Performance of Discrete Wavelet Transform (DWT) Based Speech Denoising in Impulsive and Gaussian Noise

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Abstract

The aim of this paper is to investigate the effect of impulsive noise on the performance of the speech denoising using Discrete Wavelet Transform (DWT). The employed model of impulsive noise consists of Bernoulli distributed impulse arrivals and Gaussian distributed amplitudes of the impulses.

In this study DWT algorithm has been applied for the suppression of ambient noise. This method is based on thresholding the wavelet coefficients, that can be done by standard deviation method for each frame by level dependent thresholding using different types of threshold (semisoft, hard soft and super soft) in channel contains impulsive and Gaussian noise together.

The results of simulation indicate that using discrete wavelet transform in speech denoising application provides a good quality and semisoft threshold gives the best performance.

الخلاصـــــــة

الهدف من هذا البحث هو دراسة تأثير الضوضاء النبضي ***(Impulsive)*** *على تمثيل تقليل الضوضاء باستخدام تحويل المويجة المقطعة. تم استخدام توزيع برنولي للنبضات الواردة مع توزيع* ***(Gaussian)*** *للقمم النبضية لتمثيل الموديل للضوضاء النبضي.*

تم في هذه الدراسة استخدام خوارزمية تحويل المويجة المقطعة لتقليم الضوضاء. تعتمد هذه الخوارزمية على تقليم عوامل المويجة والتي يمكن أ نجازها بوساطة طريقة الانحراف المعياري لكل مقطع ***(Frame)*** *باستخدام تقليم لكل مرحلة* ***(Level Dependent Thresholding)*** *حيث تم استخدام أنواع مختلفة من التقليم* ***(Semisoft, Hard soft and Super soft)*** *في قناة تتألف من الضوضاء النبضي و الضوضاء* ***(Gaussian)*** *معاً.*

تشير النتائج المحصلة في هذا البحث إلى إن استخدام تحويل المويجة المقطعة في تطبيقات إزالة الضوضاء من الصوت قد أعطى نتائج جيدة والتقليم ***(Semisoft)*** *أعطى أفضل النتائج.*

1. Introduction

In many speech processing applications, speech has to be processed in the presence of undesirable background noise. One of the most important branches of speech processing is speech enhancement which focuses on finding an optimal estimate of clean speech from noisy speech signal.

Application areas include the reduction of noise for listening purpose, the preprocessing of speech coding or recognition systems. Noise reduction or speech enhancement has always been a non-trivial problem for communication engineers. The total removal of background noise is practically impossible and distortion of the speech content is inevitable [1].

The discrete wavelet transform distinguishes itself in the analysis of non-stationary signals such as speech. The wavelet shrinkage is a powerful tool in denoising signal corrupted by noise. Speech denoising using Discrete Wavelet Transform (DWT) is studied in [2-5].

In the real wireless communications scenarios besides from Additive White Gaussian Noise (AWGN) there are impulsive man-made noises from ignition of automobiles or other sources such as power transport lines which affect the performance of the system. The modeling of impulsive noise has been carried out for years [6-8].

In this study AWGN and Bernoulli-Gaussian model for impulsive noise are employed. DWT using different types of thresholding will also be considered.

2. Impulsive Noise Model

The model discussed in the following is a Bernoulli-Gaussian (BG) model of an Impulsive Noise (IN) process. The random time of occurrence of the impulsive is modeled by a Bernoulli process b(k), where k is the time point and b(k) is a binary-valued process that takes a value of "1" with a probability of α and a value of "0" with probability of (1-α). The amplitude of the impulsive is modeled by a Gaussian process g(k) with mean zero and variance σ^2. Each impulsive is shaped by a filter with the impulsive response h(k). The Bernoulli-Gaussian model of impulsive noise is illustrated in **Fig.(1)**. The IN can be expressed as [8]:

$$\mathbf{n(k) = \sum_{i=0}^{P-1} h(i)g(k-i)b(k-i)} \quad \text{...} \quad \mathbf{(1)}$$

where: P is the length of the impulsive response of the impulsive shaping filter.

In a Bernoulli-Gaussian model the probability density function (pdf) of impulsive noise n(k) is given by [8]:

$$\mathbf{pdf_N^{BG}(n(k)) = (1-\alpha)\delta(n(k)) + \alpha pdf_N(n(k))} \quad \text{.......................................} \quad \mathbf{(2)}$$

where: $\delta(n(k))$ is the Kronecker delta function and

$$\mathrm{pdf}_N(n(k)) = \frac{1}{\sqrt{2\pi}\,\sigma} e^{-\frac{1}{2}\left(\frac{n(k)}{\sigma}\right)^2} \quad \ldots\ldots (3)$$

is the probability density function of a zero Gaussian process.

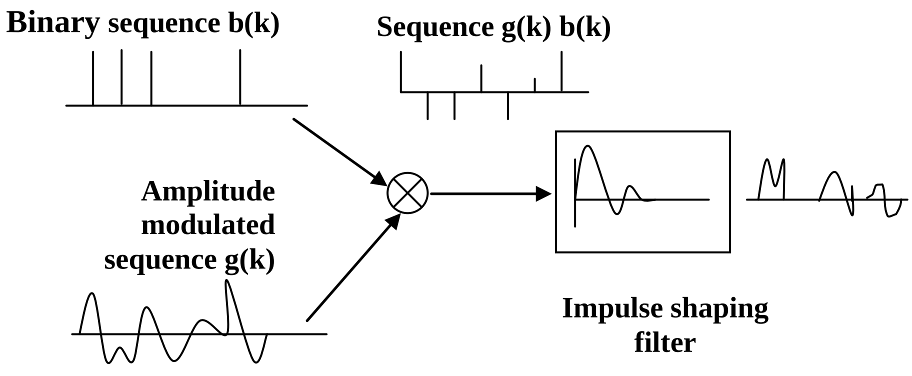

Figure (1) Impulsive noise model

The value of α is a measure of impulsivity of the impulsive noise. By decreasing α the noise becomes more impulsive. Typical values for α used in the simulations are α=1, 0.5, 0.1, 0.01, 0.001, and 0.0001. In the real world there is no impulsive noise only but a mixture of impulsive noise and AWGN. Accordingly, as shown in **Fig.(2)** in the simulation both IN and AWGN are considered. In this regard we also define a parameter that controls the power ratio of the AWGN part and the "impulsive" part of the total noise as [8]:

$$\gamma = \frac{\mathrm{power}\ (\mathrm{impulsive\_component})}{\mathrm{power}\ (\mathrm{AWGN\_component})} \quad \ldots\ldots (4)$$

with the definition of γ, the noise impinging the system consists of IN and AWGN with a manageable ratio of power. The whole set-up of the simulation is illustrated in **Fig.(2)**.

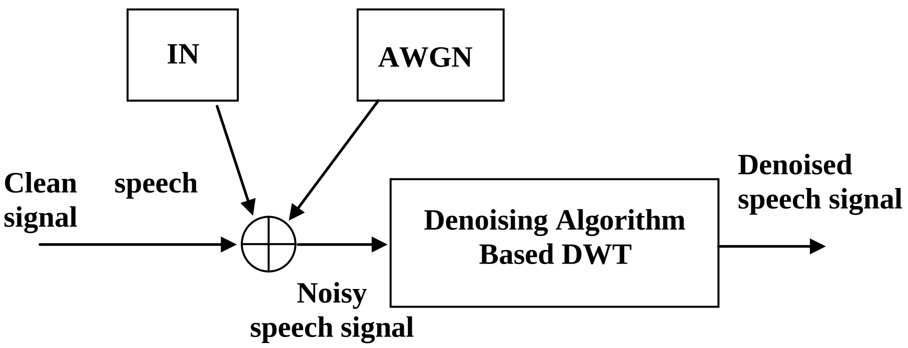

Figure (2) Block diagram of the simulation set-up

3. Discrete Wavelet Transform (DWT)

The general form of an L-level DWT is written in terms of L detail sequences, $d_j(k)$ forj=1,2,….,L, and the L-th level approximation sequence, $c_L(k)$ as follows [9]:

$$f(t) = \sum_k c_L(k)\,\phi_L(t) + \sum_{j=1}^{L}\sum_k d_j(k)\,\psi_j(t) \quad \text{.......... (5)}$$

where: $\phi_L(t)$ is the L-th level scaling function and $\psi_j(t)$ for j=1,2,…,L are wavelet function sequences for L different levels.

In order to work directly with the wavelet transform coefficients, the relationship between the detailed coefficients at a given level in terms of those at previous level is used. In general, the discrete signal assumes the highest achievable approximation sequence, referred to as 0-th level scaling coefficients. The approximation and detail sequences at level j are given by [9]:

$$c_{j+1}(k) = \sum_m h_o(m-2k)\,c_j(m) \quad \text{.......... (6)}$$

and

$$d_{j+1}(k) = \sum_m h_1(m-2k)\,c_j(m) \quad \text{.......... (7)}$$

Eqs. (6) and (7) state that approximation sequence at higher scale (lower level index), with the wavelet and scaling filters, $h_o(t)$ and $h_1(t)$ respectively, can be used to calculate the detail and approximation sequences (or discrete wavelet transform coefficients) at lower scales.

The scaling coefficients are related to wavelet coefficients by:

$$h_1(n) = (-1)^n h_o(N-n) \quad \text{.......... (8)}$$

where: N is a finite odd length of quadrature mirror filter.

Let the function f(t) be a discretely sampled function. The decomposition of f(t) in the wavelet basis is done by recursive filtering with H_o and H_1 with down-sampling of factor of two in each set. A lower resolution signal is delivered by low pass filtering with half-band low pass filter H_o followed by down-sampled by two. The higher resolution (or detail) is computed by a high pass filter H_1 followed by down- sampling by two [10].

The coefficients $h_o(n)$ and $h_1(n)$, used to construct the set of scaling and wavelet basis, are low pass (H_o) and high pass (H_1)FIR filter coefficients respectively. $H_o=\{h_o(n)\}$ and $H_1=\{h_1(n)\}$. According to the Equation (8), H_1 is the reverse of H_o. [11]

Figure (3) shows filter bank of discrete wavelet transform. The symbol ↓2 is a down-sampler (decimator) that takes a signal x(n) as input and produces an output of y(n)=x(2n), which means half of the data is discarded [12].

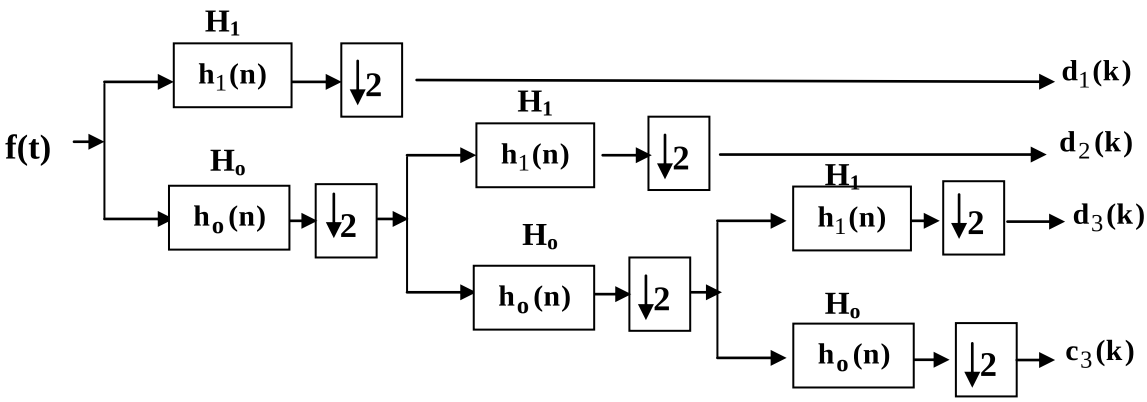

Figure (3) Filter bank of discrete wavelet transform

3-1 Wavelet Reconstruction

The wavelet reconstruction process consists of upsampling and filtering. In the upsampling process, the input signal is stretched twice its original length and zeros are inserted in the even numbered samples.

The inverse discrete wavelet transform is illustrated in **Fig.(4)**. The j scale coefficients sequence c_j is up-sampled, by doubling its length (inserting zeros between each term), then convoluting it with the scaling coefficients h(n), the same is done to the j level wavelet coefficient d_j sequence and the results are added to give the j+1 level scaling function coefficients [12].

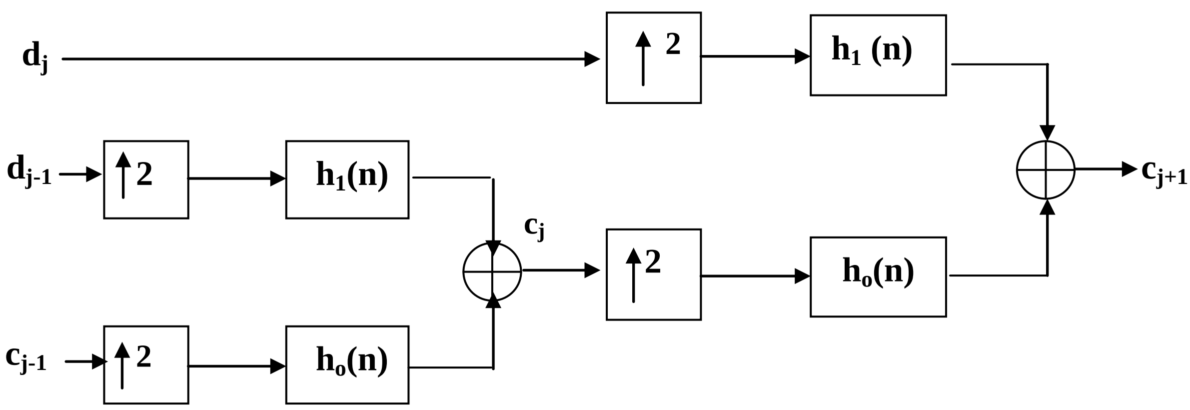

Figure (4) Two stage two-band tree signal synthesis tree of IDWT

3-2 Wavelet Thresholding

Donoho proposed a powerful approach for noise reduction .It is based on the thresholding of the wavelet coefficients. Let y be a finite length observation sequence of the signal x that is corrupted by zero-mean white Gaussian noise (G) and impulsive noise (I) [1]:

$$\mathbf{y = x+G+I} \quad \text{……………………………} \quad \mathbf{(9)}$$

or,

$$\mathbf{y = x+n} \quad \text{……………………………} \quad \mathbf{(10)}$$

where: n=G+I

Let W(.) and W^{-1}(.) denote the forward and inverse wavelet transform operators. Let D(.,λ) denote the thresholding operator with threshold λ. The practice of thresholding denoising consists of the following three steps:

1. $$\mathbf{Y=W(y)} \quad \text{……………………………} \quad \mathbf{(11)}$$

2. $$\mathbf{\tilde{X}=D(Y,\ \lambda)} \quad \text{……………………………} \quad \mathbf{(12)}$$

3. $$\mathbf{x = W^{-1}(\tilde{X})} \quad \text{……………………………} \quad \mathbf{(13)}$$

where: $\tilde{X}$ represents the wavelet coefficients after thresholding.

In this paper the following types of threshold are introduced:

3-2-1 Hard Soft-Thresholding

The hard soft-thresholding is given by [13]:

$$\mathbf{D(Y,\lambda)} = \begin{cases} \mathbf{Y} & |\mathbf{Y}| \geq \lambda \\ \rho\mathbf{Y} & |\mathbf{Y}| < \lambda \end{cases} \quad \text{……………………………} \quad \mathbf{(14)}$$

where: ρ is the attenuation factor.

3-2-2 Super Soft-Thresholding

Super soft-thresholding is given by [7]:

$$\mathbf{D(Y,\lambda)} = \begin{cases} \mathbf{Y - sign(Y)(1-\rho)\lambda} & |\mathbf{Y}| \geq \lambda \\ \rho\mathbf{Y} & |\mathbf{Y}| < \lambda \end{cases} \quad \text{……………………………} \quad \mathbf{(15)}$$

where: $\lambda \geq 0$ is the threshold value

$0 \leq \rho \leq 1$ is the attenuation factor.

3-2-3 Semisoft-Thresholding

The semisoft-thresholding function is given by [5]:

$$\mathbf{D(Y,\lambda_1,\lambda_2)} = \begin{cases} \mathbf{0} & |\mathbf{Y}| \le \lambda_1 \\ \mathbf{sgn(Y)}\dfrac{\lambda_2\left(|\mathbf{Y}| - \lambda_1\right)}{\lambda_2 - \lambda_1} & \lambda_1 < |\mathbf{Y}| \le \lambda_2 \\ \mathbf{Y} & |\mathbf{Y}| > \lambda_2 \end{cases} \qquad \text{.......................... (16)}$$

where: $D(Y,\lambda_1,\lambda_2)$ represents the output value after thresholding the wavelet coefficients and λ_1 and λ_2 denote lower and upper threshold respectively. Thresholding value λ_1 is determined by Equation (18) and λ_2 is given by:

$$\lambda_2 = \sqrt{2}\ \lambda_1 \qquad \text{.. (17)}$$

4. Discrete Wavelet Transform Based Denoising Technique

In this study the level dependent threshold is based on thresholding detailed coefficients for each level is used. **Figure (5)** shows the block diagram of speech denoising using level dependent threshold [14].

Figure (5) block diagram of speech denoising using level dependent threshold

The noisy speech signal is sectioned into frames (typical value of frame length is 256 samples). Then, the discrete wavelet transform is taken for noisy speech, after that the wavelet transform coefficients are filtered using different types of threshold (that is discussed in previous section). The threshold value (λ) can be determined by **[14]**:

$$\lambda = \sigma_j \sqrt{2 \log N_j} \qquad \text{... (18)}$$

with,

$$\sigma_j = \frac{\mathbf{MAD\,(d_j)}}{\mathbf{0.6745}} \qquad \text{... (19)}$$

where: $MAD(d_j)$ is median absolute deviation of detail coefficients for each level, and N_j is the data length for each level.

Finally, the inverse discrete wavelet transform is used to recover the clean speech signal. This procedure is repeated for each frame.

5. Objective Measures

The frequency signal-to-noise ratio (SNR) is the most widely used objective measure of speech quality. The SNR measure in frequency domain for k^{th} frame is defined by [15]:

$$\mathbf{SNR_k = 10\log_{10} \frac{\sum_n |X_k(n)|^2}{\sum_n \left[X_k(n) - \tilde{X}_k(n)\right]^2}} \quad [\mathrm{dB}] \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ \mathbf{(20)}$$

where: $X_k(n)$ is the DFT of the k^{th} frame of the clean speech, and $\tilde{X}_k(n)$ is the DFT of the corresponding frame of the denoised speech signal. These SNR_k for different frames are averaged to give the over all SNR.

The SNR enhancement (in dB) is obtained by:

$$\mathbf{SNR\ Enhancement = SNR_o - SNR_i} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ \mathbf{(21)}$$

where: SNR_o represents the output signal to noise ratio, and SNR_i represents the input signal to noise ratio.

6. Simulation Results

Simulations of speech denoising using DWT and different types of thresholding over AWGN plus IN channel were carried out. Various values of SNR_i from -10 dB to 10 dB is used for performance evaluation. Various impulsivities (α) and power of impulsive noise with respect to AWGN (i.e., γ) are considered and the SNR performance are evaluated. The effect of different impulsive noise sources is simulated by changing the impulse-shaping filter of the IN model.

The sentence that is used in the recording is "الحمد لله رب العالمين". The data is sampled at 8KHz using a computer sound blaster (in normal room conditions). The data samples are quantized into 16 bit. **Figure (6)** shows the waveform of the clean speech signal.

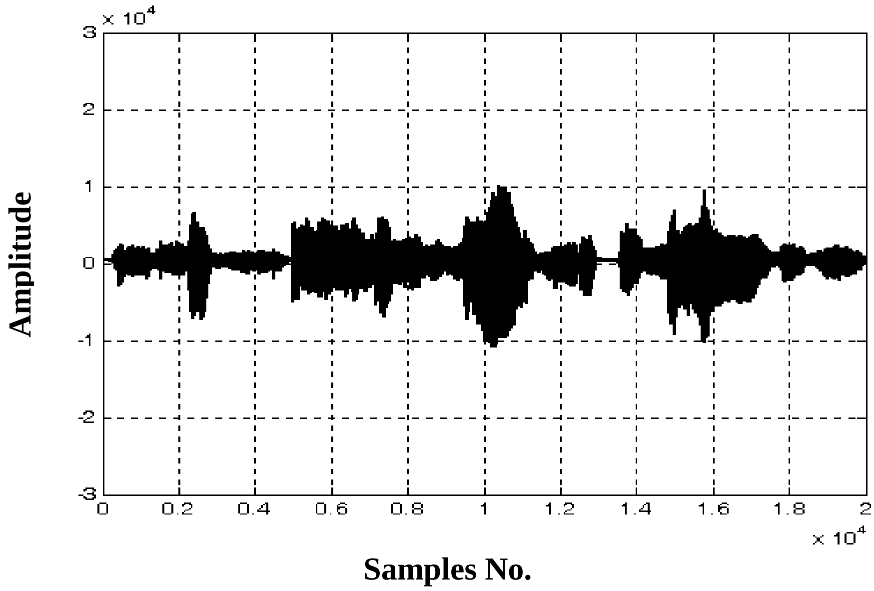

Figure (6) The waveform of the clean speech signal

6-1 Filter Shape of The Impulse Noise {h(n)}

In order to investigate how the shape of the filter h(t) affects the SNR enhancement of the denoising algorithm over the impulsive noise channel, two different impulse-shaping filters. The filter $h_{hpf}(t)$ is a High Pass Butterworth filter with cutoff frequency 4KHz. The second filter $h_{lpf}(t)$ is a Low Pass Butterworth filter with a cutoff frequency 4KHz.

Figure (7) shows the SNR enhancement results using hard soft-thresholding over impulsive noise only db6, α=0.01 and ρ= 0.1. This figure shows the effect of the impulse-shaping filter on the SNR enhancement. It is seen that for the impulse filter $h_{lpf}(t)$ provides a worse SNR enhancement than $h_{hpf}(t)$ for low SNR_i (from –10 to 0 dB). In this study, all the results that is discussed later depends on $h_{lpf}(t)$ filter.

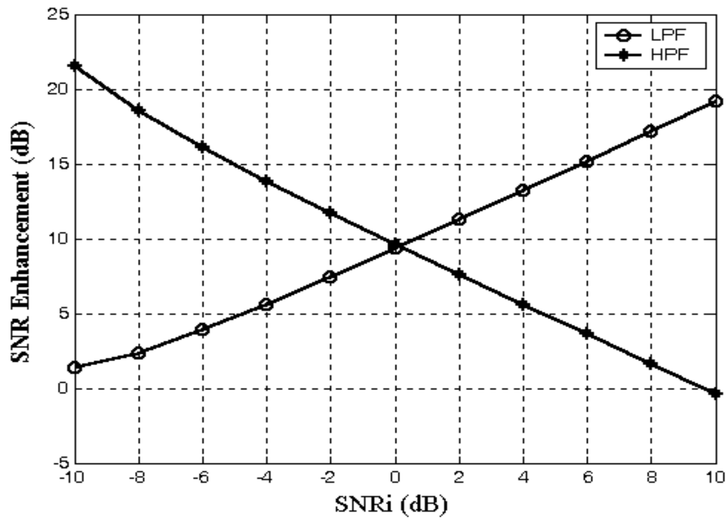

Figure (7) SNR Enhancement results using DWT based hard soft-thresholding

6-2 Hard soft-thresholding Results

Figure (8) shows the SNR enhancement results using hard soft-thresholding with different types of wavelet (db4, db6, db8, db10 and db12) for α=0.1. From this figure, all Duabechies types give approximately the same results.

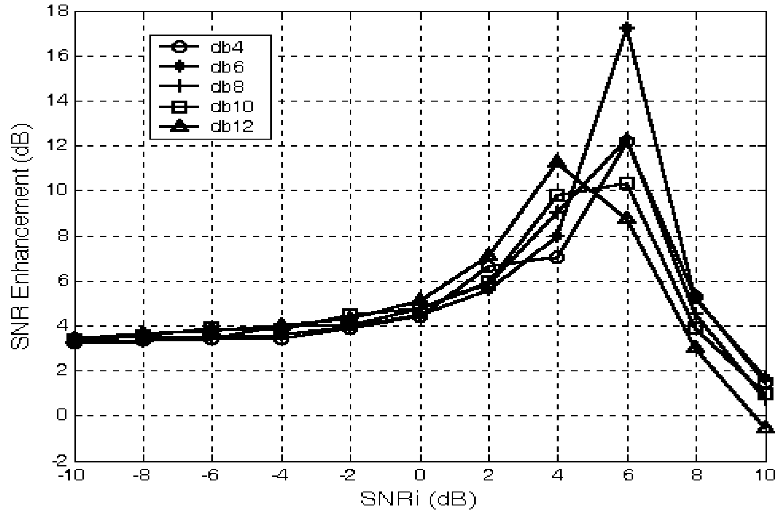

Figure (8) SNR Enhancement results using DWT based hard soft-thresholding, for α=0.1

Figure (9) shows the effective of the impulsivity of noise on the performance of SNR_o using db4 (only effect of impulse noise is taken). Form this figure, some points can be noticed:

- For given α, when the performance of SNR_o remains the same for all values of SNR_i, this mean that no effect of noise on the speech signal (that is clear for α=0.0001 and 0.001).
- When α increases, it approaches to Gaussian noise.
- For α=1, the impulsive noise appears to be the same of Gaussian noise.

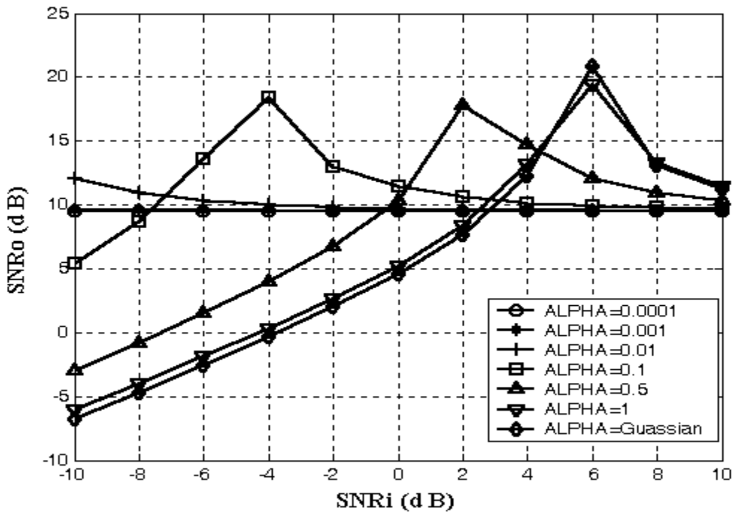

Figure (9) The influence of impulsive noise on the performance of SNR_o using db4

Figure (10) shows the SNR enhancement results using hard soft-thresholding for α=0.1 and db6 with different values of γ (γ=0, 0.1, 1, 5 and 10). From this figure, when γ=0 only effect of Gaussian noise is appeared. When γ is less than 1, the impulsive noise is slightly affects the SNR enhancement. When γ is increased, the SNR enhancement is decreased.

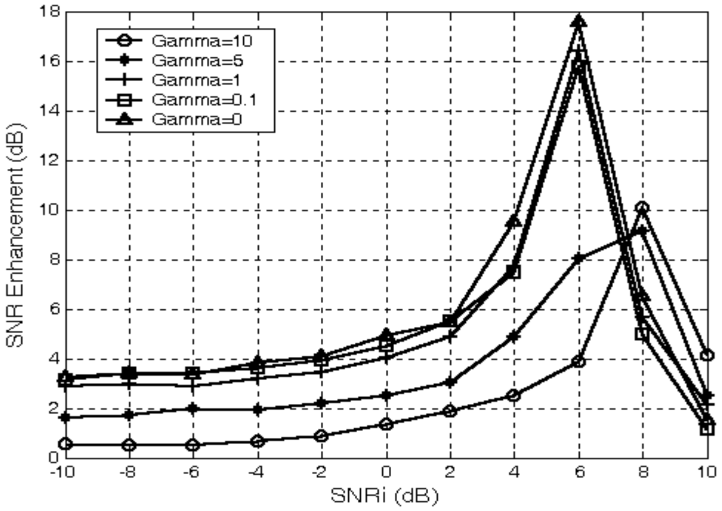

Figure (10) SNR enhancement results using DWT based hard soft- thresholding with db6 and α=0.1

Figure (11) shows the SNR enhancement versus α for different values of γ and SNR_i=5 dB. From this figure, two points can be noticed:

- When γ=0 no effect of impulsive noise on the results (only Gaussian noise exist), therefore changes the values of α does not affect the SNR enhancement.
- For given γ, when α increases, SNR enhancement is decreased.

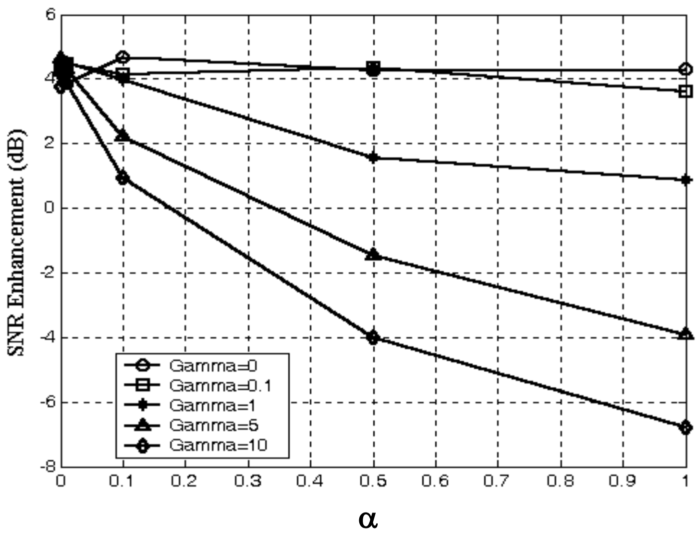

Figure (11) SNR enhancement results using hard soft-thresholding with db6 and different values of γ

All previous results are obtained for ρ=0.1. **Figure (12)** shows SNR enhancement results using DWT based hard soft-thresholding for different value of ρ and various values of SNR_i when db6, γ=1, and α=0.1 are used. From this figure, select ρ gives the best results depends on SNR_i. For low SNR_i select values of ρ near 0 (i.e. 0.1, 0.2 and 0.3) gives the best SNR enhancement, also changes ρ slightly effect on SNR enhancement. While for high SNR_i (more than 0 dB) certain value of ρ gives the best SNR enhancement, for examples, for SNR_i=2 dB the best choice of ρ is 0.1, for SNR_i=4 dB the best choice of ρ is 0.4 and for SNR_i=10 dB the best choice is 0.8.

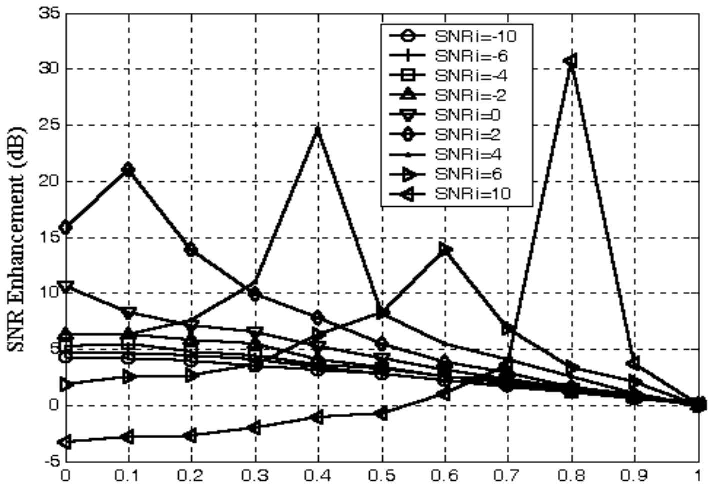

Figure (12) SNR enhancement results using DWT based hard soft-thresholding for different value of ρ when db6, γ=1, and α=0.1 are used

6-3 Super soft-thresholding Results

Figure (13) shows the SNR enhancement results using super soft-thresholding with different types of wavelet (db4, db6, db8, db10 and db12) for α=0.1, γ=1 and ρ=0.1. For low SNR_i, db12 gives the best results and for high SNR_i, db4 gives the best results. It can be seen from this figure that changing in using duabechies order affects slightly on the SNR enhancement except for SNR_i=0, 2 and 4 dB.

Figure (14) shows SNR enhancement results using DWT based super soft-thresholding for various value of ρ and different values of SNRi when db6, γ=1, and α=0.1 are used. From this figure, selection of ρ gives the best results depends on SNR_i. For low SNR_i (less than 0 dB) selecting any value of ρ gives approximately the same performance. While for high SNR_i (more than 0 dB) certain value of ρ gives the best SNR enhancement, for examples, for SNR_i=2 dB the best choice of ρ is 0.1, for SNR_i=4 dB the best choice of ρ is 0.4 and for SNR_i=10 dB the best choice is 0.8 and so on.

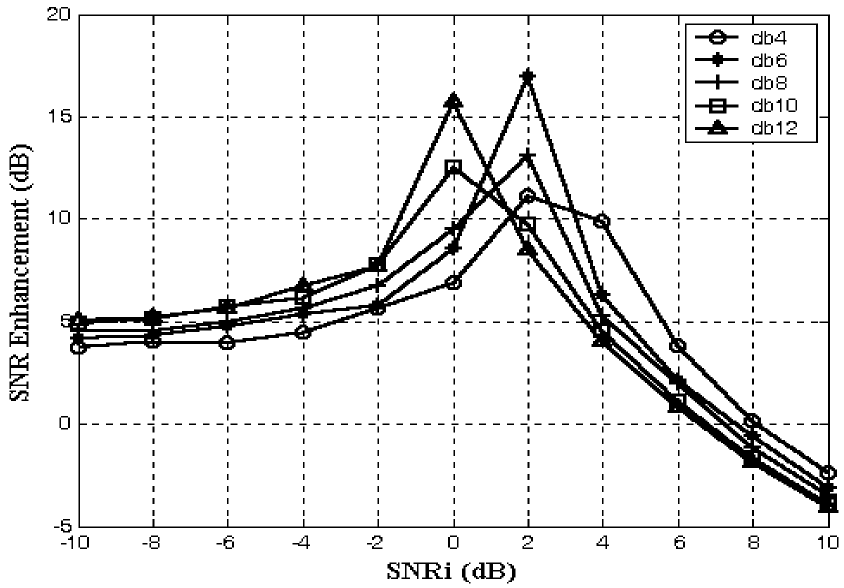

Figure (13) SNR Enhancement results using DWT based super soft-thresholding, for α=0.1, γ=1 and ρ=0.1

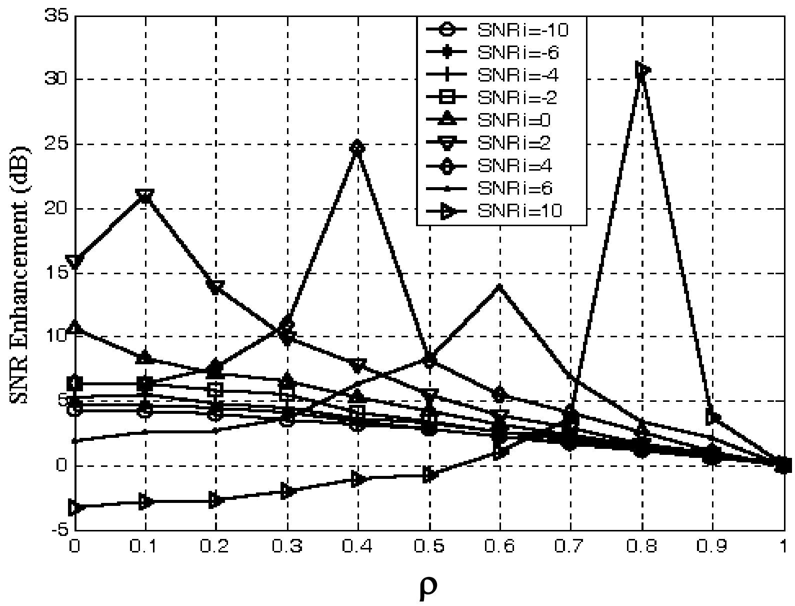

Figure (14) SNR enhancement results using DWT based super soft-thresholding for different value of ρ and different values of SNRi when db6, γ=1, and α=0.1 are used

Figure (15) shows the SNR enhancement for various values of α and different values of γ when SNR_i=5 dB. When γ increases, worst SNR enhancement can be obtained. For α=0 no effect of impulsive noise on the SNR enhancement. For γ=0 effect of impulsive is negligible (energy of impulsive noise=0), the variation of SNR enhancement is not from impulsive but from Gaussian channel.

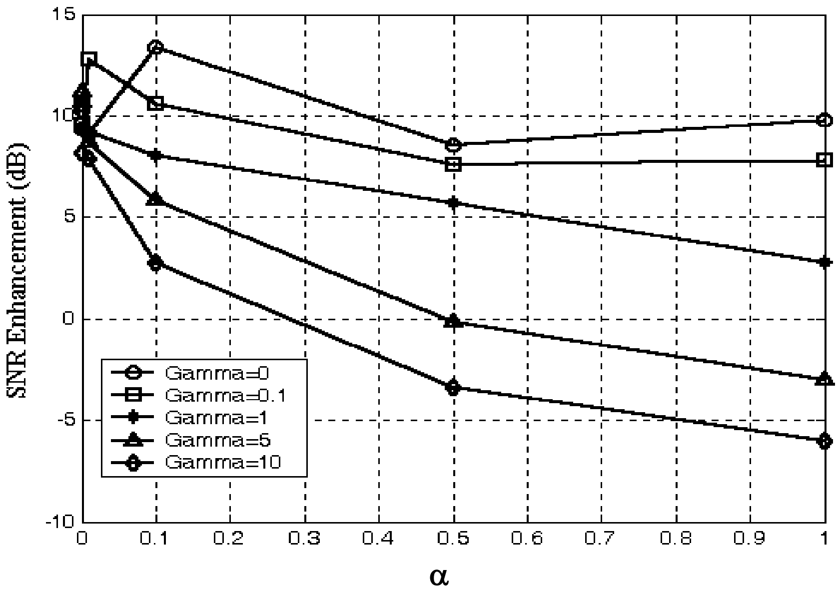

Figure (15) SNR enhancement results using super soft-thresholding with different values of γ and α when db6 and ρ=0.1 are used

6-4 Semisoft-thresholding Results

Figure (16) shows the effect of the impulsivity of noise on the performance of SNR_o using db6 (only effect of impulse noise is taken). The same discussion for **Fig.(9)** is considered here.

Figure (17) shows the SNR enhancement for DWT based semisoft-thresholding using various values of α, different values of γ and SNR_i=5 dB. Comparing these results with hard soft-thresholding, then semisoft-thresholding gives more SNR enhancement than super soft-thresholding.

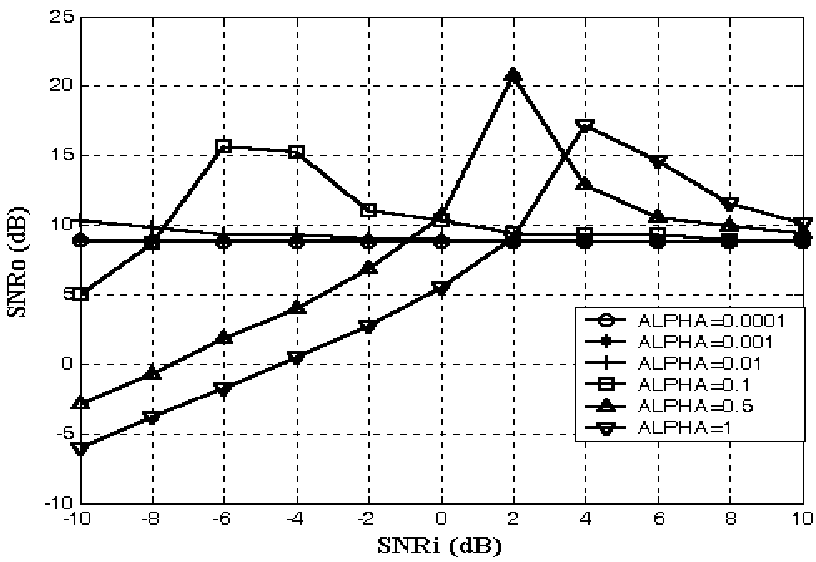

Figure (16) The influence of impulsive noise on the performance of SNR_o using db6

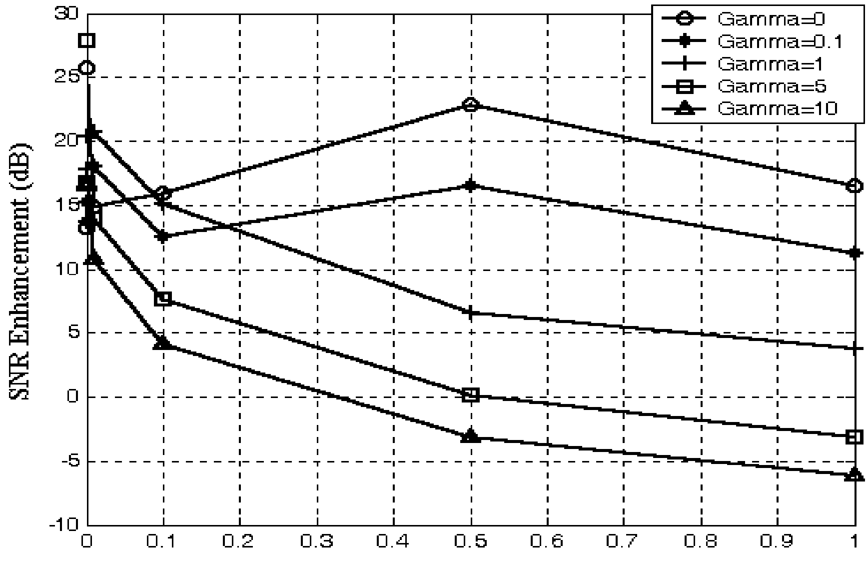

Figure (17) SNR enhancement results using semisoft-thresholding with different values of γ and α when db6 and ρ=0.1 are used

6-5 Discussion of Results

Figs.(18), (19), (20), (21), and **(22)** show comparison results for different types of thresholding (semisoft, hard soft, and super soft) using db6, SNRi=5 dB and ρ=0.1 for γ=0, 0.1, 1, 5, 10 respectively. From these figures some points can be noticed:

- Semisoft gives the best SNR enhancement.
- When γ has large value (greater than 1) and α<0.5 all methods of thresholding are failed to suppress noise from the speech.
- Hard soft threshold gives the worst results compared with other thresholds.
- When γ increases, the difference between types of thresholding is decreased.

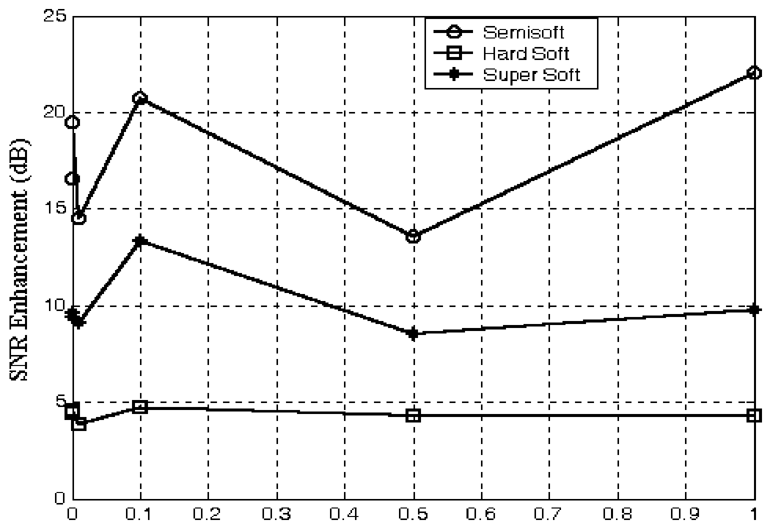

Figure (18) Comparison results between different types of thresholding using db6, γ=0 and SNR_i=5 dB are used

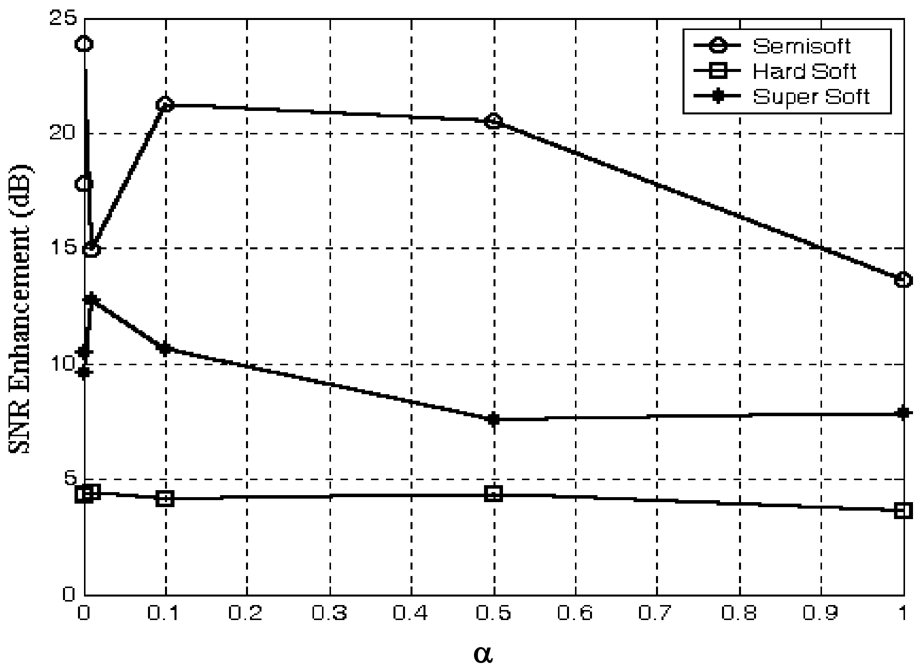

Figure (19) Comparison results between different types of thresholding using db6, γ =0.1, and SNR$_i$=5dB are used

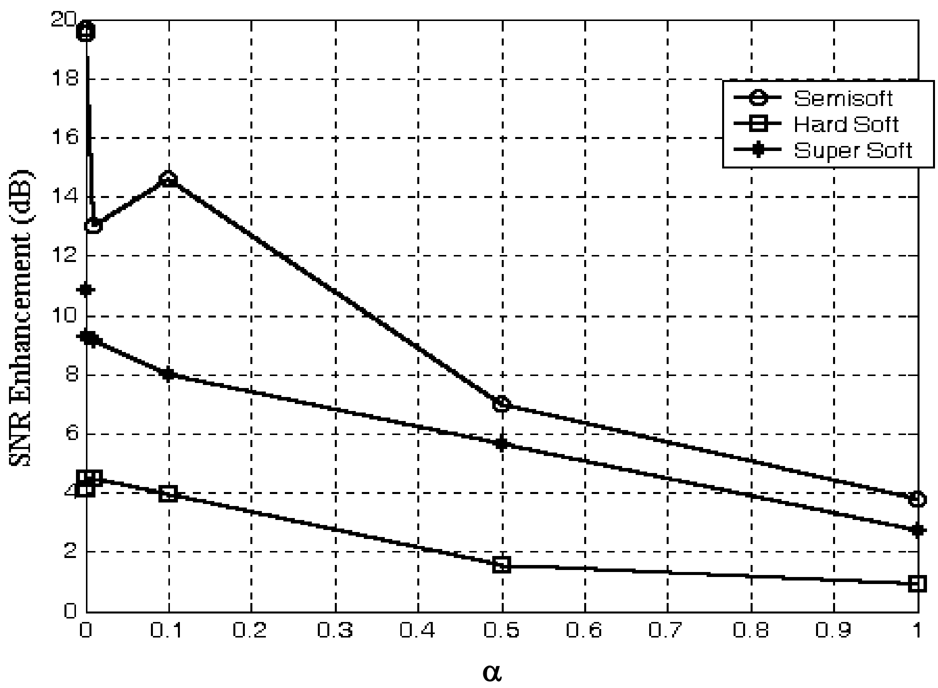

Figure (20) Comparison results between different types of thresholding using db6, γ =1and SNR$_i$=5 dB are used

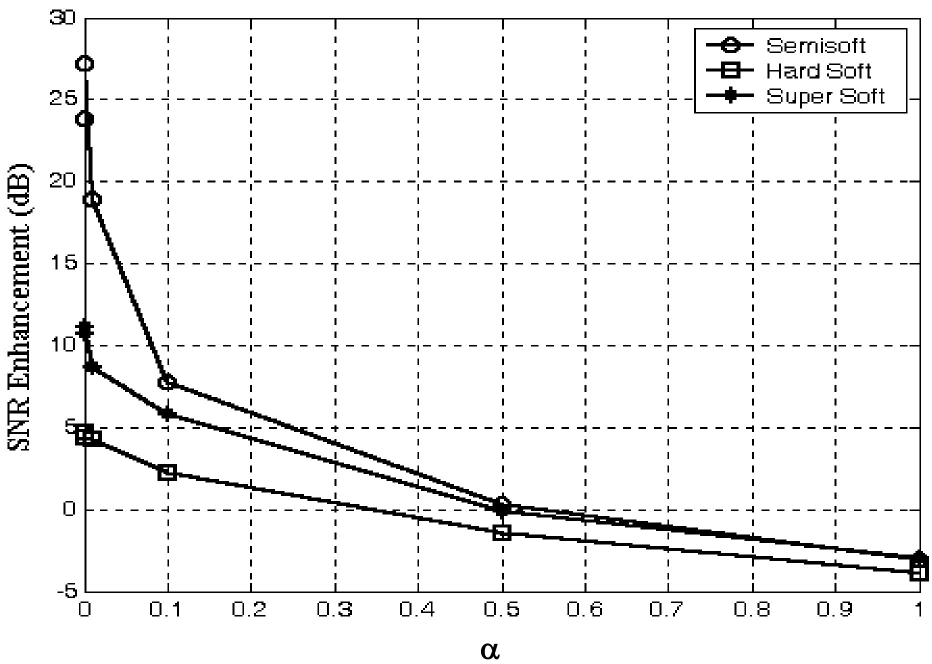

Figure (21) Comparison results between different types of thresholding using db6, γ =5 and SNR_i=5 dB are used

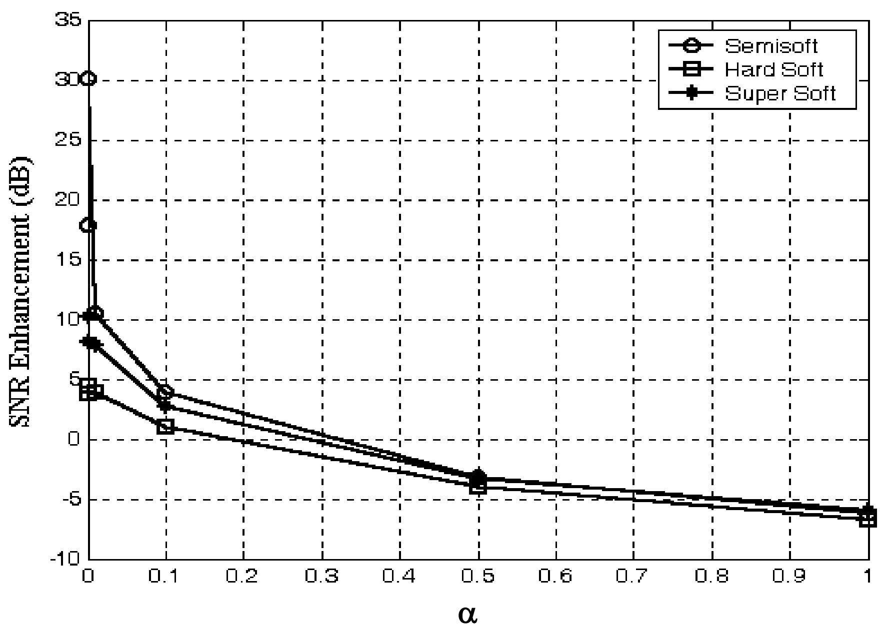

Figure (22) Comparison results between different types of thresholding using db6, γ =10 and SNR_i=5 dB are used

7. Conclusion

The following is a summary of the conclusion remarks.

The performance of speech denoising algorithm in the impulsive noisy environment depends on the impulsivity of the noise and its power relative to the AWGN.

For α=0 there is no affect of impulsive noise on the SNR enhancement, when α increases (more than 0 and less than 1), the value of SNR enhancement is decreased. For α=1 impulsive noise appears the same AWGN and gives the same effect on the SNR enhancement.

For γ=0 only Gaussian noise exist. When γ increases, SNR enhancement is decreased. Hard soft and super soft-thresholding depends on ρ value. The selection of ρ depends on SNR_i. It can be seen from **Figs.(16)** and **(19)** for low SNR_i selection the values of ρ near 0 (i.e. 0.1, 0.2 and 0.3) gives the best SNR enhancement. While for high SNR_i (more than 0 dB) certain value of ρ gives the best SNR enhancement.

DWT gives good performance for obtaining clean speech signal from impulse and AWGN channel. Semisoft threshold gives the best SNR enhancement over both super soft and hard soft threshold.

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