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REMOVAL OF ELECTRODE MOTION ARTIFACT IN ECG SIGNALS USING WAVELET BASED THRESHOLD METHODS WITH GREY INCIDENCE DEGREE

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Abstract - Cardiovascular diseases are one of the most frequent and dangerous problems in modern society in nowadays. Unfortunately electrocardiograms (ECG) signals, during their acquisition process, are affected by various types of noise and artifacts due to the movement, or breathing of the patient, electrode contact, power-line interferences, etc. The aim of this study was to develop an algorithm to remove electrode motion artifact in ECG signals.

Donoho and Johnstone proposed Wavelet thresholding de-noising method based on discrete wavelet transform (DWT) is suitable for non-stationary signals. The wavelet transform coefficient is processed by using grey relation analysis of the grey theory, and a new wavelet threshold method namely wavelet threshold method with grey incidence degree (GID) (or the GID threshold method) based is introduced. It shows that the signal smoothness and similarity of the two signal criteria have been greatly improved by the GID threshold method compared with existing threshold methods. According to the characteristics of different ECG signals, GID threshold method gets better results than it can adaptively deal with noise separation and details remaining of the two opposing signal problems, so as to provide a better choice for wavelet threshold methods of signal processing.

Performance analysis was performed by evaluating Mean Square Error (MSE), Signal-to-noise ratio (SNR) and visual inspection over the denoised signal from each algorithm. The experimental result shows that GID hard shrinkage method with sub-band or level dependent thresholding gives the best denoising performance on ECG signal. The result shows that soft threshold not always gives better denoising performance; it depends on which wavelet thresholding algorithm was chosen.

***Keywords** - ECG signal, wavelet - based de-noising, grey incidence degree, BayesShrink threshold, MSE.*

I. INTRODUCTION

Motion artifacts are transient base line changes caused by changes in the electrode-skin impedance with electrode motion. Movement of the electrode away from the contact area on the skin, leading to variations in the impedance between the electrode and skin causing potential variations in the variations in the ECG and usually manifesting themselves as rapid but continuous baseline jumps or complete saturation for up to 0.5 sec [3]. The artifact caused due to electrode's motion. It is a transient interference caused by loss of contact between the electrode and the skin that effectively disconnects the measurement system from the subject. The loss of contact can be permanent, or can be intermittent as would be the case when a loose electrode is brought in and out of contact with the skin as a result of movements and vibration. The usual cause of motion artifacts will be assumed to be vibrations or movements of the subjects. This type of interference represents an abrupt shift in base line due to movement of the patient while the ECG is being recorded [1, 2]. It is simulated by adding a dc bias for a given segment of ECG. Electrode motion artifact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as can noise of other types [4].

The electrode used for providing electrical contact between the skin and the lead cable can be modeled as a network of equivalent resistors and capacitors representing electrical parameters of different layers of the skin and the skin electrode interface. The values of these electrical parameters may be altered due to relative motion of the electrodes or skin stretch or contact [10]. This means that the equivalent impedance of the skin and the skin electrode interface gets disturbed due to any such action which results an artifact known as electrode motion artifact [3]. Unfortunately the motion artifact has a significant overlap with spectrum of the ECG signal in the frequency range 1-10 Hz and hence it is very difficult to handle this type of artifact. It is noticed that the motion artifact is more abrupt and distinct in nature as opposed to the slow baseline wander caused due to reparation. The motion artifact poses a major challenge in the long term cardiac monitoring [10, 12].

Donoho and Johnstone proposed Wavelet thresholding de-noising method based on discrete wavelet transform (DWT) is suitable for non-stationary signals [6, 7, 8, 9, 11]. The wavelet transform coefficient is processed by using grey relation analysis of the grey theory, and a new wavelet threshold method namely wavelet threshold method with grey incidence degree (GID) (or the GID threshold method) based is introduced [14, 15, 16]. In the process of denoising the signal by wavelet, the core of the steps is that the threshold acts on the coefficient of the wavelet decomposition, because the quality and effect of denoising are influenced immediately by the selection of the threshold. So a variety of theoretical and empirical models have been put forward by many scholars. In the domain of the wavelet transform, the denoising can be disposed by cutting the wavelet coefficients, reduction range of the wavelet coefficients, and other non-linear process. The thresholds to coefficients of the various layers are generally in accordance with the SNR of the original signal, so as to filtering the noise. Using this method, we can avoid blurring the mutation of signal caused by the general low-pass filter to a certain extent, but which is similar to the traditional low-pass filter will also cause a little loss of signal details. Therefore, we should consider the issue which should compromise the signal details remaining and noise suppression when the method will be used.

Grey system theory researches on uncertainty system of "small sample", "poor information" that is "part of information known, part of information unknown", the system's operation and evolution's law are described correctly and monitored effectively mainly by creating, developing, extracting the valuable information from the part of known information [14].

Based on that, a new method which is wavelet threshold method with grey incidence degree (GID) (or the GID threshold method) has been proposed in this paper. It fixes on thresholds of various wavelet layers according to the noise intensity σ and the grey incidence degree γ between similar coefficients and detail coefficients, and the threshold can also be based on the practical noise intensity to adjust the coefficients ξ of grey incidence degree in the practical example. GID threshold method can commendably compromise the problem of signal details remain and noise suppression, so that the signal processed by GID has a better smoothness and similarity.

II. THE GREY INCIDENCE ANALYSIS

Introduction to the grey incidence degree: The regression analysis, variance analysis, principal component analysis etc., are the methods for system analysis in the mathematical statistics. These methods have their own deficiency, for instance, they require large amounts of data, and they would be difficult to find statistical laws because of less datum and the computing capacity is large, and also they possibly appear as a result that quantitative analysis doesn't match with qualitative analysis, and so on.

The basic idea of grey incidence analysis is based on judging the extent of their relation from the similarity to sequences of geometric curve shapes. The closer those are, the greater incidence degree of the corresponding sequences is and vice versa. Based on this, we can calculate the grey incidence degree γ of the wavelet coefficients according to the similarity between the approximate time sequences (formed by approximate coefficients) and the detailed time sequences (formed by detailed coefficients).

Definition 1: Let X_i be the system factor, if k is the time serial number, and $x_i(k)$ is observational data for X_i in the k moment, then $X_i = \left(x_1(1), x_2(2), \ldots, x_i(n)\right)$ is known as the behavioral time sequence.

Definition 2: Let $X_i = \left(x_1(1), x_2(2), \ldots, x_i(n)\right)$ be the behavioral time sequence, and D_1 be the sequence operator, and $X_iD_1 = \left(x_1(1)d_1, x_2(2)d_1, \ldots, x_i(n)d_1\right)$ where $x_i(k)d_1 = x_i(k)/x_i(1), x_i(1) \neq 0$ and k = 1, 2, …, n, then D_1 is called the initial value operator, and $X_i D_1$ is a mapping of X_i under the D_1.

Theorem 1: Let the approximate time sequence $X_0 = \left(x_0(1), x_0(2), \ldots, x_0(n)\right)$ be the system character sequence and let the detailed time sequence $X_1 = \left(x_1(1), x_1(2), \ldots, x_1(n)\right)$, then the grey incidence degree between X_1 and X_0 is

$$\gamma\left(X_0, X_1\right) = \frac{1}{n}\sum_{k=1}^{n} \gamma\left(x_0(k), x_1(k)\right)$$

(1)

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\min_i \min_k \left|x_0(k) - x_i(k)\right| + \xi \max_i \max_k \left|x_0(k) - x_i(k)\right|}{\left|x_0(k) - x_i(k)\right| + \xi \max_i \max_k \left|x_0(k) - x_i(k)\right|}$$

(2)

Where ξ is known as the distinguished coefficient, $\xi \in (0,1)$, usually, ξ=0.5 and the value ξ can be determined by the noise intensity σ of the various layers. The greater σ is, the greater corresponding ξ is and vice versa.

Calculation of the grey incidence degree: According to the formula defined by the theorem 1, we can find the steps for calculation of the grey incidence degree as follows:

i. Calculate the mappings of the initial values for various sequences. Let $X_i' = X_i / x_i(1) = \left(x_i'(1), x_i'(2), \ldots, x_i'(n)\right)$ where *i = 0, 1, 2,…, N.*
ii. Calculate the difference of the mappings. Let $\Delta_i = \left(\Delta_i(1), \Delta_i(2), \ldots, \Delta_i(n)\right)$, where $\Delta_i(k) = \left|x_0'(k) - x_i'(k)\right|$ and i = 0, 1, 2, …, N.
iii. Calculate the biggest difference and smallest difference for $\Delta_i(k)$. Let $M = \max_i \max_k \Delta_i(k)$ and $m = \min_i \min_k \Delta_i(k)$.

iv. Calculate the incidence coefficients $\gamma_i(k) = \frac{m + \xi M}{\Delta_i(k) + \xi M}$, where $\xi \in (0,1)$; $k = 1, 2,\ldots, n$ and $i = 0, 1, 2,\ldots, N$.

v. Calculate the grey incidence degree. So $\gamma = \frac{1}{n}\sum_{k=1}^{n}\gamma_i(k)$ where i = 0, 1, 2,…,N.

$$\gamma_{0i}(k) = \gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \zeta \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \zeta \max_i \max_k |x_0(k) - x_i(k)|}$$

(3)

III. THE PROCESS OF WAVELET DENOISING

Suppose the $f(n)$ is an original signal from MIT-BIH ECG data, $s(n)$ polluted by noise, Where $e(n)$ is the noise and it is supposed as Gaussian white noise, and σ is the noise intensity. The basic noise model can be described as

$$s(n) = f(n) + \sigma e(n)\ ,\ n = 1, 2, \ldots, N.$$

(4)

The general process of signal processed by the wavelet is as follows:

1. The process of wavelet decomposition: Using the discrete wavelet transform by selecting mother wavelet, the noisy signal $s(n)$ is decomposed by the wavelet, at the decomposition level of 5. As a result approximate coefficients a_j and detail coefficients d_j were obtained. Here 'j' denotes the level of scaling.
2. The process of threshold: select an appropriate threshold to the coefficients of various layers, to obtain the estimated wavelet coefficients $\hat{d}_j$. For each level a threshold value is found, and process detailed coefficients d_j through the threshold.
3. *Manipulation* of the *empirical* wavelet coefficients:

   (a) Hard-thresholding method:

$$\hat{d}_j = \begin{cases} d_j, & |d_j| \geq \lambda_j \\ 0, & |d_j| \leq \lambda_j \end{cases}$$

   (5)

   Where λ_j is the threshold value.

4. The process of signal reconstruction: reconstruct the de-noised ECG signal $\hat{s}(n)$ through the wavelet coefficients processed by threshold, from $\hat{d}_j$ and a_j by using inverse discrete wavelet transform (IDWT).

From the wavelet denoising process, we can see that the core part of the process is the process of threshold, that is, how to select the threshold of various layers will directly influence on the effect of signal denoising.

The same steps are to be followed for soft thresholding, de-noising methods.

(b) Soft-thresholding method:

$$\hat{d}_j = \begin{cases} \operatorname{sgn}(d_j)(|d_j| - \lambda_j), & |d_j| \geq \lambda_j \\ 0, & |d_j| \leq \lambda_j \end{cases} \quad (6)$$

Threshold selection: Universal threshold $\lambda_j = \sigma \cdot \sqrt{2\ln(L)}$, where L is the length of the signal, The σ can be estimated by the wavelet coefficients with $\sigma_j = (median(|d_j|))/\ 0.6745$. Here median ($|d_j|$) denotes the median value of the absolute values of wavelet coefficients d_j. Sub-band or level-dependent threshold $\lambda_j = \sigma_j \sqrt{2\log\|d_j\|}$.

BayesShrink threshold: The goal of BayesShrink method is to minimize the Bayesian risk. Thresholding is done at each band of resolution in the wavelet decomposition. The Bayes threshold, λ_{B_j}, is defined as $\lambda_B = \frac{\sigma^2}{\sigma_f^2}$, where σ^2 is the noise variance and σ_f^2 is the signal variance without noise. Since the noise and the signal are independent of each other, it can be stated that σ_s^2 can be computed using the equation $\sigma_s^2 = \sigma^2 + \sigma_f^2$.

$$\sigma_s^2 = \frac{1}{n^2}\sum_{i=1}^{n} s_i(n) \quad (7)$$

$$\sigma_f = \sqrt{\max(\sigma_s^2 - \sigma^2, 0)} \quad (8)$$

From this the variance of the signal σ_f^2, then Bayes threshold λ_{B_j} can be computed.

The GID threshold method: The general threshold method is the threshold σ proposed by Donoho and Johnstone which they applied the normal, multi-dimensional and independent decision-making theory in the Gaussian white noise model. It is often excessively smooth true signal because the excessive focus on the smoothness of filtering, so that the results show the greater deviation. Based on that, the general threshold is amended by the grey incidence degree, and then a new threshold value method — GID threshold method is proposed, the method not only can filter most of noise, but also it can retain commendably signal details.

The threshold of various layers can be determined, according to the grey incidence degree γ between wavelet decomposition factor approximate time sequences (low frequency) and detailed time sequences (high frequency) and the noise intensity

σ of the levels of the threshold, GID threshold is $\lambda_{GID_j} = \lambda_j.\gamma_j$, where γ is the grey incidence degree between coefficients. The concrete steps of the GID filtering noise are as follows:

1. The wavelet coefficients will be gained by wavelet transform for the signal.
2. Calculate the noise intensity σ_j for various layers.
3. Calculate the grey incidence degree γ_j between the detailed coefficients d_j and approximate coefficients a_j according to the equation (3).
4. According to the wavelet threshold method with grey incidence degree (GID), calculate the threshold λ_{GID_j}, then keep down the original value when a position wavelet transform coefficient value is greater than the threshold, otherwise let the value be zero.

IV. DISCUSSION AND CONCLUSION

The orthogonal wavelets db4, db5, db6, db8 and sym8 were selected, and the signal $s(n)$ is to be decomposed for five-layer by using it. Then we threshold the decomposition coefficients respectively by Donoho universal threshold method, Sub-band threshold method, as well as the GID threshold method proposed in this paper. The original signal $f(n)$ is ECG signals taken from MIT-BIH arrhythmia database [17], and then the motion artifact signal from MIT-BIH Noise Stress Test Database [13, 18] of different intensities are added to the signal. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range, Finally, the quality of the processed signal will be evaluated with three performance indexes of the signal-to-noise (SNR), mean square error (MSE) and visual inspection respectively. The ECG signal 103 with motion artifact at SNR = -3db is denoised by hard and soft –thresolding methods with above thresholds mentioned is shown in Figure 1. In Figure 2. and Figure 3. Plots for comparison of hard and soft thresholding methods for thresholds with and without GID on signal 103 using db5 wavelet were shown.

By contrast, the GID threshold method proposed in this paper can not only effectively suppress noise, but also it commendably retains signal detail, so that the denoised signal will maintain well smoothness and similarity, and that the SNR has been greatly improved. It filters signal by threshold determined by the grey incidence degree between high-frequency coefficients and low-frequency coefficients, and by the noise intensity, which are combined the wavelet theory with the grey incidence analysis, and make use of the information regarding noise and original signal in the paper. The experiment results show that the GID can commendably solve the compromise problem between the noise suppression and signal detail retaining, it not only loses very few of energy components of the original signal, but also the SNR has been greatly improved.

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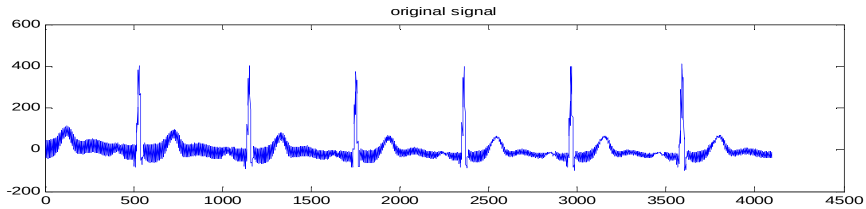
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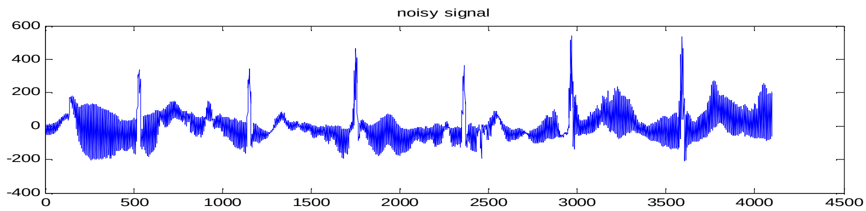
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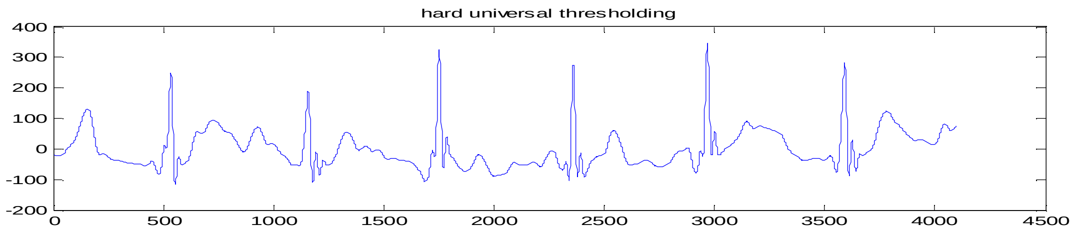
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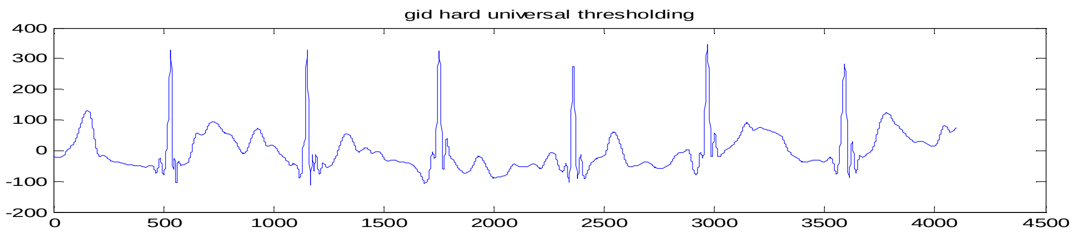
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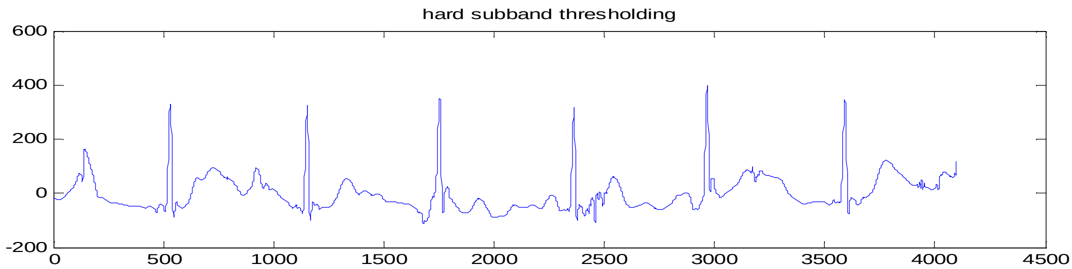
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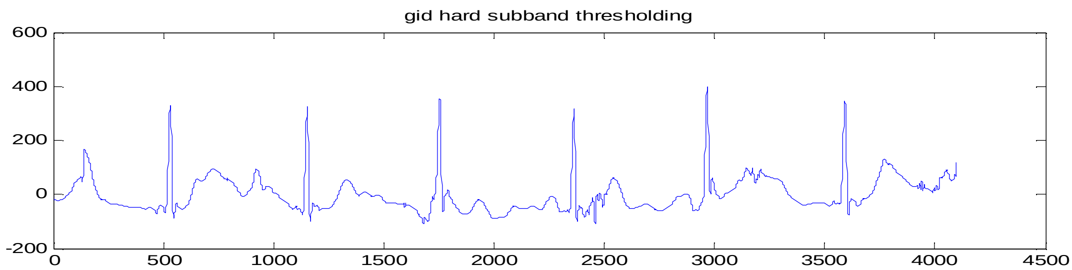
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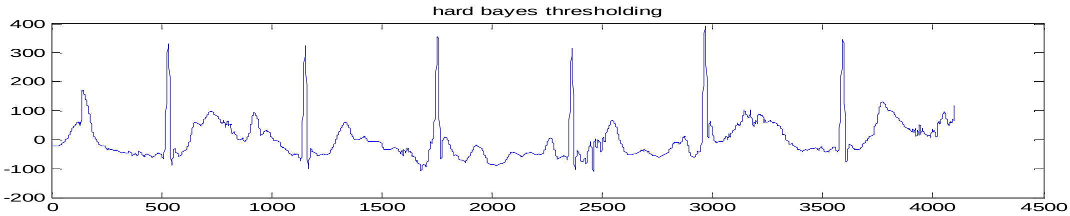
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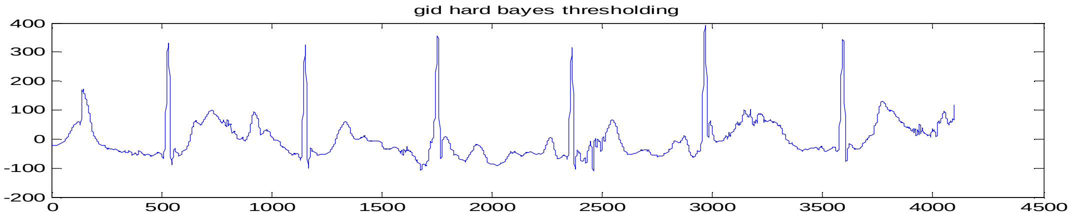
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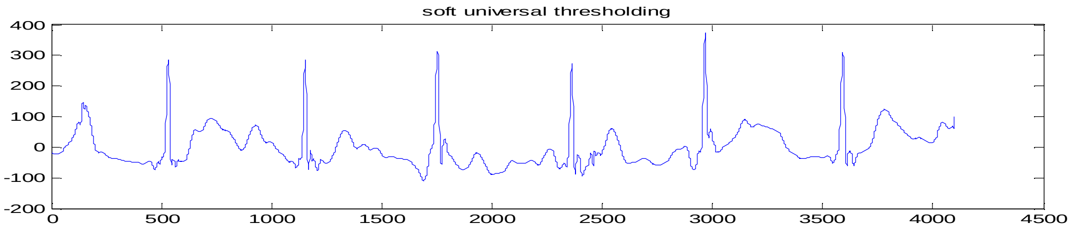
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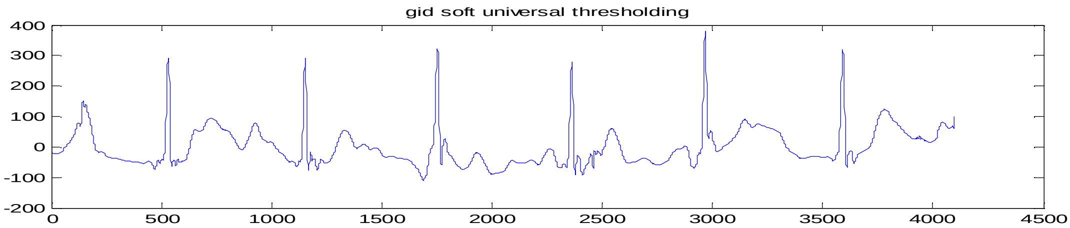
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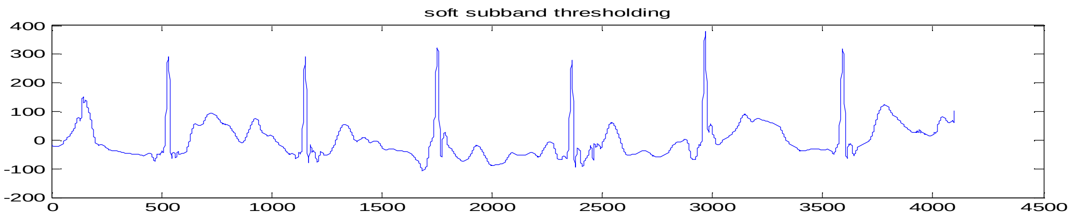
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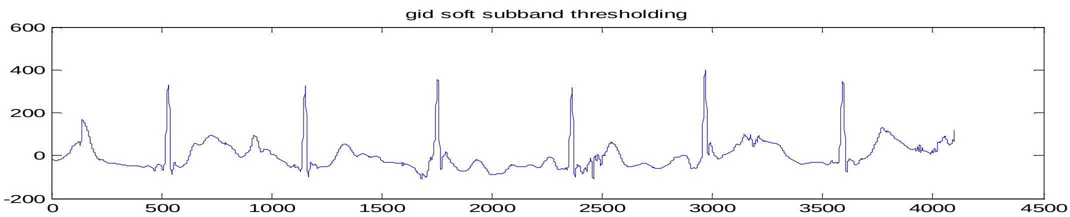
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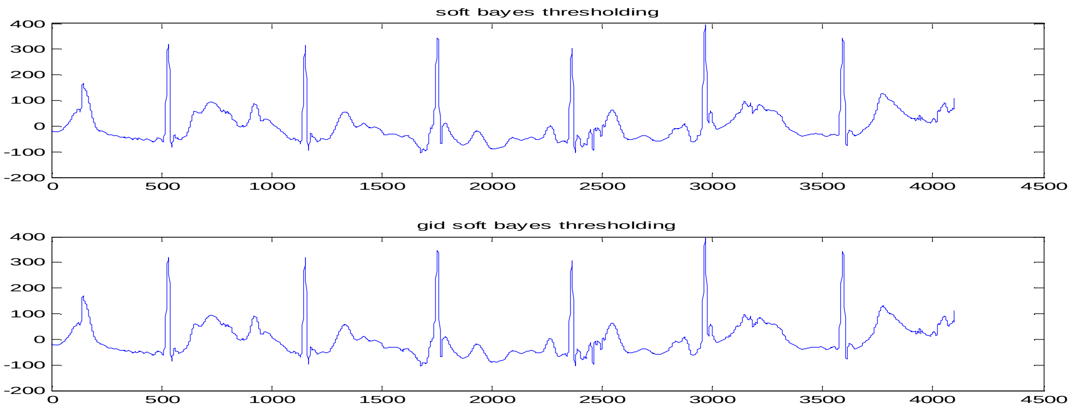
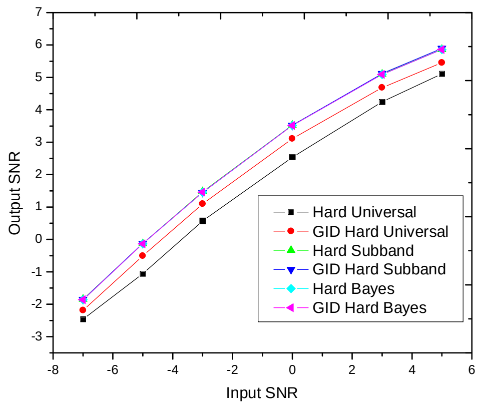
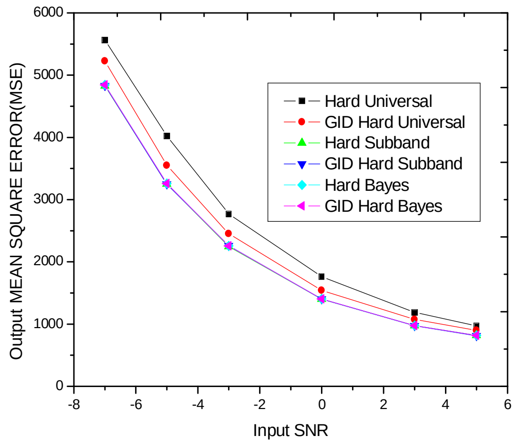


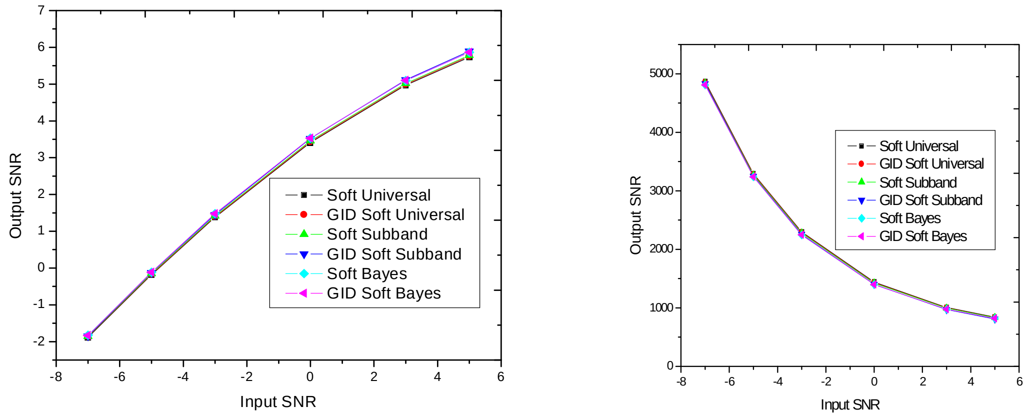
Fig.1: Signal 103 denoised signals from different thresholding methods for corrupted by em noise of input SNR = -3 dB using db5 wavelet.





(a) (b)

Fig. 2 : Plots for comparison of hard thresholding methods on signal 103 using (a) SNR, (b)MSE using db5 wavelet



(a) (b)

Fig. 3 : Plots for comparison of soft thresholding methods on signal 103 using (a)SNR, (b) MSE using db5 wavelet

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