DBMF & DWT THRESHOLDING ALGORITHMS FOR REMOVAL OF SALT & PEPPER NOISE

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Abstract: Denoising is an important aspect of image processing. There is so many kinds of disturbances encounters during transmission, storage and reproduction of image are responsible to corrupt the image. These corrupted features are known as noise. This paper is organized in such a way that first image is denoised then important features like edges, corners and other soft features are preserved. To achieve this patch based image denoising technique i.e. Decision based median filter (DBMF) algorithm followed by thresholding based DWT scheme is used to effectively reduce noise while preserving relevant features of the original image. Simulation result shows that the proposed algorithm provides better performance than other existing algorithms.

KEYWORD: DWT, PSNR, MSE, DBMF

I. INTRODUCTION

During acquisition and transmission, images are inevitably contaminated by noise. As an essential and important step to improve the accuracy of the possible subsequent processing, image denoising is highly desirable for numerous applications, such as visual enhancement, feature extraction, and object recognition. The purpose of denoising is to reconstruct the original image from its noisy observation as accurately as possible, while preserving important detail features such as edges and textures in the denoised image. To achieve this goal, over the past several decades, image denoising has been extensively studied in the signal processing community, and numerous denoising techniques have been proposed in the literature.

In general, denoising algorithms can be roughly classified into three categories: 1) spatial domain methods; 2) transform domain methods; and 3) hybrid methods. The first class utilizes the spatial correlation of pixels to smooth the noisy image, the second one exploits the sparsity of representation coefficients of the signal to distinguish the signal and noise, and the third one takes advantage of spatial correlation and sparse representation to suppress noise[1].

DENOISING an image is a fundamental task for correcting defects produced during the acquisition process of a real world scene and its reproduction on a display, due to physical and technological limitations. It can also be useful as a pre-processing stage in order to improve the results of higher level applications. The problem of removing the noise of an image while preserving its main features (edges, textures, colors, contrast, etc.) has been extensively investigated over the last two decades and several types of approaches have been developed [2].

Images are produced to record or display useful information. Due to the visibility of images and the rapid development of science and technology, images play an increasingly important role in our lives. However, because of imperfections in the imaging and capturing process, the recorded image invariably represents a degraded version of the original scene [4].

II. LITERATURE

Qiang Guo e.al [1] Nonlocal self-similarity of images has attracted considerable interest in the field of image processing and has led to several state-of-the-art image denoising algorithms, such as block matching and 3-D, principal component analysis with local pixel grouping, patch-based locally optimal wiener, and spatially adaptive iterative singular-value thresholding. In this paper, we propose a computationally simple denoising algorithm using the nonlocal self-similarity and the low-rank approximation (LRA). The proposed method consists of three basic steps. First, our method classifies similar image patches by the block-matching technique to form the similar patch groups, which results in the similar patch groups to be low rank. Next, each group of similar patches is factorized by singular value decomposition (SVD) and estimated by taking only a few largest singular values and corresponding singular vectors. Finally, an initial denoised image is generated by aggregating all processed patches.

Gabriela Ghimpe¸teanu et.al [2]: In this paper, authors consider an image decomposition model that provides a novel framework for image denoising. The model computes the components of the image to be processed in a moving frame that encodes its local geometry (directions of gradients and level lines). Then, the strategy we develop is to denoise the components of the image in the moving frame in order to preserve its local geometry, which would have been more affected if processing the image directly. Experiments on a whole image database tested with several denoising methods show that this framework can provide better results than denoising the image directly, both in terms of Peak signal-to-noise ratio and Structural similarity index metrics.

Mia Rizkinia et.al [3]: Author's propose a method for local spectral component decomposition based on the line feature of local distribution. Our aim is to reduce noise on multi-channel images by exploiting the linear correlation in the spectral domain of a local region. We first calculate a linear feature over the spectral components of an M-channel image, which we call the spectral line, and then, using the line, we decompose the image into three components: a single M-channel image and two gray-scale images.

III. IMAGE DENOISING TECHNIQUES

There are two basic approaches to image and video denoising, spatial filtering methods and transform domain filtering methods. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. The median filter replaces the middle pixel in the window with the median value of its neighbors. The idea used here is to examine a sample of the input and decide whether it is representative of the signal. This is done with a window (local filtering) consisting of an odd number of samples. The values in this window are sorted into numerical order; the median value that is the centre value of the window is selected as the output. After discarding the old sample, a new sample is acquired, and the calculation repeats [5].

Image denoising using thresholding methods means find appropriate value (threshold) which separates noise values to actual image values without affecting the significant features of the image. Discrete wavelet transforms are widely used for image denoising because of discrete nature of images presents now a day.

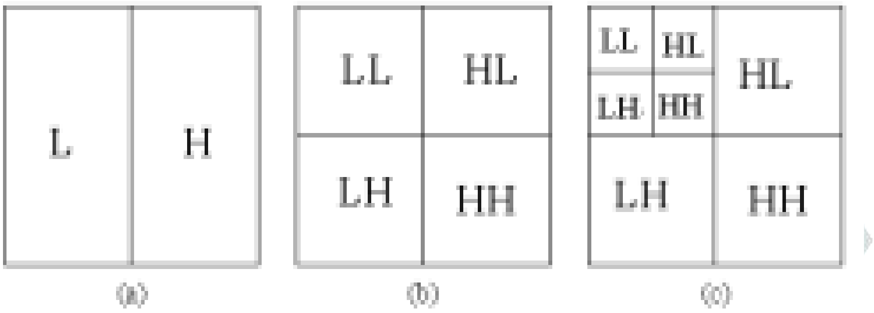

Figure.1 The two level wavelet decomposition as shown in fig (a), (b) & (c)

In wavelet domain, the noise is uniformly spread throughout the coefficients, while most of the image information is concentrated in the few largest coefficients. In DWT an image is filtered into four sub bands at each resolution and the sub band which has lowest frequency sub band is further subdivided through an iterative process to provide the multi resolution representation as shown in fig (1). When an image is decomposed using wavelet transform, the four sub images are produced approximation, horizontal details, vertical details and diagonal details.

IV. THRESHOLDING AND THRESHOLD ESTIMATION TECHNIQUE

It has been observed that in many signals, energy is mostly concentrated in a small number of dimensions and the coefficients of these dimensions are relatively large compared to other dimensions or to any other signal (especially noise) that has its energy spread over a large number of coefficients. The simpler way to remove noise or to reconstruct the original image using the wavelet coefficients used the result of decomposition in wavelet transform, is to eliminate the small coefficient associated to the noise. Threshold selection is an important question when denoising. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients. This leads to a smooth signal. Paying too much attention to smoothness, however, destroys details and in image processing may cause blur and artifacts [7]. The thresholding is classified into two categories:

A. Hard Thresholding:

Hard thresholding can be defined as follow:

$$D(U, \lambda) = U \text{ for all } |D| > \lambda \qquad \text{.... (1)}$$
$$= 0 \text{ otherwise}$$

Hard threshold is a "keep or kill" procedure and is more intuitively appealing. The Hard thresholding may seem to be natural. Sometimes pure noise coefficients may pass the hard threshold and appear as annoying “blips” in the output [6].

B. Soft Thresholding:

Soft thresholding can be defined as follows:

$$D(U, \lambda) = \text{sgn}(U) \max(0, |U| - \lambda) \qquad \text{.... (2)}$$

Soft threshold shrinks coefficients above the threshold in absolute value. The false structures in hard thresholding can overcome by soft thresholding. Now a days, wavelet based denoising methods have received a greater attention [6].

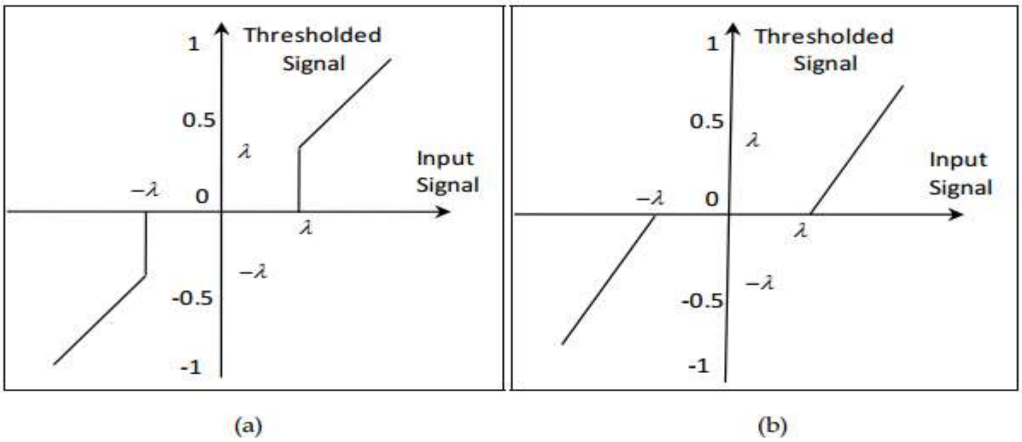

Figure.2 Threshold types: a. Hard, b. Soft.

V. PROPOSED ALGORITHM

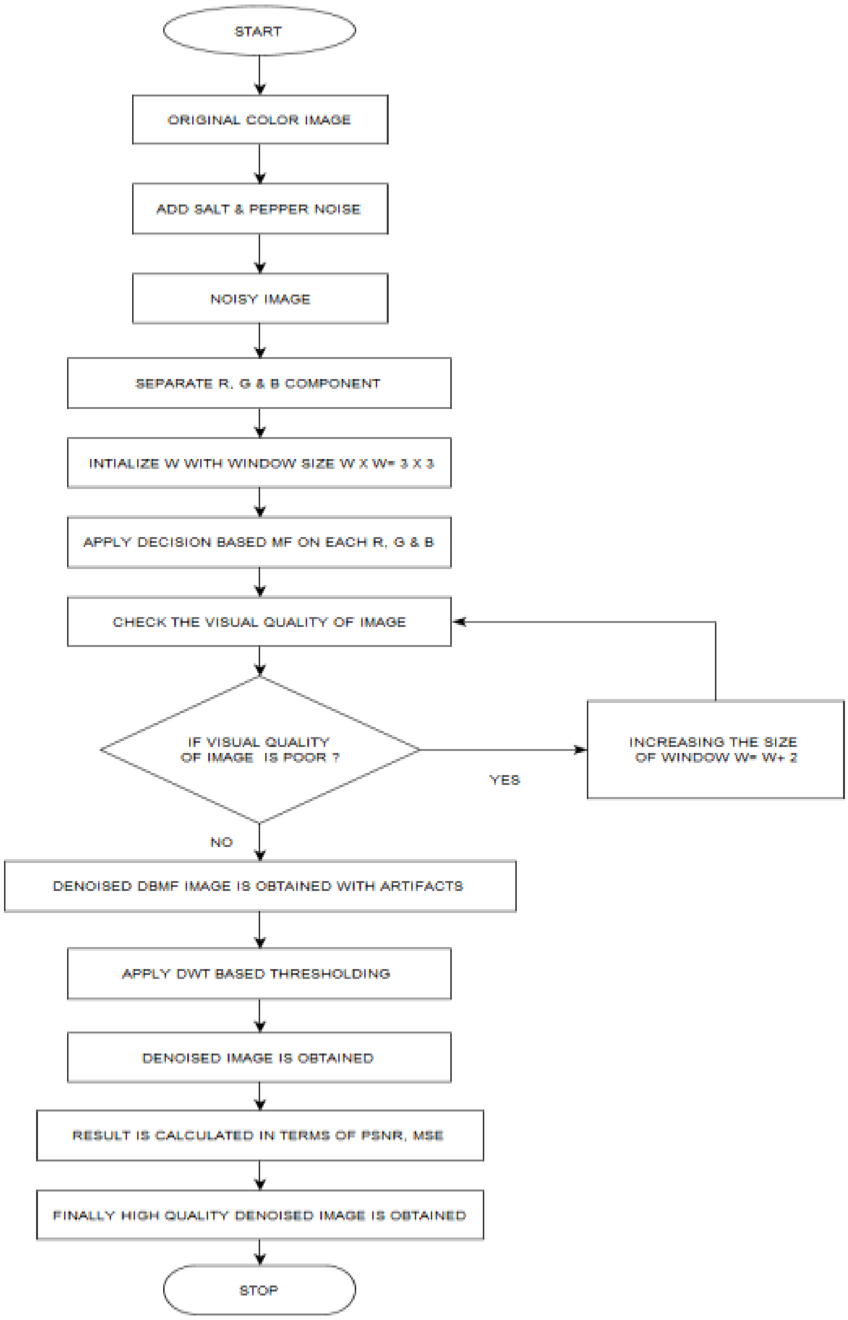

Figure 3: Flow chart of proposed algorithm

To perform the algorithm, we start with any color image and it is corrupted with impulsive noise so the image becomes noisy. Now to eliminate impulsive noise first median filter is applied on the noisy image. Initialize with window size with w= 3 x 3 increasing the size of window until to get the correct median value for noise free estimation. The output of BDMF does not take care about particular image features such as edges & other details. In this way some artifacts are obtained. It is required to smooth these artifacts & to preserve edges. To achieve this DWT based thresholding algorithm is used to smooth the artifacts. It is our proposed method. Finally denoised image is obtained by proposed DWT5 based thresholding algorithm after obtaining the denoised image is applied.

VI. EXPERIMENTAL RESULTS

Experiments are performed on the 512x512 noisy images. In this experiment images contaminated by Salt & pepper with different noise variance: σ = 10, 30, 40, 60 & 80 %. Figure 4: a, b, c & d respectively demonstrates denoising result of salt & pepper noise with noise variance σ = 10 % of test image 1 as: (a) noisy image (b) are the output of Decision based median filter (c)are the output of ref [1](d) are the output of the proposed method. Similarly fig 6,7,8 &9 shows the denoising results of test image 1 with noise variance σ = 30 %, 40 %, 60 % & 80%.

(a) (b) (c) (d)

Figure 4: Denoising result of salt & pepper noise with noise variance σ= 10 (a) Noisy image (b) output of DBMF (c) output of Ref [1] (d) output of Proposed Algorithm

(a) (b) (c)

Figure 5: Visual comparisons of the denoising results of the proposed algorithm and other state-of-the-art methods for the Test image 1 (a) output of DBMF (b) output of Ref [1] (c) output of Proposed Algorithm

(a) (b) (c) (d)

Figure 6: Denoising result of salt & pepper noise with noise variance σ= 30 (a) Noisy image (b) output of DBMF (c) output of Ref [1] (d) output of Proposed Algorithm

(a) (b) (c) (d)

Figure 7: Denoising result of salt & pepper noise with noise variance σ= 40 (a) Noisy image (b) output of DBMF (c) output of Ref [1] (d) output of Proposed Algorithm

(a) (b) (c) (d)

Figure 8: Denoising result of salt & pepper noise with noise variance σ= 60 (a) Noisy image (b) output of DBMF (c) output of Ref [1] (d) output of Proposed Algorithm

(a) (b) (c) (d)

Figure 9: Denoising result of salt & pepper noise with noise variance σ= 80 (a) Noisy image (b) output of DBMF (c) output of Ref [1] (d) output of Proposed Algorithm

TABLE 1: COMPARISION OF DENOISING METHODS FOR TEST IMAGE 1

IMAGES	NOISE VARIANCE	COMPA RISION PARAR	DIFFERENT DENOISING METHODS			
			NOISY IMAGE	DBMF	REF [1]	PROPOSED METHOD
Test Image1	σ = 10	PSNR	20.03	34.14	35.52	40.61
		MSE	645.8	22.93	15.50	6.06
	σ = 30	PSNR	18.77	32.91	32.74	38.32
		MSE	863	36.35	35.61	9.572
	σ = 40	PSNR	18.22	31.39	31.80	37.32
		MSE	979.6	29.83	31.23	13.97
	σ = 60	PSNR	17.96	28.14	29.86	34.12
		MSE	1041	99.68	67.23	21.67
	σ = 80	PSNR	12.68	26.83	27.46	32.61
		MSE	3511	151.45	114.69	35.64
	σ = 90	PSNR	10.30	25.26	26.23	30.02
		MSE	6062	198.43	142.3	64.7

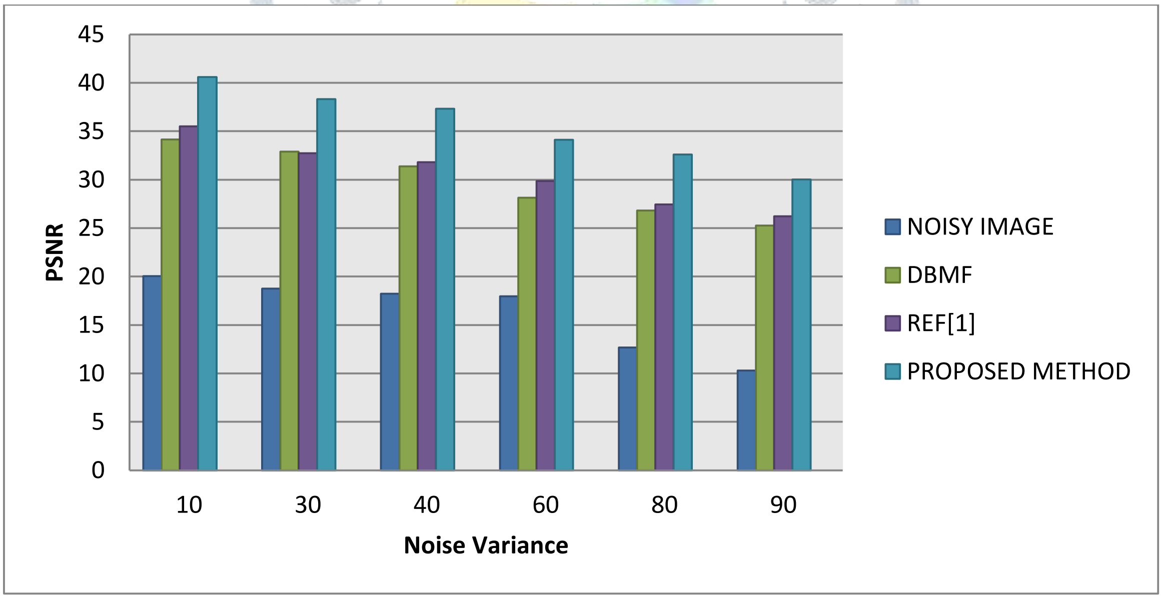

Figure 10: Comparison chart of PSNR v/s different Noise level in %for salt & pepper noisy Test image 1.

VII. CONCLUSION

In this paper, decision based median filtering (DBMF) algorithm is performed on noisy image than thresholding based DWT algorithm is applied. Our results are analyzed on the basis of performance measures like PSNR and MSE. Visual perception is also the measure. Artifacts are removed completely and edges are preserved well in this algorithm. By analyzing and comparing several other existing algorithms, we come across the conclusion that proposed algorithm provides better results among all.

REFERENCE

[1] Qiang Guo et.al : "An Efficient SVD-Based Method for Image Denoising" IEEE Transactions On Circuits And Systems For Video Technology, Vol. 26, No. 5, page no. 868-880, MAY 2016.

[2] Gabriela Ghimpe¸teanu et.al : "A Decomposition Framework for Image Denoising Algorithms" IEEE Transactions On Image Processing, Vol. 25, No. 1, Page No. 388- 399, January 2016.

[3] Mia Rizkinia et.al : "Local Spectral Component Decomposition for Multi-Channel Image Denoising" IEEE Transactions On Image Processing, Vol. 25, No. 7, Page No. 3208- 3218, July 2016.

[4] Lingli Huang et.al : "Improved Non-Local Means Algorithm for Image Denoising" Journal of Computer and Communications, 2015, vol 3, page no. 23-29.

[5] Haijuan Hu et.al : "Removing Mixture of Gaussian and Impulse Noise by Patch-Based Weighted Means" arXiv:1403.2482v1 [cs.CV] 11 Mar 2014.

[6] Jaiswal A., Upadhyay J., Somkuwar A. : Image denoising and quality measurements by using filtering and wavelet based techniques. Int. J. Electron. Commun. 2014 (AEU), 68(8):699-705.

[7] Zeinab A.Mustafa, Yasser M.Kadah : "Multi Resolution Bilateral Filter for MR Image Denoising" 2011 IEEE.

[8] Yong-Hwan Lee, and Sang-Burm Rhee: "Wavelet-based Image Denoising with Optimal Filter" International Journal of Information Processing Systems Vol.1, No.1, 2005 page no. 32-35.

[9] Caroline Chaux, Student Member, Laurent Duval, Member and Jean Christophe Pesquet : "Image Analysis Using a Dual-Tree M-Band Wavelet Transform IEEE 2006.

[10] Hossein Talebi, Student Member, IEEE, and Peyman Milanfar, Fellow, IEEE: "Global Image Denoising" IEEE Transactions On Image Processing, VOL. 23, NO. 2, FEBRUARY 2014 page no. 755-768.