

Wavelet & Multiwavelet Lost Block Reconstruction in Noisy Environment

Waleed A. Mahmoud*, Mutaz S. Abdul-Wahab** & Atheer A. Sabri 

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Abstract

In this paper, an algorithm for reconstruction of a completely lost blocks using the discrete wavelet and multiwavelet transforms are tested under noisy environment.

The algorithms examined in this paper do not require a DC estimation method. While most of the previously reconstruction methods assume that the DC value is available or a DC estimation is required.

The reconstruction is achieved using the Boundary Interpolation (BI) which is based on wavelet transform. The algorithm's performance is further improved through the modification of the Boundary Interpolation algorithm.

Another algorithm is studied in this paper which is based on the multiwavelet transform.

The effect of adding a Gaussian noise to the image on the performance of reconstruction of the algorithms mentioned in this paper is studied.

Keywords: Wavelet, Multiwavelet, Lost Blocks.

أسترجاع الكتل المفقودة بأستخدام مجال المويجة والمويجة المتعددة في وسط ضوضاء

الخلاصة

في هذا البحث تم اختبار خوارزميات لأسترجاع الكتل المفقودة بصورة كلية بأستخدام مجال المويجة المنقطعة ومجال المويجة المتعددة المنقطعة في وسط يحتوي على ضوضاء. ان الخوارزميات التي تم اختبارها لاتحتاج الى توفر DC ولا تحتاج الى طرق إضافية لتخمين DC.

أن عملية الأسترجاع تم بأستخدام خوارزمية حدود المواد البينية (Boundary Interpolation) المعتمدة على مجال المويجة والتي تم تحسينها بأستخدام بعض التعديلات على خوارزمية حدود المواد البينية.

كذلك تم في هذا البحث دراسة خوارزمية تعتمد على مجال المويجة المتعددة المنقطعة وتأثير إضافة الضوضاء اليها.

Intruduction

In common wireless scenarios; the image is transmitted over the wireless channel block by block. So the image is tiled into blocks. Due to severe fading, entire image blocks can be lost [1]. E. Chang reports that average packet loss rate in a wireless

environment are 3.6 % and occur in a bursty fashion [1,2].

Error resilient channel coding schemes (e.g., Forward Error Correction) use Reed Solomon codes or convolutional codes to reconstruct the lost portion of the bit stream, sacrificing some useful bandwidth in the process. This method, which is

Colleg of Engineering /University of Baghdad

** Department of Electrical & Electronic / University of Technology

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2412-0758/University of Technology-Iraq, Baghdad, Iraq

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designed for a fixed bit error rate (BER), cannot completely prevent loss of data when the BER is unknown, as in most practical cases [1,3].

The common techniques to recover the lost block are grouped under Automatic Retransmission Query Protocols (ARQ). ARQ lowers data transmission rates and can further increase the network congestion, which can aggravate the packet loss [1,4]. Instead, it was shown that it is possible to satisfactorily substitute the lost blocks by using the available information surrounding them. The location of lost data, i.e., lost image blocks, is known in common wireless scenarios. The proposed scheme is tested with a variety of images and simulated block losses. It was shown that the substitution has an acceptable visual quality while high SNR is obtained.

Purely decoder based error concealment in baseline JPEG coded images has been demonstrated in the image domain and in the DCT domain. Various studies have successfully used the wavelet framework for texture synthesis [1,5], substitution of edges, which are distorted during compression [1,6], and enhancement of edges, which are blurred during interpolation [1,7].

V. DeBrunner, et al, provide a survey of commonly used error control and concealment methods in image transmission [1,8]. Image domain methods use interpolation [1,9], or separate substitution methods for structure and texture [1,10]. Most transform based methods, notably those described for MPEG-2 video [1,11] and earlier for DCT-JPEG images [9], assume a smoothness constraint on the image intensity. These methods define an object function, which measures the variation at the border between the lost block and its neighbors, and then proceed to minimize this object function. Z. Alkachouch and M.

Bellanger describes a different DCT based interpolation scheme, which uses only 8 border pixels to reconstruct the 64 lost DCT coefficients [1,12].

The Importance Of Multiwavelet Transform Over Wavelet Transform

Wavelets are useful tool for signal processing applications such as image compression and denoising [13]. Until recently, only wavelets were known, these are wavelets generated by one scaling function [14]. But one can imagine a situation when there is more than one scaling function. This leads to the notation of multiwavelets, which have several advantages in comparison to wavelets [15]. Such features as short support, orthogonality, symmetry, and vanishing moments are known to be important in signal processing. A wavelet can not possess all these properties at the same time [16]. On the other hand, a multiwavelets system can simultaneously provide perfect reconstruction while preserving length (orthogonality), good performance at boundaries (via linear phase symmetry), and a high order of approximation (vanishing moments). Thus, multiwavelets offer the possibility of superior performance for image processing applications compared with wavelets [13].

One of the important differences between multiwavelets and wavelets is that each channel in the filter bank has a vector-valued input and a vector-valued output. A scalar valued input signal must somehow be converted into a suitable vector-valued signal. This conversion is called preprocessing [13].

The Boundary Interpolation (Bi) Algorithm

Once the missing block has been detected and located, its size will be assumed of size $(m \times m)$. Next, the reconstruction of the lost blocks using the Boundary Interpolation algorithm will be initiated.

The stepwise computation of this algorithm is given below [14]:

- 1) The nearest row above the lost block will be taken (which has the same size of the column of the lost block, i.e., $1 \times m$) as shown in Fig(1), denoted as N.
- 2) The nearest row below the lost block will be taken (which has the same size of the column of the lost block, i.e., $1 \times m$) as shown in Fig(1), denoted as S.
- 3) The nearest column to the right of the lost block will be taken (which has the same size of the row of the lost block, i.e., $m \times 1$) as shown in Fig(1), denoted as E.
- 4) The nearest column to the left of the lost block will be taken (which has the same size of the row of the lost block, i.e., $m \times 1$) as shown in Fig(1), denoted as W.
- 5) The 1-D discrete wavelet transform for all the surrounding will be obtained. This gives the approximate (low frequency components) and detail (high frequency components) coefficients. Each has a dimension equals to one-half of its original size, i.e., $m/2$.
- 6) The values of the detail coefficients are translated as additional elements in their approximate elements with each of the new low frequency components having dimension of m . Thus the new approximate coefficients will be arranged as
- 7) $N_n, S_n, E_n,$ and W_n have been given zero values and all are vectors of length m .
- 8) By taking the 1-D inverse discrete wavelet transform for the new values of approximation and detail coefficients give the new values of

N, S, E, and W which is of size of $2m$.

- 9) Downsample the new values of N, S, E, and W.
- 10) Reconstruction of the lost block is done according to the following equation (that is found experimentally):

$$R(i,j) = (N(i) + W(j) + S(m-i+1) + E(m-j+1)) / 2$$

$$i = 1 \dots m, j = 1 \dots m \quad (4.1)$$

where R represents the reconstructed lost block, as shown in Fig(2).

The Modified Boundary Interpolation (Mbi) Algorithm

The Modified Boundary Interpolation (MBI) algorithm is implemented using the following steps [15]:-

- 1) Apply steps 1-8 of the proposed BI algorithm as given before.
- 2) The reconstruction of the first half of the top of the lost block will be achieved through averaging the nearest values indicated in Fig (3), i.e., N and W. Thus

$$T_1 = (W_1 + N_1) / 2,$$
 then

$$T_2 = (T_1 + N_2) / 2,$$
 and so on.
- 3) The reconstruction of the second half of the top of the lost block is done by averaging the nearest values indicated in Fig (3), i.e., N and E. Hence,

$$T_m = (E_1 + N_1) / 2,$$
 then

$$T_{m-1} = (T_m + N_2) / 2,$$
 and so on.
- 4) Step (2) will be repeated for the first halves of the bottom (by using S and W), right (by using E and N), and left (by using W and N) respectively.
- 5) Step (3) will be repeated for the second halves of the bottom (by using S and E), right (by using E and S), and left (by using W and S) respectively.
- 6) Now the size of the lost block will be decreased by (2).
- 7) Repeat steps 1-6 until all pixels of the lost block are reconstructed.

The Multiwavelet Boundary Interpolation (Mwbi) Algorithm

In this algorithm, Once the missing block has been detected which has a size of $(m \times m)$, the reconstruction of the lost blocks includes the following steps:-

- 1) Apply steps 1-4 of the BI algorithm given in section (3).
- 2) Compute the 1-D discrete multiwavelet transform for all N, S, E, and W.
- 3) Add zero elements with the same size of the multiwavelet coefficients as an additional elements to the multiwavelet coefficients.
- 7) The 1-D inverse discrete multiwavelet transform is taken for the new values of multiwavelet coefficients to give us the new values of N, S, E, and W with the double size of m.
- 8) The reconstruction of the first half of the top of the lost block is done by averaging the nearest values indicated in Fig.(3), i.e., N and W.

$$T_1 = (W_1 + N_1) / 2,$$
then $T_2 = (T_1 + N_2) / 2$, and so on.
- 9) The reconstruction of the second half of the top of the lost block is done by averaging the nearest values indicated in Fig.(2), i.e., N and E.

$$T_m = (E_1 + N_1) / 2,$$
then $T_{m-1} = (T_m + N_2) / 2$, and so on.
- 10) Step (8) is repeated for the first half of the bottom (by using S and W).
- 11) Step (9) is repeated for the second half of the bottom (by using S and E).
- 12) Repeat steps (8-11) until the whole lost block (R_1) is found.
- 13) Transpose the image.
- 14) Repeat steps (1-12) to get the lost block (R_2).
- 15) The final reconstructed lost block is found by

$$R = (R_1 + R_2^t) / 2$$

where R_2^t is the transpose of the matrix R_2 .

Experimental Results

Now the effect of adding noise on the algorithms of reconstruction of lost blocks are considered here.

First of all, the effect of adding noise on the performance of reconstruction of lost blocks is considered separately on each algorithm. Next, a comparison is made among them to find the optimum algorithm for lost block reconstruction.

The Effect of Noise on the Performance of BI Algorithm

In order to test the reconstruction algorithm using the wavelet transform, the Gaussian noise effect on its performance is studied here using three well known wavelet functions. These are: Haar, Daubchies, and Biorthogonal.

Figures (4) to (6) show that adding noise to the image does not affect the performance of reconstruction when using the Daubchies and Biorthogonal wavelet function as much as it affects the performance of reconstruction when using the Haar wavelet function.

The Effect of Noise on the Performance of MBI Algorithm

Next, in order to test the performance reconstruction of the MBI algorithm using the wavelet transform, the Gaussian noise effect on its performance is studied here using three well known wavelet functions previously mentioned.

It can be easily seen from figures (7) to (9) that the Haar wavelet function gives the best performance among them.

The Effect of Noise on the Performance of MWBI Algorithm

Finally, to test the reconstruction algorithm using the multiwavelet transform, the Gaussian noise effect on its performance is studied here.

There are two methods to find the multiwavelet coefficients [16]. These are Repeated Row of Preprocessing (RRP) and Critically-Sampled scheme of Preprocessing (CSP).

Figures (10) to (12) show that RRP is better than CSP in the reconstruction the lost blocks.

Comparison Among the Performance of the Algorithms

Figures (13) to (15) compare between BI, MBI, and MWBI algorithms for the Lena, Clown, and Trees images respectively. It can be easily concluded that the MWBI algorithm which is based on the multiwavelet transform is the best among them when the image is contaminated by noise.

Conclusions

Algorithms are presented in this paper and their performance are examined in noisy environment.

Without noise, and for BI algorithm, it can be concluded that the reconstruction is not good when using Daubchies and Biorthogonal wavelet basis function by using the human visual display. This is because the Haar wavelet function has only two taps for the low and high frequency filters, while for Daubchies and Biorthogonal there are more than two taps for the two low and high frequency filters which make the pixel values distributed over more pixels not in the vicinity of the nearest pixels. So to improve the algorithm, some modifications have been made to reconstruct the lost blocks from the nearest pixels which is done using the MBI. Also, it is found that the MBI algorithm which is based on wavelet

transform gives the best performance among them.

After adding noise, it is found that MWBI algorithm which is based on the multiwavelet transform gives the best performance among them because of the existence of the multifilters (which is a 2-D filter) in the multiwavelet transform.

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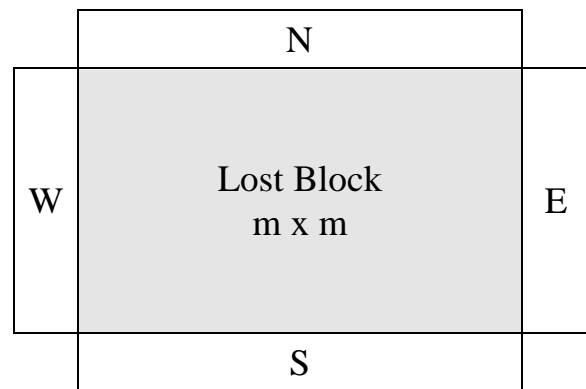


Fig.(1). The Demonstration of N, S, E, and W

	N₁	N₂	N_{m-1}	N_m	
W₁	R(1,1)	R(1,2)	R(1,m-1)	R(1,m)	E₁
W₂	R(2,1)	R(2,2)	R(2,m-1)	R(2,m)	E₂
⋮	⋮
⋮	⋮
⋮	⋮
W_{m-1}	R(m-1,1)	R(m-1,2)	R(m-1,m)	E_{m-1}
W_m	R(m,1)	R(m,2)	R(m,m-1)	R(m,m)	E_m
	S₁	S₂	S_{m-1}	S_m	

Fig(2) The Reconstruction of the Lost Block Using the BI Algorithm

	N₁	N₂	...	N_{m/2}	N_{m-1}	N_m	
W₁	T ₁	T ₂					T _{m-1}	T _m	E₁
W₂									E₂
⋮									⋮
W_{m/2}									E_{m/2}
⋮									⋮
⋮									⋮
W_{m-1}									E_{m-1}
W_m									E_m
	S₁	S₂	...	S_{m/2}	S_{m-1}	S_m	

Fig.(3). The Reconstruction of The Lost Block Using the MBI & MWBI Algorithms

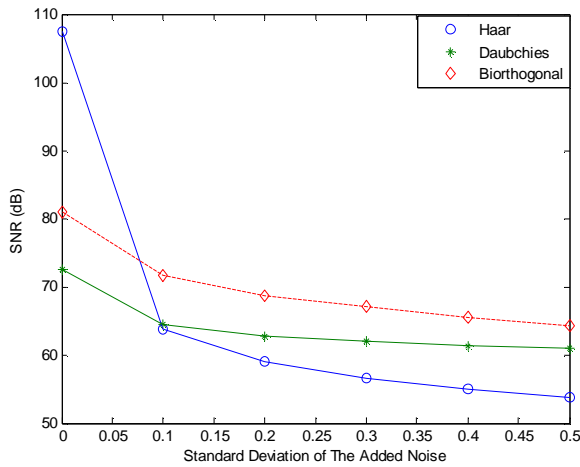


Fig (4) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using BI algorithm for Lena image

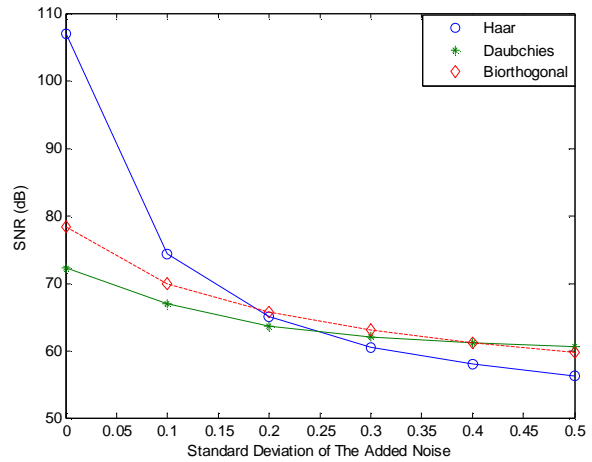


Fig (5) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using BI algorithm for Clown image

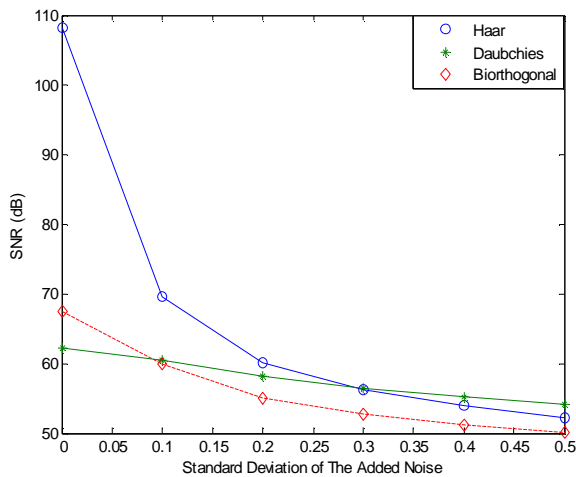


Fig (6) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using BI algorithm for Trees image

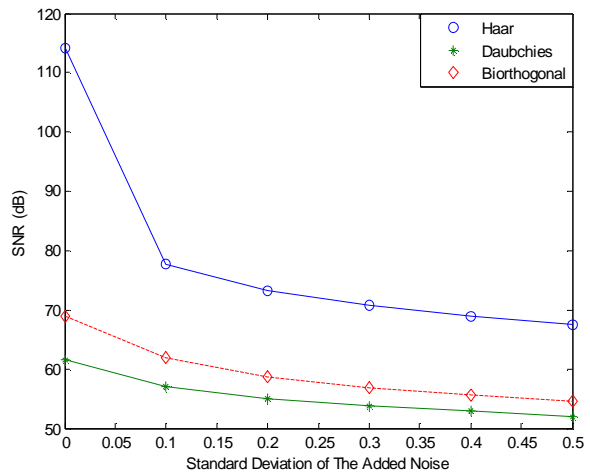


Fig (7) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using MBI algorithm for Lena image

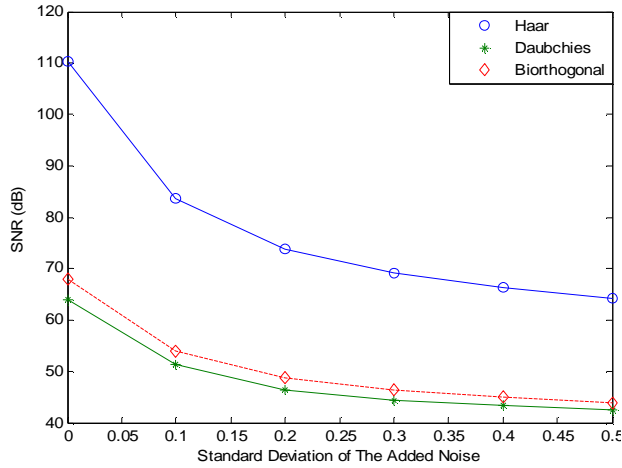


Fig (8) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using MBI algorithm for Clown image

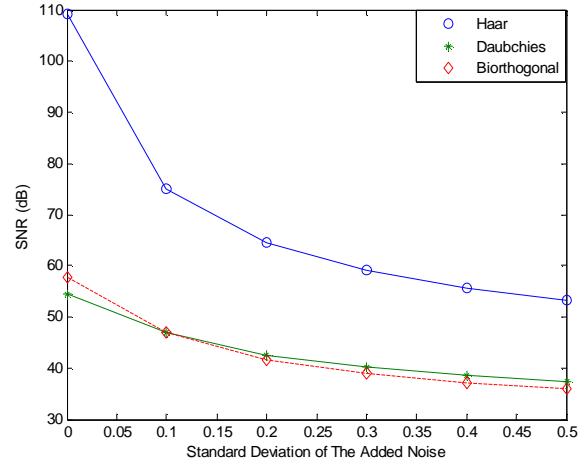


Fig (9) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using MBI algorithm for Trees image

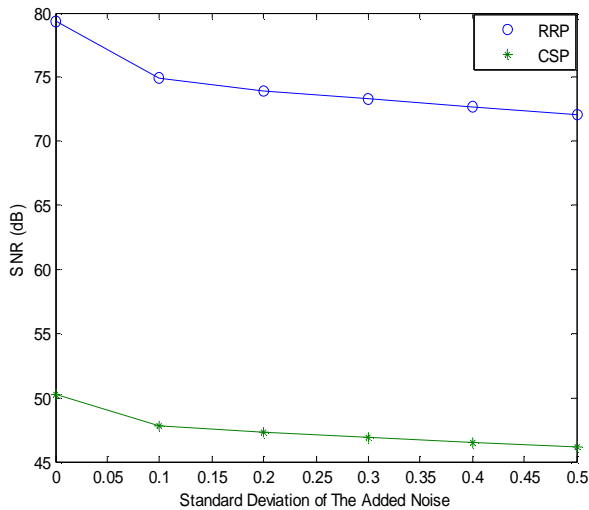


Fig (10) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using MWBI algorithm for Lena image

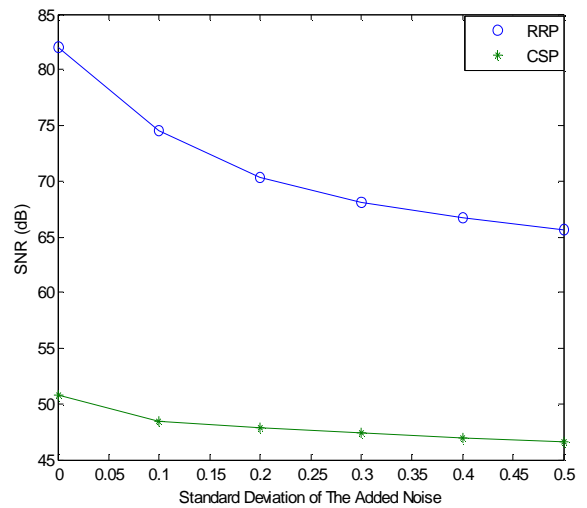


Fig (11) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using MWBI algorithm for Clown image

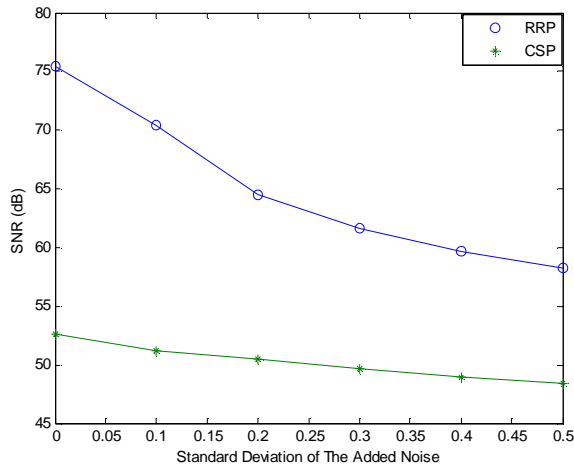


Fig (12) The effect of the Gaussian noise on the performance of reconstruction of the lost blocks using MWBI algorithm for Trees image

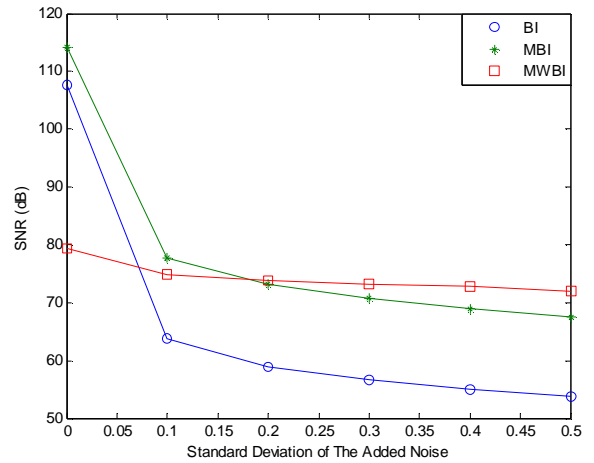


Fig (13) Comparison between BI, MBI, and MWBI algorithms when a Gaussian Noise is added to them for the Lena Image

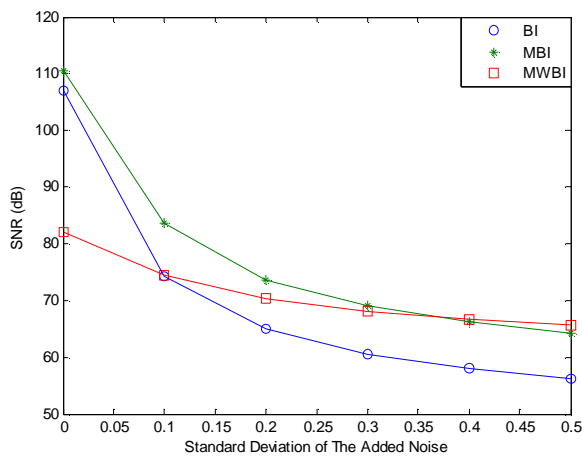


Fig (14) Comparison between BI, MBI, and MWBI algorithms when a Gaussian Noise is added to them for the Clown Image

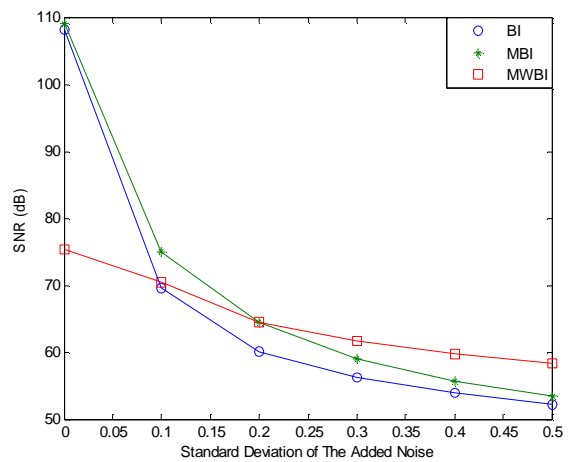


Fig (15) Comparison between BI, MBI, and MWBI algorithms when a Gaussian Noise is added to them for the Trees Image