12	35.78	33.08	26.06	29.05	31.80
db	34.89	35.65	34.26	34.54	32.26	35.24	33.95	26.88	30.38	30.64
coif	35.54	37.45	34.93	37.76	34.74	36.69	38.56	30.84	30.88	33.74
sym	32.37	35.78	33.94	42.35	37.17	36.98	40.32	28.45	29.38	33.55
bior1.1	38.53	38.44	36.10	34.78	32.81	33.34	34.47	25.56	30.11	34.76
bior2.2	31.75	33.54	31.77	33.74	29.63	31.69	33.79	26.25	25.17	29.58
bior2.4	33.62	32.57	31.28	32.37	31.42	31.92	32.37	26.73	28.84	27.57
bior2.6	34.24	32.31	34.21	33.93	30.24	34.08	29.78	27.38	25.45	29.38
bior2.8	38.34	31.20	33.32	32.23	33.37	30.83	33.47	27.46	28.65	30.61
bior3.1	27.98	26.33	25.42	28.01	24.39	24.05	25.33	22.10	23.14	26.15
bior3.3	29.30	29.62	30.46	30.43	29.23	28.52	26.70	24.68	25.36	26.45
bior4.4	34.03	34.51	34.93	37.74	38.01	36.12	37.58	30.07	29.40	32.15
bior5.5	40.11	39.15	37.20	41.00	41.16	36.96	41.20	35.11	32.58	33.81
bior6.8	36.54	35.65	33.73	37.23	31.59	35.51	38.69	29.51	30.56	35.42
rbio1.1	37.09	37.96	35.82	38.08	33.35	33.61	28.16	27.23	30.55	35.82
rbio1.3	37.78	38.08	37.84	36.52	32.02	34.41	32.71	29.40	31.88	34.00
rbio1.5	39.67	35.17	36.62	38.83	34.59	32.09	31.53	29.43	29.48	34.57
rbio2.2	43.56	41.96	41.98	40.29	37.54	39.32	35.49	32.08	32.76	35.75
rbio2.4	40.74	42.12	42.50	40.45	35.57	38.52	38.26	32.29	30.60	36.23
rbio2.6	40.85	42.51	40.09	43.09	35.69	38.14	41.87	32.67	30.19	37.92
rbio2.8	42.55	37.54	40.02	42.28	36.71	38.77	38.99	32.46	34.42	41.39
rbio3.1	41.72	38.16	41.49	40.35	37.97	38.56	40.57	32.03	34.49	40.53
rbio3.3	38.33	39.27	38.90	48.14	42.51	41.66	44.16	38.27	38.60	40.40
rbio3.5	42.33	35.63	42.11	44.17	45.22	40.53	46.35	39.61	35.15	40.90
rbio3.7	44.24	45.00	43.60	47.79	45.29	39.72	43.82	36.18	33.56	42.40
rbio3.9	42.82	42.26	43.04	49.37	41.40	42.83	40.92	35.02	31.85	42.67
rbio4.4	37.04	41.32	36.06	35.17	34.08	33.02	37.11	30.92	32.34	38.97
rbio5.5	31.90	31.25	30.91	31.23	34.52	26.73	31.35	24.34	25.45	27.11
rbio6.8	34.12	36.13	38.17	37.78	35.52	35.53	37.73	30.99	31.88	39.95

TABLE VIII
PRD VALUES OF 10 ECG SIGNALS FOR CR = 4:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	0.06%	0.08%	0.10%	0.08%	0.13%	0.09%	0.14%	0.30%	0.21%	0.14%
db	0.10%	0.09%	0.10%	0.12%	0.13%	0.10%	0.13%	0.28%	0.18%	0.16%
coif	0.09%	0.07%	0.10%	0.08%	0.10%	0.08%	0.07%	0.18%	0.17%	0.11%
sym	0.13%	0.09%	0.11%	0.05%	0.07%	0.08%	0.06%	0.23%	0.20%	0.11%
bior1.1	0.06%	0.07%	0.08%	0.11%	0.12%	0.12%	0.12%	0.32%	0.19%	0.10%
bior2.2	0.14%	0.12%	0.14%	0.13%	0.18%	0.15%	0.13%	0.30%	0.33%	0.18%
bior2.4	0.11%	0.13%	0.14%	0.15%	0.14%	0.14%	0.15%	0.28%	0.22%	0.23%
bior2.6	0.10%	0.14%	0.10%	0.13%	0.16%	0.11%	0.20%	0.26%	0.32%	0.19%
bior2.8	0.07%	0.15%	0.11%	0.15%	0.11%	0.16%	0.13%	0.26%	0.22%	0.16%
bior3.1	0.22%	0.27%	0.28%	0.25%	0.32%	0.36%	0.34%	0.48%	0.41%	0.27%
bior3.3	0.18%	0.18%	0.16%	0.19%	0.18%	0.21%	0.29%	0.36%	0.32%	0.26%
bior4.4	0.11%	0.11%	0.10%	0.08%	0.07%	0.09%	0.08%	0.19%	0.20%	0.14%

TABLE IX
MSE VALUES OF 10 ECG SIGNALS FOR CR = 6:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	35.08	35.20	62.96	105.41	46.00	40.45	62.96	105.41	69.41	68.51
db	34.31	32.05	49.10	59.76	32.54	36.26	49.10	59.76	42.84	64.25
coif	23.90	28.61	50.82	108.57	35.62	39.09	37.01	108.57	52.26	61.08
sym	39.20	30.93	28.71	91.84	30.29	36.97	28.71	88.16	34.45	53.97
bior1.1	22.80	27.79	60.84	99.34	44.88	41.15	60.84	99.34	62.28	53.83
bior2.2	20.48	55.57	34.69	50.63	67.44	65.32	79.26	103.92	74.33	65.57
bior2.4	42.46	56.08	62.39	119.64	33.06	50.90	62.39	119.64	64.46	116.44
bior2.6	48.90	62.97	45.40	52.00	61.26	76.77	64.04	114.76	69.19	60.42
bior2.8	34.99	44.03	51.54	49.53	55.65	49.75	62.48	98.65	58.27	47.41
bior3.1	86.95	85.75	85.77	81.21	90.41	93.05	37.29	176.30	101.64	96.81
bior3.3	51.64	58.80	65.09	68.36	65.08	83.92	109.21	151.97	92.22	73.88
bior4.4	37.89	24.04	36.61	89.94	35.30	42.59	36.61	89.94	57.89	68.27
bior5.5	23.59	29.48	31.55	71.60	25.62	30.98	31.55	71.60	58.92	57.77
bior6.8	29.65	27.76	37.29	31.46	39.36	45.05	37.29	54.30	63.25	72.38
rbio1.1	25.58	26.57	76.19	129.58	36.72	35.37	76.19	129.58	50.56	53.66
rbio1.3	30.21	30.39	40.22	35.51	50.97	38.51	64.37	98.52	49.67	48.25
rbio1.5	28.65	35.70	41.09	34.18	40.54	40.84	47.81	90.85	50.32	45.57
rbio2.2	25.73	29.09	33.28	31.46	34.23	43.46	21.78	68.35	52.74	62.29
rbio2.4	30.51	28.35	25.72	75.91	35.18	34.88	25.72	75.91	51.52	36.22
rbio2.6	20.62	33.69	27.48	26.14	33.12	38.88	31.08	66.83	54.86	28.09
rbio2.8	20.77	28.16	28.91	28.53	36.87	36.33	34.95	48.51	51.68	25.34
rbio3.1	22.33	33.91	32.01	45.85	42.83	35.45	50.60	53.25	30.29	41.93
rbio3.3	33.75	28.09	24.48	28.94	36.80	27.63	17.89	52.34	36.53	34.46
rbio3.5	20.13	39.97	37.25	49.33	37.39	33.72	37.25	49.33	34.86	57.13
rbio3.7	32.73	26.61	18.46	23.66	24.91	30.27	41.38	59.82	52.27	37.95
rbio3.9	18.74	25.37	41.23	43.29	21.85	39.07	41.23	43.29	38.05	56.89
rbio4.4	34.56	35.43	59.13	97.41	44.03	52.86	59.13	97.41	56.54	77.29
rbio5.5	42.86	41.39	70.67	118.76	63.47	48.70	70.67	118.76	79.62	102.78
rbio6.8	39.30	38.29	37.39	74.98	31.84	42.42	37.39	74.98	40.63	76.45

TABLE X
PSNR VALUES OF 10 ECG SIGNALS FOR CR = 6:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	30.56	30.82	27.04	22.41	28.28	29.82	27.04	22.41	23.99	26.23
db	30.75	31.64	29.20	27.34	31.28	30.77	29.20	27.34	28.18	26.79
coif	33.89	32.63	28.90	22.15	30.50	30.12	31.66	22.15	26.45	27.23
sym	29.59	31.95	33.86	23.61	31.91	30.61	33.86	23.96	30.07	28.30
bior1.1	34.30	32.88	27.34	22.92	28.49	29.67	27.34	22.92	24.93	28.33
bior2.2	35.23	26.86	30.68	28.73	24.96	25.66	25.04	22.53	23.39	25.55
bior2.4	28.90	26.78	27.12	21.31	31.15	27.83	27.12	21.31	24.63	21.63
bior2.6	27.67	25.77	28.34	28.50	25.79	24.26	26.90	21.67	24.01	26.26
bior2.8	30.58	28.88	27.24	28.93	26.62	28.03	27.11	22.98	25.51	28.37
bior3.1	22.67	23.09	22.82	24.63	22.41	22.52	21.46	17.94	20.67	22.16
bior3.3	27.20	26.37	25.21	26.13	25.26	23.48	22.26	19.23	21.52	24.51
bior4.4	29.89	34.14	31.75	23.79	30.58	29.38	31.75	23.79	25.56	26.26
bior5.5	34.00	32.36	33.04	25.77	33.36	32.14	33.04	25.77	25.41	27.71
bior6.8	32.02	32.89	31.59	28.17	29.63	28.89	31.59	28.17	24.79	25.75
rbio1.1	33.30	33.27	25.39	20.62	30.24	30.99	25.39	20.62	26.74	28.35
rbio1.3	31.86	32.10	29.39	31.82	27.39	30.25	26.85	23.00	26.89	28.21
rbio1.5	32.32	30.70	29.21	32.15	29.38	29.74	29.43	23.70	26.78	28.71
rbio2.2	33.25	32.48	31.04	32.87	30.85	29.20	36.26	26.17	26.37	25.99
rbio2.4	31.77	32.70	34.82	25.26	30.61	31.11	34.82	25.26	26.57	31.77
rbio2.6	35.17	31.21	32.70	34.48	31.13	30.17	33.17	26.37	26.03	32.91
rbio2.8	35.11	32.76	32.26	33.72	30.20	30.76	32.16	29.15	26.55	33.81
rbio3.1	34.48	31.15	31.38	29.60	28.90	30.97	28.94	28.34	31.19	29.43
rbio3.3	30.89	32.78	33.70	33.59	30.22	33.13	37.97	28.49	29.56	31.13
rbio3.5	35.38	29.72	31.60	29.00	30.08	31.40	31.60	29.00	29.97	27.81
rbio3.7	31.16	33.25	36.15	35.34	33.61	32.34	30.69	27.33	26.45	30.30
rbio3.9	36.00	33.67	30.72	30.14	34.74	30.12	30.72	30.14	29.21	27.85
rbio4.4	30.69	30.77	27.59	23.09	28.66	27.50	27.59	23.09	25.77	25.18
rbio5.5	28.82	29.42	26.04	21.37	25.48	28.21	26.04	21.37	22.79	22.71
rbio6.8	29.57	30.09	31.57	25.37	31.47	29.41	31.57	25.37	28.64	25.28

TABLE XI
CoC VALUES OF 10 ECG SIGNALS FOR CR = 6:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	0.6350	0.7392	0.6283	0.7970	0.6677	0.8104	0.6283	0.7970	0.5378	0.7675
db	0.6504	0.7663	0.7992	0.9402	0.8596	0.8468	0.7992	0.9402	0.8407	0.8198
coif	0.8462	0.8290	0.7681	0.7839	0.8214	0.8160	0.8853	0.7839	0.7518	0.8185
sym	0.5446	0.7839	0.9355	0.8509	0.8740	0.8421	0.9355	0.8720	0.8968	0.8622
bior1.1	0.8706	0.8293	0.6415	0.8255	0.6896	0.8086	0.6415	0.8255	0.6446	0.8709
bior2.2	0.8963	0.3585	0.7329	0.6025	0.3391	0.3869	0.3820	0.8062	0.4610	0.5229
bior2.4	0.4908	0.2073	0.6304	0.7270	0.8474	0.6680	0.6304	0.7270	0.5722	0.2416
bior2.6	0.2371	0.1027	0.4970	0.5954	0.4005	0.2271	0.6242	0.7587	0.5417	0.5552
bior2.8	0.6315	0.5190	0.4009	0.6268	0.5559	0.7026	0.6451	0.8274	0.6753	0.7616
bior3.1	0.1350	0.1977	0.0832	0.3275	0.2643	0.2499	0.1805	0.3683	0.2053	0.3652
bior3.3	0.2771	0.1706	0.3010	0.2656	0.3894	0.2162	0.1621	0.5302	0.1663	0.4025
bior4.4	0.5672	0.8783	0.8864	0.8562	0.8213	0.7818	0.8864	0.8562	0.6937	0.7673
bior5.5	0.8523	0.8078	0.9195	0.9127	0.9104	0.8915	0.9195	0.9127	0.6582	0.8444
bior6.8	0.7492	0.8301	0.8830	0.9499	0.7717	0.7512	0.8830	0.9499	0.5932	0.7320
rbio1.1	0.8247	0.8546	0.3811	0.6838	0.8159	0.8547	0.3811	0.6838	0.7692	0.8800
rbio1.3	0.7400	0.7965	0.6184	0.8288	0.5775	0.8300	0.6224	0.8262	0.7753	0.7427
rbio1.5	0.7672	0.7026	0.5955	0.8407	0.7615	0.8011	0.8019	0.8559	0.7640	0.7725
rbio2.2	0.8268	0.8115	0.7866	0.8714	0.8385	0.7689	0.9632	0.9268	0.7392	0.5164
rbio2.4	0.7344	0.8283	0.9471	0.9023	0.8211	0.8585	0.9471	0.9023	0.7587	0.9424
rbio2.6	0.8917	0.7361	0.8487	0.9115	0.8456	0.8179	0.9243	0.9258	0.7095	0.9252
rbio2.8	0.8863	0.8252	0.8263	0.8954	0.8011	0.8496	0.9014	0.9643	0.7480	0.9426
rbio3.1	0.8758	0.7539	0.7940	0.7362	0.7242	0.8572	0.7923	0.9589	0.9245	0.8129
rbio3.3	0.6612	0.8255	0.8775	0.8973	0.8052	0.9136	0.9499	0.9564	0.8836	0.8772
rbio3.5	0.8983	0.6062	0.8829	0.9668	0.8022	0.8666	0.8829	0.9668	0.8965	0.8509
rbio3.7	0.7098	0.8639	0.9365	0.9298	0.9145	0.8948	0.8519	0.9416	0.7528	0.8533
rbio3.9	0.9102	0.8626	0.8606	0.9699	0.9366	0.8244	0.8606	0.9699	0.8738	0.8473
rbio4.4	0.6454	0.7007	0.6634	0.8330	0.7013	0.6676	0.6634	0.8330	0.7055	0.6953
rbio5.5	0.5031	0.6045	0.5608	0.7379	0.4330	0.7203	0.5608	0.7379	0.4091	0.5004
rbio6.8	0.5070	0.6542	0.8894	0.9057	0.8700	0.7790	0.8894	0.9057	0.8549	0.7061

TABLE XII
PRD VALUES OF 10 ECG SIGNALS FOR CR = 6:1

Wavelet	ECG1	ECG2	ECG3	ECG4	ECG5	ECG6	ECG7	ECG8	ECG9	ECG10
haar	0.16%	0.16%	0.27%	0.46%	0.21%	0.18%	0.28%	0.46%	0.38%	0.34%
db	0.16%	0.15%	0.22%	0.26%	0.15%	0.17%	0.22%	0.26%	0.23%	0.32%
coif	0.11%	0.13%	0.23%	0.48%	0.16%	0.18%	0.16%	0.48%	0.28%	0.30%
sym	0.18%	0.14%	0.13%	0.40%	0.14%	0.17%	0.13%	0.39%	0.19%	0.27%
bior1.1	0.10%	0.13%	0.27%	0.44%	0.20%	0.19%	0.27%	0.44%	0.34%	0.27%
bior2.2	0.09%	0.25%	0.16%	0.23%	0.30%	0.30%	0.35%	0.46%	0.40%	0.29%
bior2.4	0.19%	0.26%	0.28%	0.53%	0.15%	0.23%	0.28%	0.53%	0.35%	0.58%
bior2.6	0.22%	0.29%	0.20%	0.24%	0.27%	0.35%	0.28%	0.51%	0.37%	0.27%
bior2.8	0.16%	0.20%	0.23%	0.22%	0.25%	0.23%	0.28%	0.43%	0.32%	0.21%
bior3.1	0.40%	0.39%	0.38%	0.37%	0.40%	0.43%	0.53%	0.78%	0.55%	0.43%
bior3.3	0.24%	0.27%	0.29%	0.31%	0.29%	0.38%	0.48%	0.67%	0.50%	0.33%
bior4.4	0.17%	0.11%	0.16%	0.40%	0.16%	0.19%	0.16%	0.40		

TABLE XIII
BEST WAVELET FAMILIES FOR 10 DIFFERENT ECG SIGNALS

CR	2:1	4:1	6:1
ECG1	rbio3.7	rbio3.7	rbio3.9
ECG2	rbio3.3	rbio3.7	rbior4.4
ECG3	rbio3.1	rbio3.7	rbio3.7
ECG4	rbio3.1	rbio3.9	rbio3.7
ECG5	rbio3.7	rbio3.7	rbio3.9
ECG6	rbio3.9	rbio3.9	rbior3.3
ECG7	rbio3.9	rbio3.5	rbio3.3
ECG8	rbio3.9	rbio3.5	rbio3.9
ECG9	rbio3.5	rbio3.3	rbio3.1
ECG10	rbio3.9	rbio3.9	rbio2.8
Result	rbio3.9	rbio3.7	rbio3.9

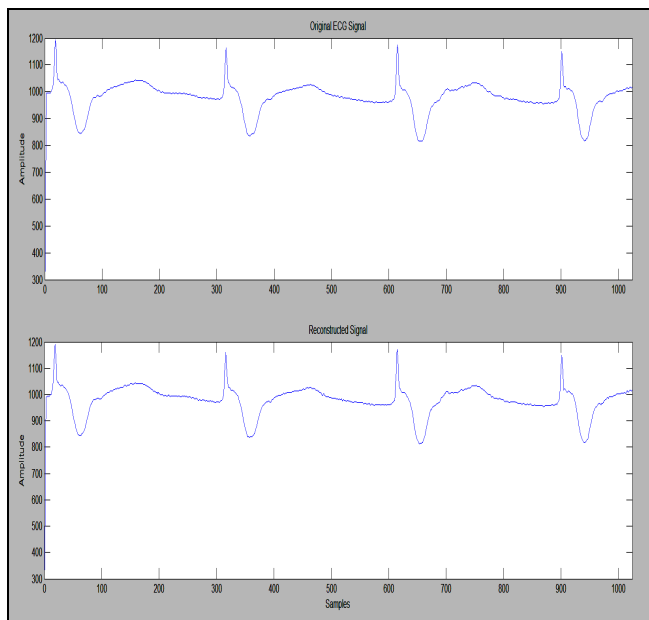


Fig. 5. Original and reconstructed ECG104 with CR = 2:1

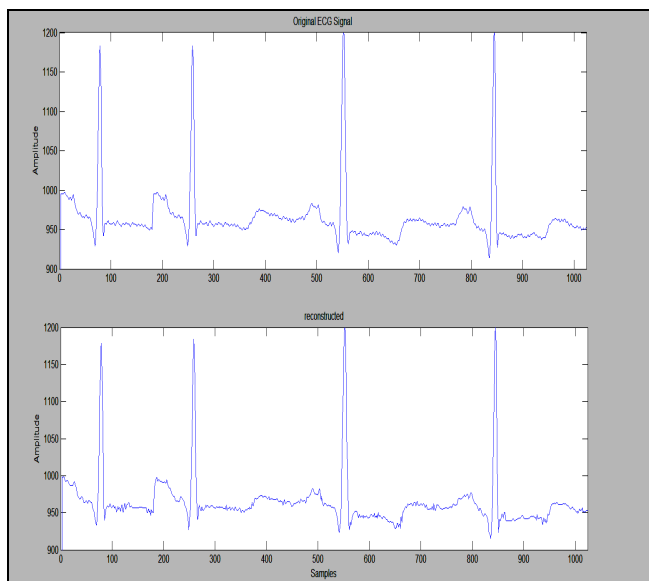


Fig. 6. Original and reconstructed ECG100 with CR = 4:1

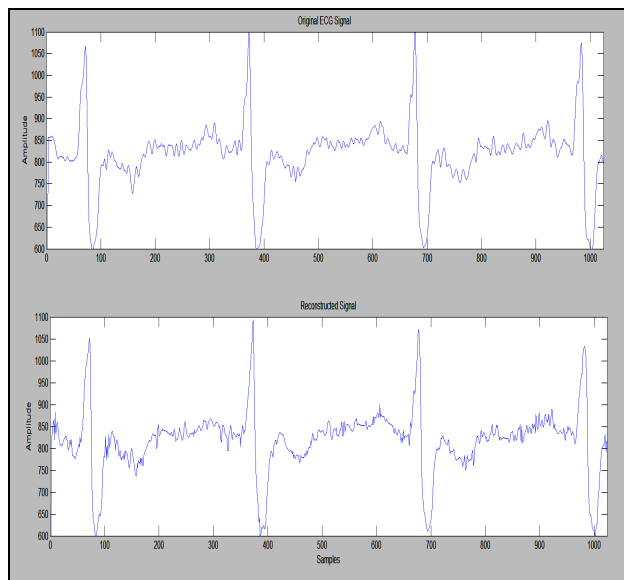


Fig. 7. Original and Reconstructed ECG118 with CR = 6:1

Akanksha Mishra received her B. E. (Electronics & Communication Engineering) from Parul Institute of Engineering & Technology, India in 2010. Currently she is pursuing M. E. (Communication Engineering) from G H Patel College of Engineering & Technology, Vallabh Vidyanagar, India.

Falgun Thakkar received B. E. (Electronics) from Birla Vishvakarma Mahavidyalaya and M. E. (Communication Engineering) from G H Patel College of Engg & Tech, Vallabh Vidyanagar, India in 2004 and 2010, respectively. His research interests include Digital Signal & Image Processing and Medical Image Analysis.

Chintan Modi received B. E. (Electronics & Communication) from Dharmsinh, M. E. (Communication Engineering) from Desai University, Nadiad, India and Ph. D. (Electrical Engineering) from Indian Institute of Technology, Bombay, India in 1997, 2002 and 2011 respectively. His research interests include interval arithmetic, statistical data analysis and digital image processing & applications.

Rahul Kher received B. E. (Electronics) from Birla Vishvakarma Mahavidyalaya, Vallabh Vidyanagar, India and M. Tech (Measurement & Instrumentation) from Indian Institute of Technology, Roorkee, India in 1997 and 2006, respectively. Currently he is Pursuing Ph. D. from Sardar Patel University, Vallabh Vidyanagar, India in ECG signal processing. His areas of interests include Digital Signal & Image processing, Biomedical Signal processing and Medical Image Analysis.