A Comparative Analysis to Determine the Optimum Approach for Image Denoising

KalyanChatterjee, PrasenjitMaji, Arka Banerjee, Debarati Das, Manisha Gupta

Abstract: Image denoising demands serious attention and is usually the first and foremost step in any image processing application. Erroneous denoised results lead to improper and inaccurate final results. So it is of prime importance to eliminate the noise from the image to the utmost extent..In this paper an analysis is performed for image denoising by imposing different types of noise on the original image,using a choice of wavelet decomposition techniques and also different feasible thresholding techniques to find the optimum denoised result image and also the best combination involved in the process .

Index Terms: Image Denoising,Discrete Wavelet Transformation,Wavelet Decomposition,Wavelet Thresholding

I. INTRODUCTION

Denoising[1] is the process of elimination of noise from a signal or an image. Random noises of type Gaussian,salt & pepper,speckle,poisson etc. may get generated in an image or signal in the due course of processing . This alteration or modification has adverse impacts on the image quality and also causes the deterioration of the final obtained result .

Image denoising by itself is a very crucial step which may either be the sole purpose or a secondary stage in an image processing application. The denoising of images may happen during acquisition or may also be the result of modifications during the course of processing. Denoising aims at removal of noise without causing loss of information and all the while conserving vital features .As can be gauged from above, image denoising has animportant role to play in the field of image processing.

A lot of research work has been done on image denoising involving wavelet decomposition,wavelet thresholding and discrete wavelet transformation.

Wavelets are extremely efficient in distinguishing between the noise and the image or signal features since they are very good at energy compaction creating small coefficients for noise and large coefficients for other features.

Thresholding further helps in reducing noise by making the value of the smaller coefficients zero.

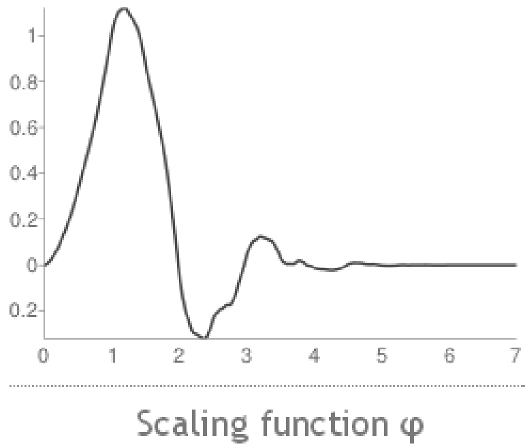
In this paper we have done a comparative analysis by taking different inputs at each stage of the denoising process and comparing the PSNR and MSE values to check which combination of inputs outperforms the rest.

II. WAVELET DECOMPOSITION

In this paper the following wavelets have been used:

A. Symlet Wavelet

1. The symlet wavelets are the proposed modified wavelets to the db unit which are nearly symmetrical in nature characterized by the symlet function .The symlet functions range from sym2 to sym8. In this analysis the sym2 wavelet function has been used.[2,3]



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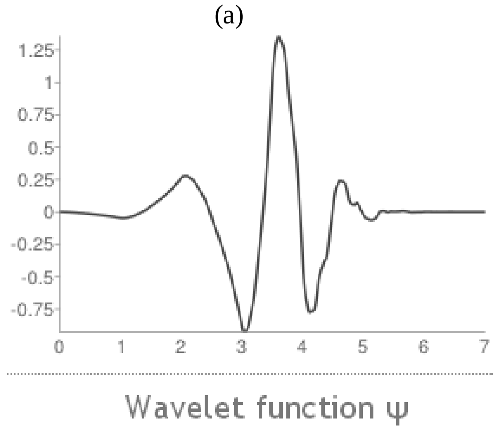

(b)

Fig 1. (a)Sym2 wavelet scaling function (b) Sym2 wavelet function

B. Daubechies Wavelet

The DaubechiesWavelet[4,5] are a set of orthogonal wavelets , characterized by a maximum number of vanishing moments for a given support .

An orthogonal multiresolutionanalysis is generated with each

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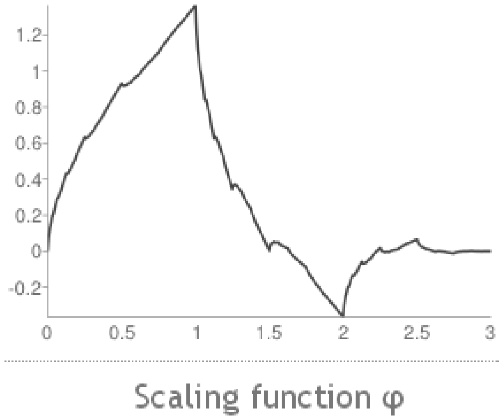
scaling function for a particular class of wavelet.

- *Db2*



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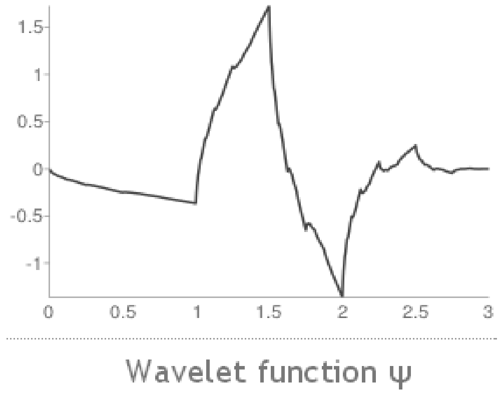

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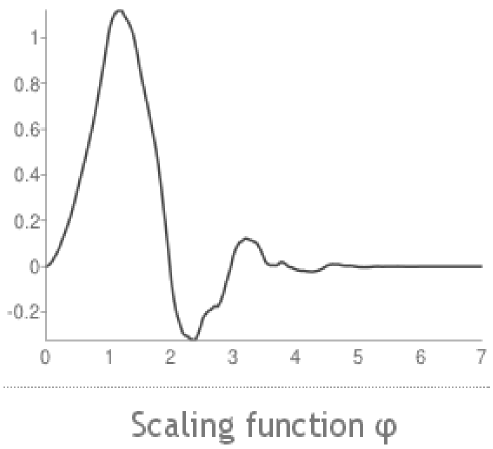
Fig 2. a) Db2 scaling function b) Db2 wavelet function

- *Db4*



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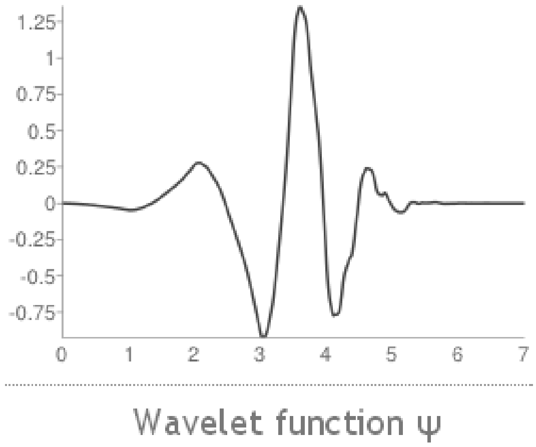

(b)

Fig 3. a) Db4 scaling function b) Db4 wavelet function

III. WAVELET THRESHOLDING

The wavelet denoising technique can be specified as follows. Let us assume that the noisy data is given by the following equation,

X (t) = S (t) + N (t)…………………….(1)

Where, S(t) represents the original or uncorrupted signal and N(t) is the additive noise in the signal. When noise isintroduced into the signal it produces the corrupted image X(t) . Gaussian Noise is uniformly distributed over the signal. As a result every pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. In Salt and Pepper Noise the corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a “salt and pepper” like appearance. Uncorrupted pixels remain unchanged. Let W (.) and W-1(.) denote the forward and inverse wavelet transform operators. Let D (., λ) denote the de-noising operator with threshold λ. We aim to de-noise X(t) to recuperate Ŝ(t) as an approximation of S(t).The technique can be abridged in three steps

Y = W(X)…………………………….. (2)

Z = D(Y, λ) …………………………….(3)

Ŝ = W-1 (Z) ……………………………(4)

D (., λ) being the thresholding operator and λ being the threshold.WaveletThresholding[6,7,8,9] is a signal assessment technique that exploits the potential of wavelet transform essential for signal de-noising. Denoising is done by eradicating the extraneous coefficients that are relative to various threshold values.Wavelet shrinkage is generally performed using one of two principal thresholding schemes, namely hard and soft thresholding.The hard threshold filter removes coefficients below a threshold value, determined by the noise variance. The mentioned technique is occasionally referred to as the “keep or kill” method. On the other hand, wavelet coefficients are shrinked above and below the threshold in Soft thresholding. Soft thresholding tends to reduce coefficients towards zero. The hard thresholding(5) and soft thresholding(6) operator are defined as follows:

D (U, λ) = U for all |U|> λ……………..(5)

D (U, λ) = sgn (U) max (0, |U| - λ)……(6)

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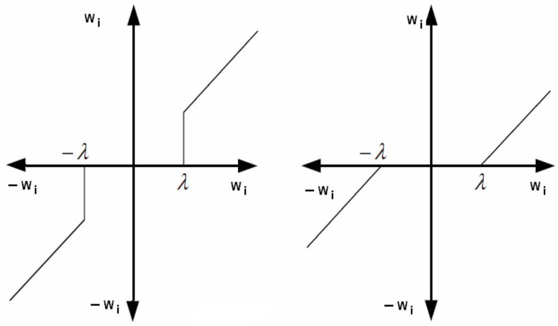

Fig 4. Hard Thresholding and Soft Thresholdingrespectively.[10]

In hard-thresholdingfunction all wavelet coefficients are selected that are larger than the given λ (threshold) and the other values are set to zero. In Soft thresholding wavelets coefficients are shrinked by λ towards zero. According to the signal energy and the noise variance (σ2) λ is chosen.

IV. DISCRETE WAVELET TRANSFORMATION

Wavelet transformation is one of the most accepted application of the time-frequency-transformations where a multi resolution decomposition technique is applied with respect to expansion of an image onto a set of wavelet basis functions. Discrete Wavelet Transform (DWT)[11,12] is the discrete variant of the wavelet transform based on the tree structure with D levels that can be applied by using a suitable pool of filters.The DWT is a dominant iterative procedure for decomposition of a signal into approximation (low frequency) and detail(high frequency) waveforms. The first level of decomposition of the signal is into coefficients of approximation, *cA1*, and coefficients of detail, *cD1*. The coefficients *cA1* are further processed accordingly into*cA2* and *cD2* to produce the second level of decomposition. The steps can continue for the *ith*level of decomposition for which *cAi*and *cDi*are calculated from *cAi*-1. The DWT coefficients can be used at each level to restructure the approximationand the elementof the original signal.

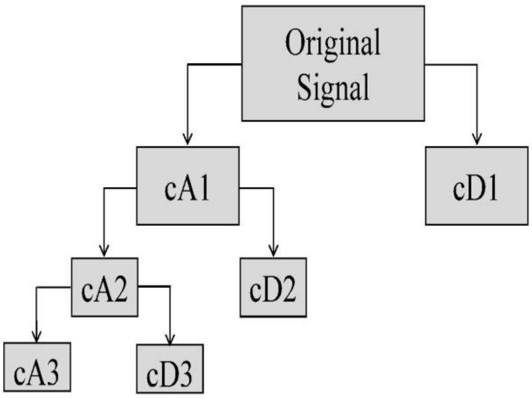

Fig 5.A Three Level Decomposition of the DWT Coefficients[11]

V. PROPOSED METHOD

A. *Add noise to the original image*

We have taken into consideration four types of noise :

i. Gaussian
ii. Salt and pepper
iii. Speckle
iv. Poisson

B. *Wavelet decomposition of the original image*

Three types of wavelets have been considered :

i. Sym2
ii. Db2
iii. Db4

C. *Thresholding*

The thresholding techniques taken into account are:

- Soft thresholding
- Hard thresholding

D. *Discrete Wavelet Transformation using level 1 and 2*

The repetitive decomposition of an image is performed at level 1 and 2 respectively and the corresponding values are calculated.

E. *Calculation of PSNR and MSE values of the denoised image*

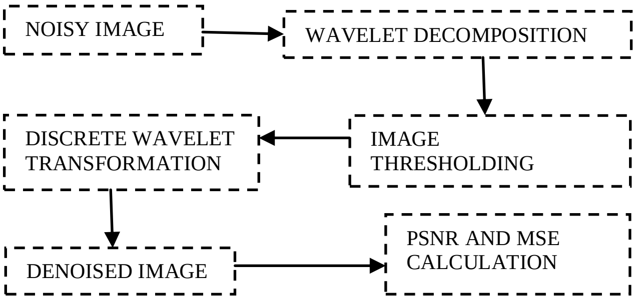

Fig 6. Process of denoising and calculation of values

VI. RESULTS AND DISCUSSIONS

To measure the image quality after denoising we use two error calculation metrics, PSNR (Peak Signal to Noise Ratio)and MSE (Mean Square Error).

A. *Peak Signal To Noise Ratio(PSNR)*

Peak signal to noise ratio is a parameter that is used to measure the difference between two images, in this case(original image and denoised image).It measures the peak error value. The value of the psnr is based on the mse(mean square error), which is given by the formula,[7]

$$\text{MSE}=\frac{1}{M*N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(f(i,j)-g(i,j))^2 \;\ldots\ldots.(1)$$

And likewise PSNR can be calculated from the formula,

$$\text{PSNR}=10*\log_{10}\left(\frac{255^2}{MSE}\right)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.....(2)$$

Hence,PSNR can be defined as the ratio of the square of the peak signal value to the noise variance. Preferably the value of PSNR should be high which would mean greater similarity between the original and denoised image.The following tables shows the comparative study based on different parameters in the cases of wavelet thresholding at different decomposition levels. We have taken the percentage of noise imposed as 0.2 in each case.

TYPE OF NOISE	WAVELET	THRESHOLDING	LEVEL OF DECOMPOSITION	PSNR	MSE
GAUSSIAN	SYM	SOFT	1	62.3243	49.9535
SALT AND PEPPER	SYM	SOFT	1	65.6517	34.0562
SPECKLE	SYM	SOFT	1	66.5459	30.7247
POISSON	SYM	SOFT	1	76.038	10.3181
GUASSIAN	SYM	HARD	1	62.327	49.9050
SPECKLE	SYM	HARD	1	66.5941	30.5544
POISSON	SYM	HARD	1	76.5220	9.7428
GUASSIAN	SYM	SOFT	2	62.3576	49.7622
SALT AND PEPPER	SYM	SOFT	2	68.5465	24.4037
SPECKLE	SYM	SOFT	2	69.0126	23.1287
GUASSIAN	SYM	HARD	2	62.3509	49.8008
SALT AND PEPPER	SYM	HARD	2	66.6617	30.3176
SPECKLE	SYM	HARD	2	68.9616	23.2649
POISSON	SYM	HARD	2	75.4682	10.9995

I. Comparison of PSNR and MSE values for different inputs

(a)

(b)

(c)

Fig 7 (a).Original Image (b). Noisy image (Salt & Pepper) (c).Denoisedimage(using sym wavelet and soft thresholding)

II. Comparison of PSNR and MSE values for different inputs

GAUSSIAN	DB2	SOFT	1	62.3404	49.8611
SALT AND PEPPER	DB2	SOFT	1	65.7086	33.8339
SPECKLE	DB2	SOFT	1	66.5710	30.6360
POISSON	DB2	SOFT	1	76.0269	10.3141
GAUSSIAN	DB2	HARD	1	62.3531	49.8352
SALT AND PEPPER	DB2	HARD	1	64.5192	38.7991
SPECKLE	DB2	HARD	1	66.4788	30.9627
POISSON	DB2	HARD	1	76.4948	9.7824
GAUSSIAN	DB2	SOFT	2	62.3164	49.9987
SALT AND PEPPER	DB2	SOFT	2	68.6439	24.1316
SPECKLE	DB2	SOFT	2	68.9924	23.0713
POISSON	DB2	SOFT	2	74.1965	12.7337
GUASSIAN	DB2	HARD	2	62.3447	49.8359
SALT AND PEPPER	DB2	HARD	2	66.5831	30.5933
SPECKLE	DB2	HARD	2	70.7849	23.0979
GUASSIAN	DB4	SOFT	1	62.3429	49.8467
SALTAND PEPPER	DB4	SOFT	1	65.6938	33.8914
SPECKLE	DB4	SOFT	1	66.5767	30.6158
POISSON	DB4	SOFT	1	76.4963	9.7716
GUASSIAN	DB4	HARD	1	62.3537	49.7845
SALTAND PEPPER	DB4	HARD	1	64.7163	37.9286
SPECKLE	DB4	HARD	1	66.5186	30.8214
POISSON	DB4	HARD	1	76.8509	9.3807
GUASSIAN	DB4	SOFT	2	62.3748	49.6639
SALTAND PEPPER	DB4	SOFT	2	68.7618	23.8062
SPECKLE	DB4	SOFT	2	69.1628	22.7322
POISSON	DB4	SOFT	2	74.5577	12.2150
GUASSIAN	DB4	HARD	2	62.3687	49.6986
SALTAND PEPPER	DB4	HARD	2	66.7897	29.8742
SPECKLE	DB4	HARD	2	69.1177	22.8505
POISSON	DB4	HARD	2	75.7808	10.6107

VII CONCLUSION

As the results indicate the values of PSNR and MSE are tremendously affected by change in any parameter whether it be the noise imposed, the wavelet used for decomposition,the thresholding method or the level of decomposition. As for the image under anlaysis ,i.e lena.jpg the best result is obtained by imposing poisson noise , followed by db4 wavelet decomposition and using hard thresholding and level of decomposition as 1.

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