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Application of Wavelet Based Security and Compression Techniques for Biomedical Instrumentation Signals

Seshapu Prassanna, Sandeep Chittem, Papani Srinivas, Shyamala Mamatha

Abstract*: The reliably creating amounts of restorative computerized pictures and the need to share them among bosses and facilities for better and continuously exact end require that patients' security be guaranteed. Biomedical signs from various sources including heart, cerebrum and endocrine structure speak to a test to analysts who may need to confine delicate signs getting in contact from various sources spoiled with antiquated rarities and fuss. Biomedical signs as a result of its colossal moderations are extensively associated in a couple of restorative applications; Electrocardiogram, Electroencephalogram and Electromyogram are to give a few precedents. Regardless, these signs experience the development of racket and result in an inefficient presentation. In the present open society and with the advancement of human rights, people are progressively increasingly stressed over the security of their information and other basic information. This examination uses electrocardiography (ECG) information in order to verify singular information. An ECG flag can't solely be used to analyze ailment, yet furthermore to give critical biometric information to unmistakable evidence and affirmation. ECG watermarking can ensure the security and immovable nature of a customer's information while reducing the proportion of information. In the appraisal, we apply as far as possible, piece botch rate (BER), motion to-disturbance extent (SNR), pressure extent (CR), and stuffed flag to commotion extent (CNR) strategies to assess the proposed . In the present work a solidified arrangement of applying denoising and pressure for biomedical signs using wavelets has been presented. An unequivocal examination of Discrete Wavelet Transform (DWT) denoising using distinctive wavelet families on biomedical signs (ECG, EMG and EEG) is shown in the hypothesis. The standard desire for the work is to explore the wavelet work that is perfect in perceiving and denoising the diverse biomedical signs.

***Keywords* : electrocardiography (ECG), commotion extent (CNR), pressure extent (CR), Discrete Wavelet Transform (DWT).**

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I. INTRODUCTION

The biomedical signs discussed before are unfortunately tainted by various parts in the midst of acquiring or transmission, which result as commotion sway. These boisterous effects decline the execution of visual and electronic investigation. Clearly the removals of the commotion from the flag energize the preparing. The denoising procedure can be portrayed as the procedure to empty the commotion while holding the nature of handled flag. The regular strategy for clearing out the clamor from a flag is to use a low pass or band pass channel with cut off frequencies. Regardless, the standard sifting strategies are simply prepared to empty an imperative piece of the clamor yet they can't if the commotion is in the band of the flag is to be penniless down. Along these lines, various denoising procedures are proposed to beat this issue. As a multi-objectives flag examination strategy, the wavelet change offers the probability of explicit commotion sifting and reliable parameter estimation, and in this manner, can contribute capably to morphological investigation. Subsequently wavelets have been comprehensively used in biomedical flag preparing, essentially due to the versatility of the wavelet change apparatuses. Discrete wavelet Transform has been illuminated in the past part. DWT is used in this proposition for disintegration of signs.

In the wavelet decay, a wavelet work is lifted and disintegrated up to measurement l. The underlying advance of the Denoising framework using wavelet change is decision of the mother wavelet – which shapes a great deal of capacities (group of wavelets), by weight or expanding or elucidation.

The accompanying stage is the deterioration level. In Wavelet deterioration, it is possible to modify the ensuing coefficient as of now for a flag and flag amusement is to wipe out bothersome flag parts. A wavelet work with level N is picked and wavelet disintegration of the signs at level N is determined. The unmistakable techniques for decay of a flag are seeks after:

- Discrete Wavelet Transform based Decomposition
- Empirical Mode Decomposition
- Multi Resolution Analysis
- Shift Invariant strategy
- Discrete Wavelet Transform based Decomposition

The DWT is realized by a channel bank that breaks down the flag in dynamically coarser approximations and subtleties, showed up in Figure 1

H1 speaks to a high-pass complementary filter and H0 speak to a low-pass complementary filters, $d_{j+k,n}$ are detail coefficients and $a_{j+k,n}$ are guess coefficients at level (j + k). The output coefficient picked up by the low pass filter is the estimation coefficient.

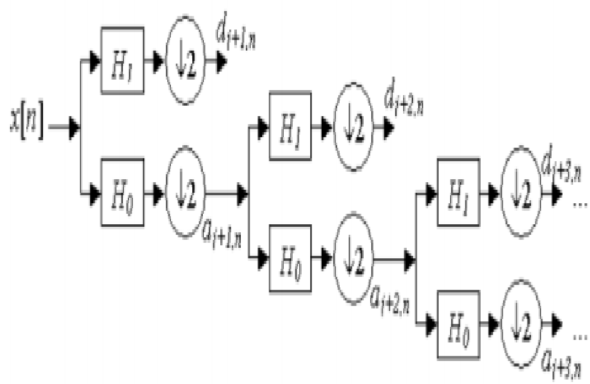

Figure 1: Filter bank for a 3 level DWT decomposition

This is communicated as:

$$a_{i+1}\,[n] = \begin{cases} a_i \ * \ \bar{K}[2n], & i < N \\ a_i \ * \ \bar{K} - N[n], & \text{otherwise} \end{cases} \qquad (1)$$

The output of the high pass filter is the detailed coefficient. This is expressed as:

$$y_{i+1}\,[n] = \begin{cases} a_i * \bar{f}[2n], & i < N \\ a_i * \bar{f} - N[n], & \text{otherwise} \end{cases} \qquad (2)$$

The approximation coefficient is then divided into detail and approximation coefficients. This is expressed as given below:

$$a_i\,[n] = \begin{cases} \breve{a}_{i+1} * \hat{k}\,[n] + \breve{y}_{j+1} * \hat{f}\,[2n], i < N \\ 1/2\ (a_{i+1} * \hat{k}_{i-N}[n] + y_{i+1} * \hat{f}_{i-N}[n]), otherwi \end{cases} \qquad (3)$$

For example, think about the flag, indicated as Sj . In the amalgamation channel, the flag is then disintegrated using a high pass channel which is meant as H1(n) and a low pass channel which is meant as H0(n) and in like manner the detail coefficient and estimation coefficient independently are grabbed . By then in the accompanying dimension of deterioration the gauge coefficients are again decayed and the procedure is reiterated up to N levels as showed up in Figure 1, where, N =3 is considered in this work. If the greatest number of levels L has been accomplished, the flag is said to be totally deteriorated.

II. PROPOSED METHODOLOGY

This section assesses the denoising techniques with the assistance of ANN regarding SNR and MSE of the denoised signal. The computation of SNR and MSE is exhibited in the following section.

(A) Signal to Noise Ratio:

Essentially signal to noise ratio (SNR) is an engineering term for the power ratio between a signal and noise. It is communicated as far as the logarithmic decibel scale. The signal to noise ratio is the ratio of the genuine signal amplitude to the standard deviation of the noise. The quality of the signal is named as the signal-to-noise ratio, which is communicated as:

$$\text{SNR}= 10 \log \frac{S_{\text{original}}}{S_{\text{noise}}} \qquad (4)$$

Where

S_{Original} : Original signal without noise

S_{noise} : Noisy signal.

(B) Denoising of ECG Signal

The original ECG signal has been taken from MIT-BIH database from the site www.physionet.org which is appeared in the Figure2

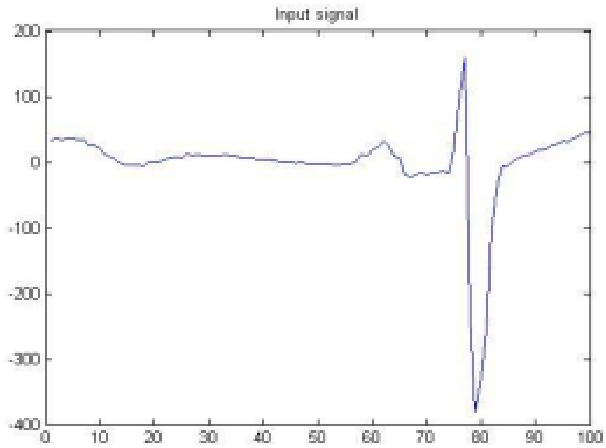

Figure 2 Original ECG signal

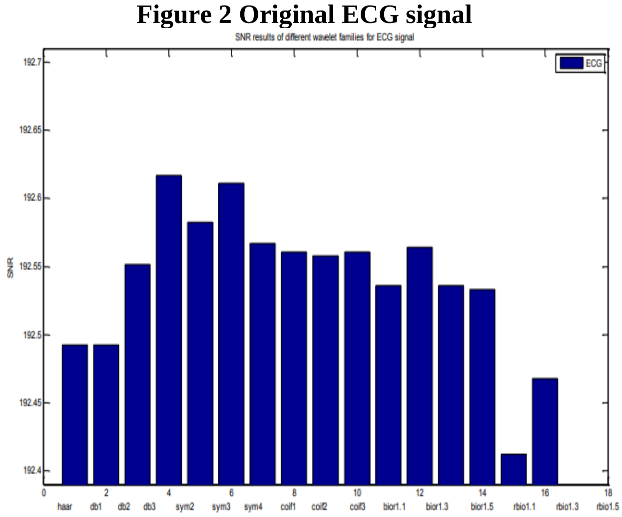

Figure 3: SNR results of different wavelet functions for an ECG signal.

Different wavelet functions utilized to calculate the SNR values of ECG signal have been appeared in Figure 4. It is obvious from the graph that every wavelet function offers different SNR values. All the Coiflet family functions provide nearly the equivalent SNR result. The most exceedingly awful value of the SNR is given by the function 'rbio1.3' and the best SNR is provided by the wavelet function 'db3'.

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Sym3 is the second best SNR offered wavelet function. It is clear from the graph that none of the bio-symmetrical family functions provide better SNR execution. All other wavelet families offer better outcomes.

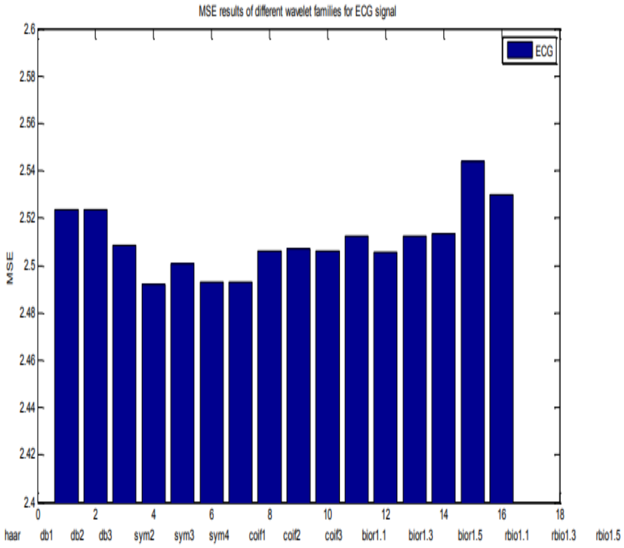

Figure 4: MSE results of different wavelet functions for an ECG signal.

The graph in Figure 5 demonstrates the MSE values of ECG signal for different wavelet functions utilized. Every wavelet function offers different MSE values. All the Daubechies wavelet family functions provide nearly a similar value. The most exceedingly terrible value of MSE is given by the function 'rbio1.3' trailed by 'rbio1.5' and the best MSE is provided by the wavelet function 'db3'. Both 'sym3' and 'sym4' are the second best MSE offered wavelet functions.
Denoised ECG signal is as shown in Figure 5.

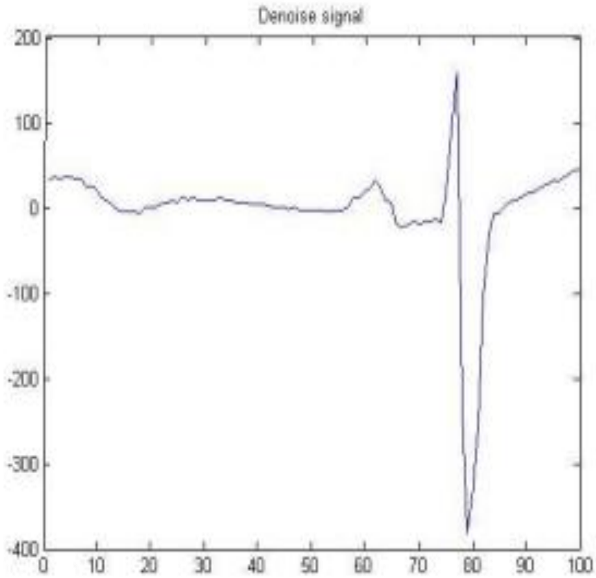

Figure 5: Denoised ECG Signal

SNR and MSE are looked at between utilized method and the Improved Thresholding method for different wavelet functions for ECG signal quantitative given in Table 1 and Table 2.

Table.1. Comparison of SNR for different wavelet functions for ECG signal

Wavelet Type	Improved Thresholding [110]	Used Method
db2	15.1877	192.5581
db3	15.9901	192.5737
sym2	15.6014	192.5705
sym3	16.0977	192.6112
sym4	16.3072	192.555

Examination between the utilized method and the Improved Thresholding plan introduced in is appeared Table 1.

Table 2: Comparison of MSE for different wavelet functions for ECG

Wavelet Type	Improved Thresholding [110]	Used Method
db2	8.1042	2.507
db3	6.7172	2.5031
sym2	7.3250	2.5039
sym3	6.4657	2.4938
sym4	6.2522	2.5078

The Table 3 provides the SNR aftereffects of different wavelet based ECG denoising techniques. Among them, the utilized method yields the most elevated SNR value of 192.8105, while the least value is given by the method. The second higher value is offered by the method

Table 3.Comparison of SNR for ECG signal

Wavelet Denoising Method	SNR
The optimized wavelet(rbio1.1)	192.8105
CL multi wavelet [147]	7.932
Wavelet transform [116]	4.493
Wavelet transform [130]	26.872

Among the different ECG denoising schemes with which examinations have been made, the wavelet transform exhibited in has the most astounding SNR value beside the Shift Invariant method utilized in the postulation.

III. DENOISING OF EEG SIGNAL

The original EEG signal is taken from MIT-BIH database from the site www.physionet.org which is appeared in Figure 6

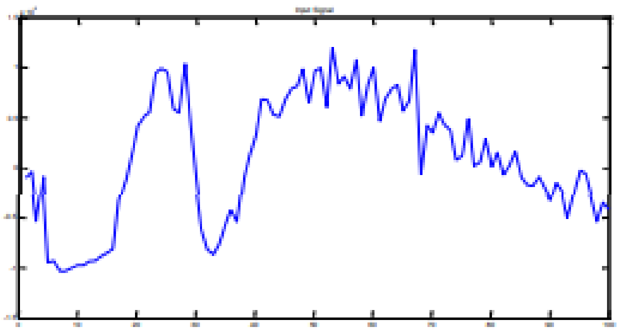

Figure 6: Original EEG Signal

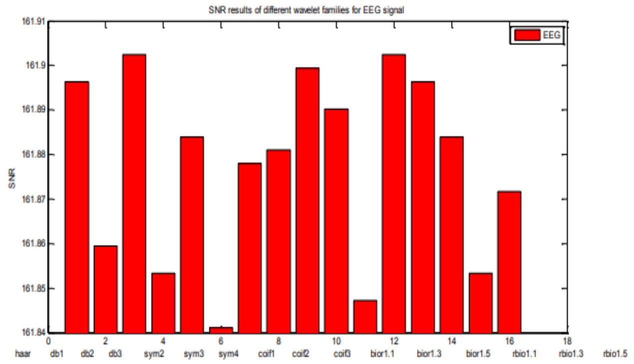

Figure 7: SNR results of different wavelet functions for an EEG signal.

Different wavelet functions have been utilized to acquire the SNR values of EEG signal. From the Figure 7, unmistakably the every wavelet function offers different SNR values. The most exceedingly bad value of SNR is given by the function 'sym3' and the best SNR is provided by the wavelet function 'db2'. The second best SNR is offered by 'coif2' wavelet function pursued by 'Haar' and 'bior1.5', both giving the equivalent SNR value of 161.8964.

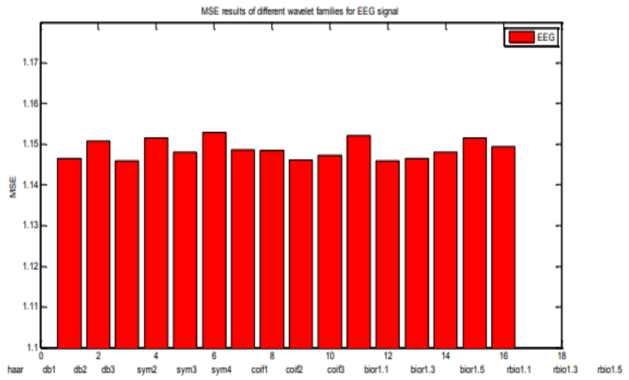

Figure 8: MSE results of different wavelet functions for an EEG signal.

The graph in Figure 8 demonstrates the MSE values of EEG signal for different wavelet functions utilized. From the graph, plainly the every wavelet function offers nearly the equivalent MSE values. It is appeared all the Daubechies wavelet family functions provide nearly a similar value for MSE of EEG signal. The most exceedingly worst value of MSE is given by the function 'sym3' trailed by 'bior1.1' and the best MSE is provided by the wavelet functions 'bior1.3' and 'db2'. Wavelet function 'coif2' provides the second best MSE for EEG signal. The Figure 9 shows the denoised EEG waveform obtained after the applying the denoising procedure.

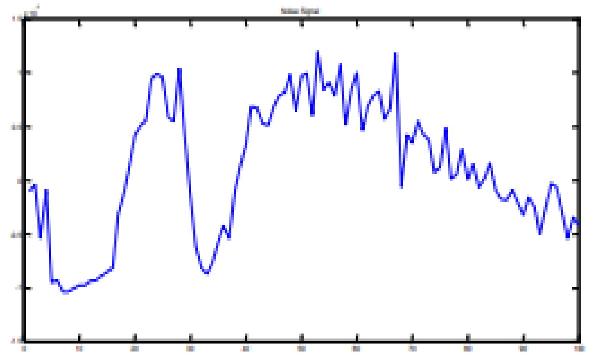

Figure 9: Denoised EEG Signal

Table 4 is a comparison of SNR values of the used method with WT for denoised EEG signal.

Table 4: SNR comparison for EEG signal

Method	SNR
Used wavelet transform (with sym3)	161.9373
Wavelet transform [115]	38.96

The method using Shift Invariance in thesis achieves a much greater SNR.

IV. PROPOSED METHODOLOGY DENOISING OF EMG SIGNAL

The original waveform of EMG signal is acquired from MIT-BIH database from the site www.physionet.org which is appeared in Figure 10.

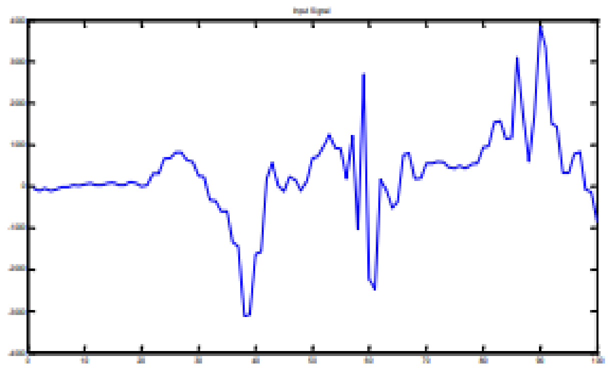

Figure 10: Original EMG Signal

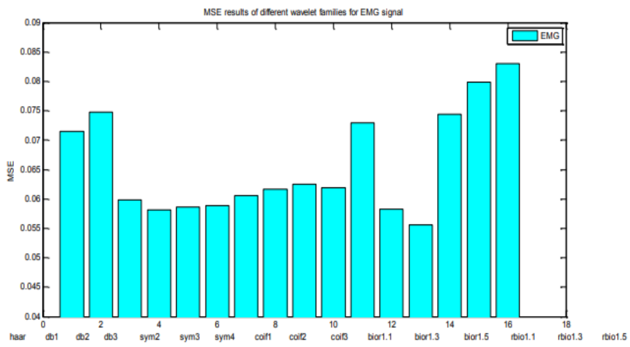

Figure 11: SNR results of different wavelet functions for an EMG signal.

Figure 11 demonstrates the SNR values of EMG signal for different wavelet functions utilized. From the figure, obviously every wavelet function offers different SNR values. The most noteworthy value of SNR is given by the function 'bior1.5' and 'db3' offers the second best SNR value. The least SNR is provided by the wavelet function 'rbio1.5' trailed by 'rbio1.3'.

V. PROPOSED METHOD (INVERSE DISCRETE WAVELET TRANSFORM (IDWT))

The original signal is delivered from the wavelet coefficients in the vast majority of the wavelet transform applications. The analysis and synthesis filters need to satisfy certain criteria to accomplish an ideal reconstruction. Utilizing the wavelet coefficients the original signal is recreated by applying inverse discrete wavelet transform .

The inverse discrete wavelet transform (IDWT) is acquired by a quadrature filter bank. This filter bank starts from the most minimal level, which speaks to the coarser approximation, and logically includes an ever increasing number of details, until the original signal is recouped. The filter structure is appeared in Figure 4.14, where G1 and G0 are, separately, the high and low-pass reflect filters of H1 and H0.

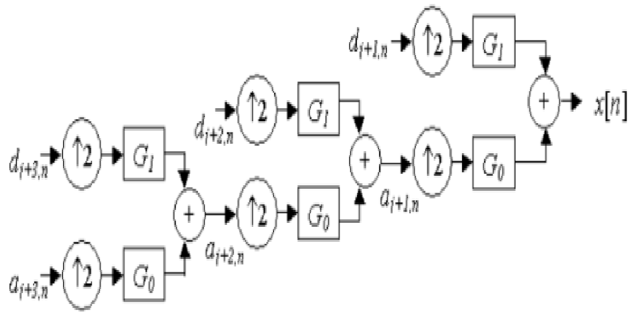

Figure 12: Filter bank for the 3-level reconstruction

The method of wavelet reconstruction includes up sampling by embeddings zeros among the samples and filtering to development of the signal. A global reconstruction of the denoised signal is given by

$$\hat{y}(t) = \sum_{j=N_1}^{N_2} \overline{\overline{K}}^{(j)}(t) + \sum_{j=N_{2+1}}^{P} K^{(j)}(t) \tag{5}$$

The IDWT is connected as a turn around process of discrete wavelet transform to the decomposed signals. Because of IDWT, the original signal is remade. Since DWT is a multiresolution portrayal of signal, also by virtue of its multi-resolution portrayal ability, the discrete wavelet transform has been utilized successfully in imperative applications. In the thesis, different wavelets families have been introduced to accomplish the best execution for denoising ECG, EEG and EMG signals. Because of the properties of such different signals, execution of the wavelets can be differed starting with one signal then onto the next. This movement makes a refined decision select the fitting wavelet family or type. Then again, a Classifier accomplishes its target by settling on a characterization decision dependent on certain attributes. Thusly, in the thesis, an outstanding classifier is utilized to streamline the wavelets for the given input signal. In this manner, the ideal wavelet can be chosen for the specific input signal for denoising.

The outcomes for denoising of ECG, EEG and EMG signals which were assessed in part 3 have been utilized here to locate the optimal wavelet for the biomedical signals. For those equivalent values of MSE and SNR of every ECG, EEG and EMG signals, PRD value has been calculated which has been appeared in the Tables. For ECG signal1, the wavelet db3 provides better outcomes as far as all parameters MSE, SNR and PRD. The rbio1.1 wavelet delivers the most minimal MSE value and a most elevated value of SNR for the second ECG signal. For the primary EEG signal, both db2 and bior1.3 produce the most astounding value for SNR and the least value for MSE. The Sym3 wavelet generates better outcomes for EEG signal 2. For both the EMG signals 1 and 2, better outcomes are given by the wavelet bior 1.5.

Table 5: Denoising results of different wavelets for ECG signal 1

Wavelet Name	Mean Square Error	Signal Noise Ratio	PRD
Haar	2.5234	192.4924	0.0066082
db1	2.5234	192.4924	0.0066082
db2	2.5086	192.5514	0.0065887
db3	2.4922	192.617	0.0065671
sym2	2.5008	192.5826	0.0065784
sym3	2.4932	192.6108	0.0065692
sym4	2.5047	192.567	0.0065836
coif1	2.5063	192.5608	0.0065856
coif2	2.507	192.5577	0.0065866
coif3	2.5063	192.5608	0.0065856
bior1.1	2.5125	192.5359	0.0065938
bior1.3	2.5055	192.5639	0.0065846
bior1.5	2.5125	192.5359	0.0065938
rbio1.1	2.5133	192.5328	0.0065948
rbio1.3	2.5438	192.4123	0.0066347
rbio1.5	2.5297	192.4677	0.0066163

Table 6 Denoising results of different wavelets for ECG signal 2

Wavelet Name	Mean Square Error	Signal Noise Ratio	PRD
Haar	2.4453	192.8073	0.0065049
db1	2.4453	192.8073	0.0065049
db2	2.507	192.5581	0.00665865
db3	2.5031	192.5737	0.0065814
sym2	2.5039	192.5705	0.0065824
sym3	2.4938	192.6112	0.006569
sym4	2.5078	192.555	0.0065875
coif1	2.4953	192.6049	0.0065711
coif2	2.5047	192.5674	0.0065834
coif3	2.5148	192.527	0.0065968
bior1.1	2.4461	192.8041	0.006506
bior1.3	2.4953	192.6049	0.0065711
bior1.5	2.4969	192.5987	0.0065731
rbio1.1	2.4445	192.8105	0.0065039
rbio1.3	2.4469	192.8009	0.006507
rbio1.5	2.4508	192.785	0.0065122

Table7. Denoising results of different wavelets for EEG signal 1

Wavelet Name	Mean Square Error	Signal Noise Ratio	PRD
haar	1.1466	161.8964	0.030512
db1	1.1508	161.8595	0.030568
db2	1.1459	161.9025	0.030502
db3	1.1515	161.8533	0.030577
sym2	1.148	161.884	0.03053
sym3	1.1529	161.8411	0.030596
sym4	1.1487	161.8779	0.03054
coif1	1.1484	161.881	0.030535
coif2	1.1462	161.8994	0.030507
coif3	1.1473	161.8902	0.030521
bior1.1	1.1522	161.8472	0.030587
bior1.3	1.1459	161.9025	0.030502
bior1.5	1.1466	161.8964	0.030512
rbio1.1	1.148	161.884	0.03053
rbio1.3	1.1515	161.8533	0.030577
rbio1.5	1.1494	161.8717	0.030549

Table 8. Denoising results of different wavelets for EEG signal 2

Wavelet Name	Mean Square Error	Signal Noise Ratio	PRD
haar	1.1382	161.8694	0.030553
db1	1.1378	161.8725	0.030548
db2	1.1347	161.9002	0.030506
db3	1.1343	161.9033	0.030501
sym2	1.134	161.9064	0.030496
sym3	1.1305	161.9373	0.030449
sym4	1.1329	161.9156	0.030482
coif1	1.1315	161.928	0.030463
coif2	1.1336	161.9095	0.030492
coif3	1.1322	161.9218	0.030473
bior1.1	1.1371	161.8786	0.030539
bior1.3	1.1354	161.894	0.030515
bior1.5	1.1312	161.9311	0.030459
rbio1.1	1.1357	161.891	0.03052
rbio1.3	1.1389	161.8633	0.030562
rbio1.5	1.135	161.8971	0.03051

Table9. Denoising results of different wavelets for EMG signal 1

Wavelet Name	Mean Square Error	Signal Noise Ratio	PRD
haar	0.071475	160.5723	0.0326
db1	0.074775	160.1209	0.033344
db2	0.059875	162.3432	0.029838
db3	0.0582	162.6269	0.029417
sym2	0.05865	162.5499	0.029531
sym3	0.058875	162.5116	0.029587
sym4	0.060525	162.2352	0.029999
coif1	0.061675	162.047	0.030283
coif2	0.0625	161.9141	0.030485
coif3	0.06195	162.0025	0.03035
bior1.1	0.072925	160.3715	0.032929
bior1.3	0.05825	162.6183	0.02943
bior1.5	0.0556	163.0839	0.028753
rbio1.1	0.074425	160.1679	0.033266
rbio1.3	0.079925	159.4549	0.034473
rbio1.5	0.083	159.0774	0.03513

VI. RESULTS ANALYSIS

Figure 13 depicts the PRD values of denoised ECG signal. The best PRD value is provided by the wavelet function 'db3'. The second best PRD offered wavelet function is 'sym3'. The most noticeably awful value of PRD is given by the function 'rbio1.3' trailed by 'rbio1.5'. The wavelet functions 'Haar' and 'db1' offer precisely the equivalent PRD value.

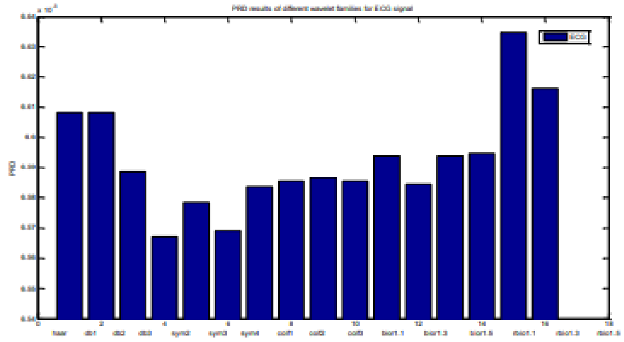

Figure 13: PRD results of different wavelet functions for an ECG signal

The Figure 14 depicts the Compression Ratio of different wavelet functions for ECG signal used in the work.

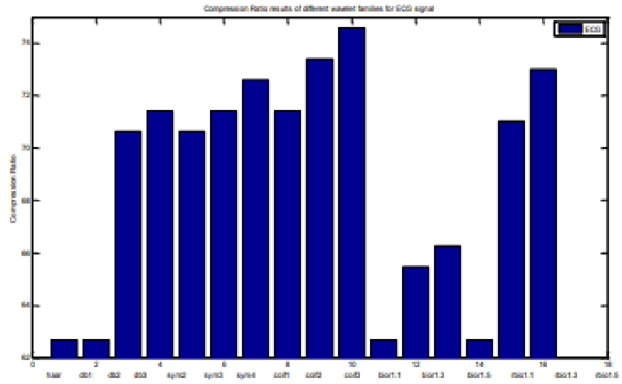

Figure 14: Compression Ratio of different wavelet functions for an ECG signal

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The most astounding CR is given by the function 'coif3' trailed by 'coif2', 'rbio1.5', 'sym4' and so on. Minimal CR of precisely 62.6984 is given by four different wavelet functions, for example, 'haar','db1','bior1.1'and 'rbio1.1'.
PRD and CR are looked at between different methods and the Shannon Fano method utilized in the thesis for ECG signal in Figure 15 and Figure 16.

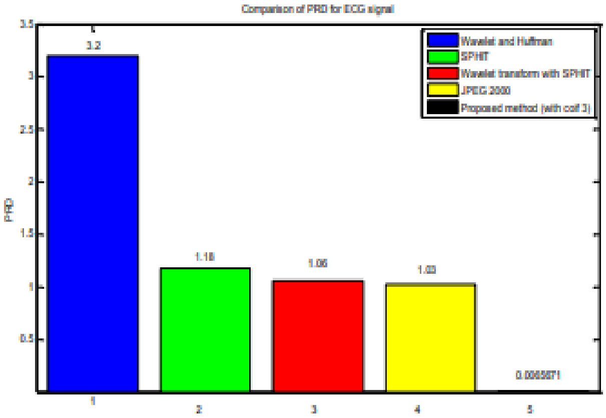

Figure 16: Comparison of PRD for different ECG compression schemes

Figure 17 depicts the PRD consequences of some compression techniques for ECG signal. The best PRD is offered by the utilized method with coif3 wavelet function. JPEG 2000 is the second best PRD offered technique. The worst value of PRD is given by the method Wavelet and Huffman.

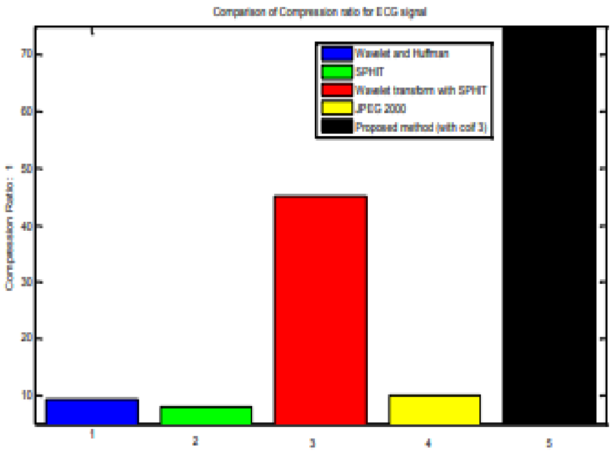

Figure 17 Comparison of Compression Ratio for different ECG compression techniques.

Figure 17 depicts the Compression Ratio of some compression techniques for ECG signal. The best CR is offered by the Shannon Fano method with coif3 wavelet function. Wavelet transform with SPHIT offers second best CR. The worst Compression Ratio is given by the method SPHIT.

a) Compression of EEG Signal

Figure 18 illustrates the PRD values of EEG signal for different wavelet functions. From the graph, plainly the every wavelet function offer different PRD values. The best value of PRD is given by the functions 'db2' and 'bior1.3' with 0.30502 and the most noteworthy PRD is provided by the wavelet function 'sym3'. 'Haar' and 'bior1.5' offer the second best PRD value.

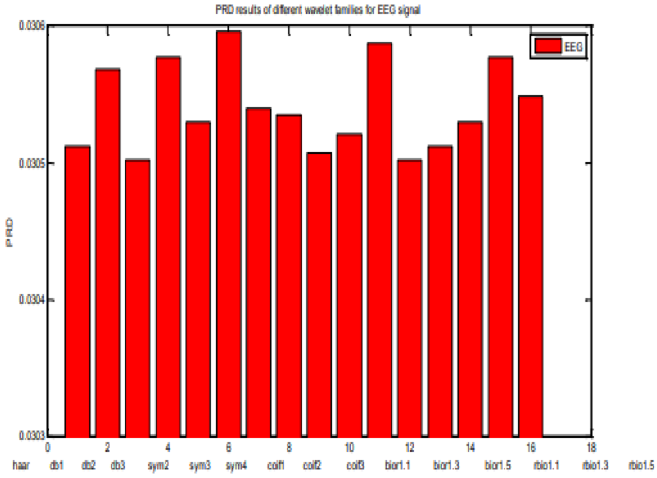

Figure 18: PRD results of different wavelet functions for an EEG signal.

Compression of EMG Signal

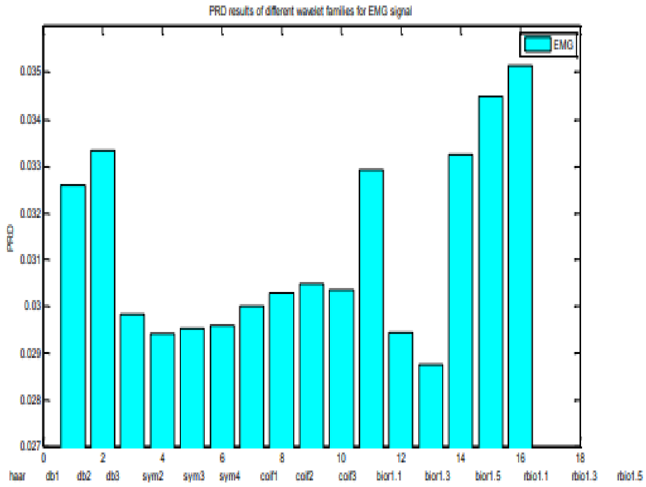

Figure 19: gives the PRD results of various wavelet functions used for an EMG signal.

From the graph, unmistakably about all the wavelet functions provide nearly the equivalent PRD values. The best value of PRD is given by the function 'bior1.5' and the second best PRD is offered by the function 'db3' trailed by 'bior1.3'. The worst PRD is provided by the wavelet function 'db1' trailed by 'rbio1.1'.

VII. CONCLUSION

Preserving security and authenticity of medical images has become a necessity since the ever-increasing distribution of digital medical images between clinical centers and hospitals. This manifests through the widespread usage of telemedicine, teleradiology, telediagnosis, and teleconsultation. Over previous years, various medical watermarking algorithms have been proposed by a number of different researchers in this field, but each proposed method has a number of associated drawbacks as well as strengths. In this paper, we have demonstrated a comprehensive survey on medical image watermarking and discussed important issues relevant to each method.

At first, the main framework of the security system is depicted, and the location of digital watermarking is shown in the scheme. In this paper, we explained the essential parts of the typical watermarking system, along with an analysis of different attacks, applications, and requirements of digital watermarking. Afterwards, the advantages and disadvantages of various transform techniques used in watermarking algorithms were discussed. During the course, useful metrics to measure the quality of watermarked image and accuracy of extracted watermark were presented. We also illustrated the importance of medical watermarking in general, discussing the advantages it holds. Finally, we presented a number of medical watermarking methods with explanations and comparisons drawn between them. Wavelets are topic of pure mathematics and they have shown great potential and applicability in many fields. Therefore in the first part of thesis, wavelet theory is described more generally and gives basic ideas serving as an overview of the concept of wavelets. A new ECG signal denoising method based on an adaptive thresholding technique is proposed. It was shown that the approach could be generalized to non-Gaussian additive noise cases and results of applying the method to the real ECG data contaminated with three different types of practical noise were shown to be promising. The results of this research could be generalized to other bio-signals also. The newly proposed method, Wavelet Based Threshold Methods with Grey Incidence Degree i.e., choosing of threshold value using Grey Incidence degree (GID) in wavelet transform based threshold methods is applied for denoising of ECG Signals. It is focused to solve the means of wavclel analysis in removal of physiological artifacts in ECG signals (baseline wandering, muscular artifact and electrode-motion artifact). Among the wavelet-based threshold methods used, the performance of Improved-thresholding method with CilD sub-band threshold is better than other methods for BW and EM noises, whereas for muscle artifacts in ECG signals improved threshold method with universal threshold with GID is better than other methods. In ECG denoising problem, it is studied the issue of an optimum wavelet selection for a given ECCi signal is studied. It is observed that the wavelets db4, db5, db6 and sym8 were optimum wavelets for analysis of ECG signals.

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