Photometrical and Geometrical Similar Patch Based Image Denoising Using Wavelet Decomposition

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***Abstract*—Image denoising has been a well studied problem in the field of image processing and it is still a challenging problem for researches. Faster shutter speeds and higher density of image sensors (pixels) result in higher levels of noise in the captured image, which must then be processed by denoising algorithms to yield an image of acceptable quality. In this paper, we propose a method to denoise the images based on Discrete Wavelet Transform and Wavelet Decomposition using PLOW (Patch Based Locally Optimal Wiener Filter). Transformation and Decomposition provide the approximation and detailed coefficients, for reconstructed image PLOW technique is applied. The patch-based wiener filter exploits the patch redundancy for image denoising. It uses photometrically, geometrically and graphically similar patches to estimate the different filter parameters. This describes how these parameters can be accurately estimated directly from the input noisy image. The denoising framework can also be generalized to exploit such photometric redundancies within any given noisy image. Our noise removal system uses the LARK features which improve the finer estimates of pixel value and its gradients of original image. Experimental results demonstrate that our proposed study achieves good performance with respect to other denoising algorithms being compared. Experimental results are based on Peak Signal to Noise Ratio (PSNR), Mean squared error (MSE) and Structural Similarity Index Measure (SSIM).**

***Index Terms*—patch based locally optimal wiener filter (plow), discrete wavelet transform (dwt), structural similarity index measure (ssim)**

I. Introduction

Image denoising has been a well-studied problem in the field of image processing and it continues to attract researchers with an aim to perform better restoration [1] in the presence of noise. With the rise in the number of image sensors (or pixels) per unit area of a chip, modern image capturing devices are increasingly sensitive to noise [2]. Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission [3] is often corrupted with noise. Therefore the received image needs processing before it can be used in applications. Significant work has been done in both hardware and software to improve the Signal-to-Noise Ratio in digital photography. Image denoising involves the manipulation of the image data to produce visually high quality image. Hence, it is necessary to have knowledge about the noise present in image so as to select the appropriate denoising algorithm [4]. The main properties of good image denoising model are i. The Reduction of Randomness ii. Intensity Bias iii. Structure and Edge Preservation iv. Generality v. Reliability vi. Automation vii. Computational cost viii. Pixel ix. Squared Image Error and x. Signal Intensity Range. Applications of image denoising [5] are Satellite Television, Magnetic Resonance Imaging, Computer Tomography, Geographical Information System, Astronomy, etc.

Problem definition: The distortions of images by noise are common during its acquisition, processing, compression, transmission, and reproduction. Images may contain various types of noises like Salt and Pepper noise, Speckle noise and Poisson noise [3]. Usually the real and imaginary parts of image are considered corrupted by additive white Gaussian noise (AWGN). So denoising of images corrupted by additive white Gaussian noise is a classical problem in image processing and it has become a promising and very challenging research area in recent years. Shrinkage methods are often used for suppressing additive white Gaussian noise, where thresholding is used to retain the larger wavelet coefficients [6] alone. Shrinkage Algorithms fail to retain the edges, corners and flat regions of the image being processed. Therefore, it is necessary to suppress noise while producing sharp images without loss of finer details.

Related works: Proposed a method of denoising motivated from our previous work in analyzing the performance bounds of patch-based denoising methods[7], have developed a locally optimal Wiener-filter-based method and have extended it to take advantage of patch redundancy to improve the denoising performance, analyzed the framework in depth to show its relation to nonlocal means and residual filtering methods. This method achieves near state-of-the-art performance in denoising but not color images. The denoising performance cannot be expected to improve further by taking into account the correlation across color components. Proposed researchers continue to focus

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attention on it to better the current state-of-the-art. This paper estimates a lower bound [2] on the mean squared error of the denoised result and compares the performance of current state-of-the-art denoising methods with this bound, show that despite the phenomenal recent progress in the quality of denoising algorithms, some room for improvement still remains for a wide class of general images, and at certain signal-to-noise levels. Therefore, image denoising is not dead--yet.

Proposed a method for localizing homogeneity [8] and estimating additive white Gaussian noise (AWGN) variance in images. The proposed method uses spatially and sparsely scattered initial seeds and utilizes particle filtering techniques to guide their spatial movement towards homogeneous Locations. This way, the proposed method avoids the need to perform the full search associated with block-based noise estimation methods. In order to achieve this, the paper proposes the particle filter as a dynamic and homogeneity observation model based on Laplacian structure detectors. The variance of AWGN is robustly estimated from the variances of blocks in the detected homogeneous areas. A proposed adaptive trimmed-mean based robust estimator is used to account for the reduction in estimation samples from the full search approach. Proposed an improved non-local means (NLM) filter for image denoising. Due to the drawback that the similarity is computed based on the noisy image, the traditional NLM method [1], [9] easily generates the artifacts in case of high-level noise. The proposed method first preprocesses the noisy image by Gaussian filter. Then, a moving window at each pixel of the noisy image is chosen as the search window, and meanwhile, an improved calculation method of spatial distance based on the preprocessed image is used for computing the similarity.

Proposed a method that is relatively fast and that performs satisfactory segmentation of the image into geometrically similar regions [10] based on the steering weights. So make use of a version of the standard K-means algorithm. This clustering algorithm is one of the simplest unsupervised methods where the motivation of clustering is to segment the image into some prefixed number of clusters (k) such that for each class, the squared distance of any feature (normalized weight) vector to the center of the class is minimized. Proposed K-LLD: a patch-based, locally adaptive denoising method [6], [11] based on clustering the given noisy image into regions of similar geometric structure. In order to effectively perform such clustering, the local weight functions derived from our earlier work on steering kernel regression or employed as features. These weights are exceedingly informative and robust in conveying reliable local structural information about the image even in the presence of significant amounts of noise. Next, model each region (or cluster)--which may not be spatially contiguous--by “learning” a best basis describing the patches within that cluster using principal component analysis.

Shrinkage methods are often used for suppressing AWGN, where thresholding is used to retain the larger wavelet coefficients [6] alone. In this paper the various shrinkage methods in DWT- Domain Filters and the comparison between the efficiency of the filters are examined. The Proposed 3D image denoising [12] procedure consists of three major steps. Firstly edge vowels are detected using a 3D edge detector that is constructed under the JRA framework. Secondly in a neighborhood of a given vowel, the underlying edge surfaces are approximated by a surface template chosen from a pre-specified surface template family. Thirdly the true image intensity at the given voxel is estimated by a weighted average of the observed image intensities in the neighborhood whose voxels are located on the same side of the surface template as the given voxel. The ultimate idea of this paper is to propose better results in terms of quality [5] and in the removal of different noises. This paper is compared with three methods namely NL Means, NL-PCA, and DCT. The PSNR and SSIM are used for quantitative study of denoising methods.

Proposed an efficient algorithm for removing additive white Gaussian noise from corrupted image by incorporating a wavelet-based [13] trivariate shrinkage filter In the wavelet domain, the wavelet coefficients are modeled as Gaussian distribution, taking into account the statistical dependencies. Wavelet-based methods are efficient in image denoising. Also they are prone to producing salient artifacts such as low-frequency noise and edge ringing which relate to the structure of the underlying wavelet. Proposed a nonparametric PCA-NLM filter [14] that is a useful alternative to the PCA-NLM filter for Rician noise reduction in MR images. The proposed filter uses PCA with ranked data instead of the original pixel data. We refer to this as the NPCA- NLM filter. We estimate the subspace dimensionality from parallel analysis based on the artificial rank correlation matrix. In contrast to the method reported by Tasdizen our estimation does not require the assumption of a Gaussian distribution and produces a more robust subspace dimensionality regardless of the images being denoised.

II. Existing Method

A statistical optimization process along with adaptive and subband-dependable methodologies is applied to both the thresholding function and wavelet transform, in order to advance the denoising even further. Unlike standard wavelet-based methods, we used WP transform (WPT) along with optimal wavelet basis (OWB) for image decomposition. Then, for each wavelet subband [15], an adaptive and subband dependent threshold value is calculated based on analyzing the subband’s statistical parameters. Next, a new thresholding function, called OLI-Shrink, is proposed to shrink small coefficients leading to calculate a modified version of dominant coefficients. The modification is done using optimal linear interpolation [16] between each coefficient and the mean value of the corresponding subband.

A. *Wavelet Packet Transformation (WPT)*

Splitting the 'H' parts would result in a representation with respect to another basis with a full binary tree of possible basis functions, or the WPTs. The algorithm starts with computing the cost values from the deepest level nodes. If the sum of the cost values for two children nodes is lower than the cost value of their parent node, then the children are retained, otherwise, they are eliminated. Daubechies wavelet with eight vanishing moments (Db8) is employed [15] to decompose the input image into four wavelet levels. Either a pair of blocks in the bottom row or the block immediately above them may be selected from the decomposed image.

B. *Threshold Function (OLI-SHRINK)*

OLI-Shrink is the combination of both WaveShrink and Bayeshrink. An optimum threshold value, which is adaptable to each subband characteristics, is desired to maximize the signal and minimize the noise. Optimum threshold selection algorithm is used. In this algorithm [17], an adaptive threshold value λ_s for each subband S at level d is calculated as

$$\Lambda s=\alpha_{d,s}\,(\sigma_\eta^{2}\,/\!-\,\sigma_{X}{}^{2}{}_{,s}) \tag{1}$$

where σ_η^2 and $\sigma_{X}{}^{2}{}_{,s}$ are the variances of noise and clean image coefficients in the subband S, respectively. The term $\alpha_{d,s}$ was set to one.

Demerits of Existing Method: It doesn't suppress noise while producing sharp images without loss of finer details. Image clarity is not good visually. Image is blurred after denoising. Shrinking Algorithms are great to analyze signals but it eliminates (shrinking) coefficients that are smaller than a specific value, called threshold. To retain the edges more efficiently Wavelet decomposition is required.

III. Proposed Method

The Proposed system builds an efficient two level Decomposition of the image. By applying Discrete Wavelet Transform (DWT) and Wavelet Decomposition, Approximated and detailed coefficients are obtained. The reconstructed image is passed as input to the PLOW (Patch based Locally Optimal Wiener Filter) Estimator. Using LARK (Locally Adaptive Regression Kernels), we run K-means to cluster the noisy image into Geometrical and Photometrically similar patches. A Final aggregation step is used to optimally fuse the multiple estimate for pixels lying on the patch overlap to form the denoised image. In our frame work, graphically illustrated in Fig. 1 and Fig. 2.

A. *System Architecture*

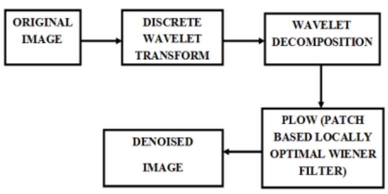


Figure 1. System architecture of proposed method.

B. *Block Diagram*

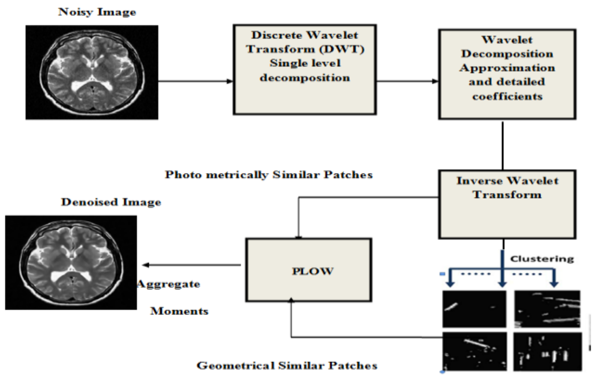


Figure 2. Block diagram of proposed method.

C. *Discrete Wavelet Transform*

The Wavelet Transform (WT) has gained widespread acceptance in signal and image compression. Because of the inherent multi – resolution nature, wavelet – codings are specially for suitable for applications where scalability and tolerable degradation are important. DWT is an implementation of the wavelet transform [18], [19] using a discrete set of wavelet scales. Fig. 3 shows transform decomposes the signal into mutually orthogonal set of wavelets (LL, LH, HL, HH).

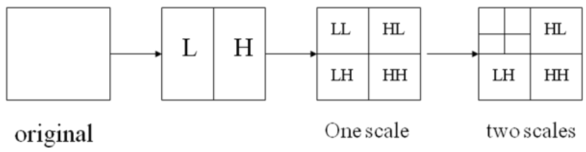


Figure 3. Discrete wavelet Transform

The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression. Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where scalability and tolerable degradation are important. The frequency band of a signal is split into various sub-bands. The filters used in sub-band coding are known as quadrature mirror filter (QMF). The octave tree decomposition of an image data is used into various frequency sub-bands. The output of each decimated sub-bands is quantized and encoded separately.

D. *Wavelet Decomposition*

Wavelet decomposition, the generic step splits the approximation coefficients into two parts. After splitting, a vector of approximation coefficients and a vector of detail coefficients, both at a coarser scale are obtained. The information lost between two successive approximations [20], [21] is captured in the detail coefficients. Then the next step consists of splitting the new approximation coefficient vector; successive details are never reanalyzed. In the corresponding wavelet packet situation, each detail coefficient vector is also decomposed into two parts using the same approach as in approximation vector splitting. This offers the richest analysis: the complete binary tree is produced as shown in the following Fig. 4.

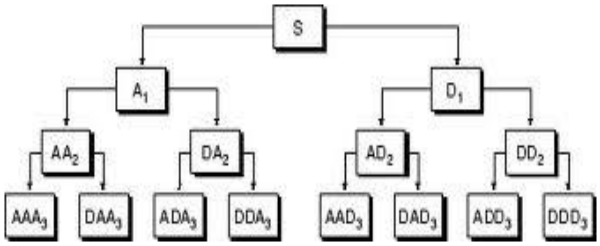


Figure 4. Wavelet decomposition

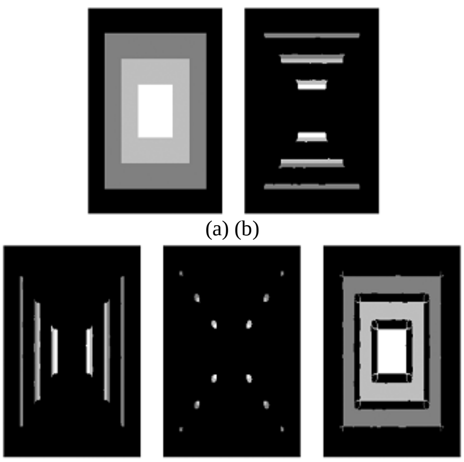
Reconstructed DWT Image is given as input to the Wavelet Decomposition, where it provides the Approximated and Detailed Coefficients of the image. The detailed coefficients are Horizontal (H), Vertical (V) and Diagonal (D).

E. Plow Filter

The procedure is algorithmically represented in Algorithm. First geometrically similar patches [7], [22] are identified within the noisy image. Once such patches are identified, these patches can be used to estimate the moments of the cluster, taking care to account for noise. Next, identify the photo metrically similar patches are identified and the weights that control the amount of influence that any given patch exerts on denoising patches similar to it are calculated. These parameters are then used to denoise each patch. Clustering is based on the geometric similarity of patches. Overlapping patches are used and multiple estimates are obtained for pixels lying in the overlapping regions. These multiple estimates are then optimally aggregated to obtain the final denoised image. Each step is described below in greater detail.

K-Means Clustering: Once the image is segmented into structurally similar regions, the moments are estimates namely, mean and covariance, from the noisy member patches of each cluster.

Geometrical similar patches: To perform practical clustering, it is necessary to identify features that capture the underlying geometric structure of each patch from its noisy observations. Such features need to be robust to the presence of noise, as well as to differences in contrast and intensity among patches exhibiting similar structural characteristics shown in Fig. 5.



(a) (b)

(c) (d) (d)

Figure 5. Clustering of an image based on geometric similarity. Note how pixels in any particular cluster can have quite different intensities but similar geometric Structure (edge, corner, flat regions, etc.) (a) Box image. (b) Cluster 1. (c) Cluster 2. (d) Cluster 3. (e) Cluster 4. Noisy image is first segmented.

Estimating cluster moments: Once the image is segmented into structurally similar regions, estimate the moments, namely, mean and covariance, from the noisy member patches of each cluster. Since the noise patches are assumed to be zero mean, the mean of the underlying noise-free image can be approximated by the expectation of the noisy patches within each cluster as

$$\overline{\mathbb{Z}} = E[y_i \in \Omega_k \approx \frac{1}{M_K} \sum_{y_i \in \Omega_k} y_i \qquad (2)$$

Calculating weights for similar patches: First patches are identified within the noisy image that is photometrically similar to a given reference patch. Once the similar patches are identified for a given reference patch, denoising is proposed with the more similar patches exerting greater influence in the denoising process. Weight is related to the inverse of the expected squared distance between the underlying noise-free patches and a noise.

$$w_{ij} \approx \frac{1}{\sigma^2} \exp\left\{ -\frac{\left\| y_i - y_j \right\|^2}{h^2} \right\} \qquad (3)$$

Aggregating multiple pixel estimates: The filter is run on a per-patch basis yielding denoised estimates for each patch of the noisy input. To avoid block artifacts at the patch boundaries, the patches are chosen to overlap each other. As a result, multiple estimates are obtained for the pixels lying in the overlapping regions, where estimated multiple times are as a part of different patches. These multiple estimates need to be aggregated to form a final denoised image**.**

F. Proposed Algorithm

Get the Input Image
Y- Add White Gaussian Noise
Perform 2D Discrete Wavelet Transform on the Noisy Image
Perform Wavelet Decomposition
Inverse Discrete Wavelet Transform (IDWT)
Set parameters: patch size n=11 x 11, number of clusters k=15
Estimate noise standard deviation
Geometric clustering with K – means (L, K);
    foreach Cluster do
        Estimate mean patch
        Estimate cluster covariance
    foreach Patch do
        Identify photometrically similar patches
        Compute weights for all photometrical similar patches
        Estimate denoised patch
        Calculate estimate error covariance
    end
    end

Z->aggregate multiple estimates

G. Merits of the Proposed System

- The Proposed system uses multilevel decomposition, which recovers the best estimate of the original image from its noisy version.
- Photometrically and geometrically similar patches obtain the edges, corners and flat regions of image accurately**.**

The quantitative results are achieved more compared to the existing system in terms of PSNR, MSE and SSIM.

IV. Experimental Analysis and Result

Simulations are carried out to verify the noise removing capability of the wavelet decomposition based photometrical and geometrical similar patches image denoising methods and results are compared with several existing methods. The proposed method produces results superior to those of most methods in both visual image quality and quantitative measures. Simulations are made on several 512 X 512 8 bit gray scale standard test images with AGWN. In the experiment, the researcher has strive to be impartial while collecting data. In the proposed method the parameters are varied exhaustively (as suggested by its authors) to obtain the best possible results.

Furthermore, to eliminate the bias created by different manifestations of noise, a standard set of noisy images is created. Five noisy images are created for each test image and noise level. The numerical results shown are the average results for these five images. The detailed results, observation, and discussion are described as follows. From the above simulation, the new denoising framework gets the more accurate results and more robust to the noise ratio than the methods used in the comparison. Although the proposed method is successful, the results could be better. How to improve the performance, particularly when the noise ratio is high, is an important point for future researchers.

In Table I, we quantify the performance for a variety for benchmark images (it shown in Fig. 6), across different noise level, with different performance measures (PSNR, SSIM and MSE). The existing system (OLI-SHRINK) has got PSNR value as 33.4867 for noise level (σ) = 5. In the proposed method for the same House image, PSNR value achieved is 42.2584, which is higher than the existing system.

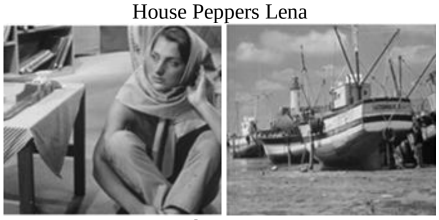
Mean Square Error (MSE) for House image in OLI-SHRINK is 29.2558, which is achieved lower as 29.0727 in the proposed method compared to the existing system. The existing system (OLI-SHRINK) has achieved maximum SSIM (Structure Similarity Index Measure) value in Lena image as 0.90764, which has been increased in the proposed system as 0.9272.

In Comparison with OLI-SHRINK and PLOW Algorithms, the proposed method has achieved significantly higher values (PSNR, SSIM) and it has lowered the MSE, in all type of images, at various noise levels (it shown in Fig. 7).

TABLE I: Denoising Performance of the Existing Method (OLI-SHRINK), PLOW (Patch Based Locally Optimal Wiener Filter) and the Proposed Method (Photometrical and Geometrical Similar Patches Based Image Denoising Using Wavelet Decomposition). Results Compared Are PSNR, MSE and SSIM.

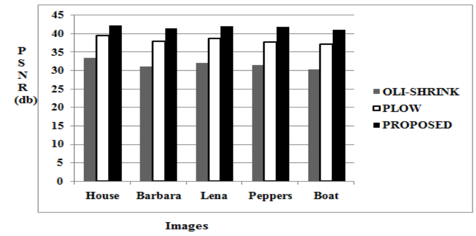
Noise (σ) (db)		House (256 X 256)			Peppers (256 X 256)		
		OLI-SHRINK	PLOW	Proposed	OLI-SHRINK	PLOW	Proposed
5	PSNR	33.467	39.52	42.2584	31.4324	37.69	41.8799
	MSE	29.2558	42.20	29.0727	46.7561	75.60	56.7031
	SSIM	0.88868	0.954	0.88787	0.88728	0.954	0.91756
10	PSNR	30.5198	36.21	38.8322	28.3508	33.51	36.842
	MSE	57.6906	15.54	32.9518	95.0613	28.92	63.4962
	SSIM	0.82797	0.918	0.87241	0.82136	0.917	0.90481
15	PSNR	28.7921	34.72	37.6887	26.5598	31.82	35.3678
	MSE	85.8765	36.98	35.3212	143.5830	64.99	68.9773
	SSIM	0.78646	0.893	0.86444	0.77155	0.899	0.89731
20	PSNR	27.5766	33.58	36.9481	25.3498	30.43	34.403
	MSE	113.6099	28.46	37.3026	189.7389	58.85	74.1804
	SSIM	0.75593	0.873	0.85904	0.73275	0.875	0.89087
25	PSNR	26.6606	32.70	36.5199	24.4153	29.53	33.8292
	MSE	140.2894	20.39	38.8175	235.259	50.13	77.9702
	SSIM	0.73118	0.859	0.85563	0.70054	0.859	0.88614
Noise (σ) (db)		Lena (256 X 256)			Barbara (256 X 256)		
		OLI-SHRINK	PLOW	Proposed	OLI-SHRINK	PLOW	Proposed
5	PSNR	32.1346	38.66	42.0929	31.0452	37.98	41.4268
	MSE	39.7764	34.75	43.3249	51.1158	69.14	65.9423
	SSIM	0.90764	0.946	0.9272	0.89224	0.946	0.87132
10	PSNR	28.7281	34.385	36.4447	28.0959	32.883	36.3633
	MSE	87.1500	23.688	50.8096	100.807	33.476	73.5442
	SSIM	0.83593	0.9359	0.91052	0.81717	0.935	0.85577
15	PSNR	26.8750	33.90	34.8016	26.4388	32.17	34.9986
	MSE	133.529	21.59	57.4396	147.638	55.28	78.3286
	SSIM	0.78016	0.890	0.89979	0.76016	0.916	0.84738
20	PSNR	25.6744	30.899	33.8728	25.3109	29.889	34.1322
	MSE	176.052	52.866	63.0813	191.422	66.703	82.56
	SSIM	0.7364	0.8868	0.8895	0.71527	0.8570	0.84045
25	PSNR	24.8106	31.92	33.3852	24.4272	30.20	33.6326
	MSE	214.793	11.69	66.7646	234.6168	37.72	85.7984
	SSIM	0.7017	0.859	0.88362	0.67646	0.879	0.83551
Noise (σ) (db)		Boat (256 X 256)					
		OLI-SHRINK	PLOW	Proposed			
5	PSNR	30.3018	37.24	41.0645			
	MSE	60.6597	36.95	86.9256			
	SSIM	0.8724	0.941	0.86554			
10	PSNR	27.3202	32.147	34.6658			
	MSE	120.519	39.658	100.9773			
	SSIM	0.78246	0.900	0.83109			
15	PSNR	25.6749	31.53	33.0856			
	MSE	176.031	28.38	109.909			
	SSIM	0.71433	0.840	0.81553			
20	PSNR	24.5980	28.875	32.0115			
	MSE	225.571	84.238	118.252			
	SSIM	0.6631	0.830	0.80143			
25	PSNR	23.8137	29.59	31.4689			
	MSE	270.216	14.19	123.645			
	SSIM	0.62296	0.794	0.7926			

House Peppers Lena

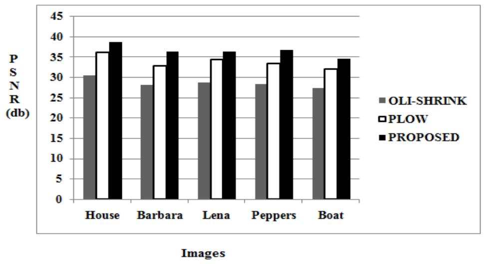


Barbara Boat

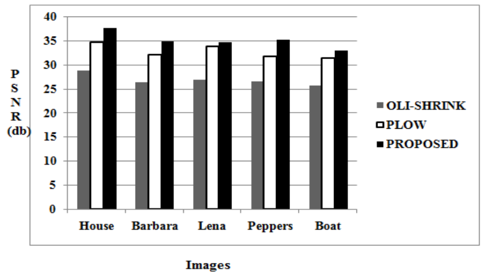
Figure 6. Some standard images that we use to perform the quantitative evaluation of method performance.



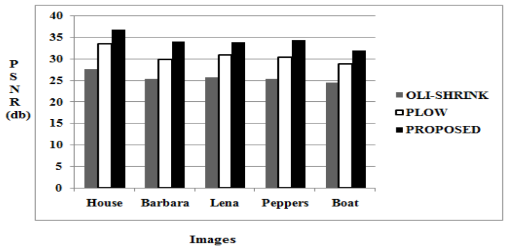
(a)



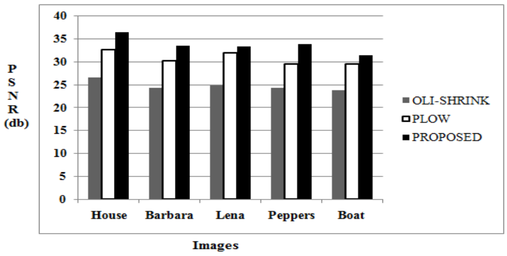
(b)



(c)



(d)



(e)

Figure 7. Comparing PSNR values of OLE-SHRINK, Plow and the Proposed method (a) Noise Level (σ) = 5, (b) Noise Level (σ) = 10, (c) Noise Level (σ) = 15, (d) Noise Level (σ) = 20, (e) Noise Level (σ) = 25

V. CONCLUSION

In summary, a new method to remove high-density additive white Gaussian noise using Two-Level decomposition combined with PLOW is proposed. The proposed algorithm removes noise even at higher densities and the edges and finer details are preserved. The proposed algorithm gives better result compared to the existing systems. The performance of the denoised image is measured by the following parameters such as peak signal-to-noise ratio (PSNR), Mean Square Error (MSE) and Structural Similarity (SSIM). In addition, the computational cost is modest; so it is suitable for many image processing applications, such as medical image analyzing systems and noisy texture analyzing systems. In future, the two-level decomposition combined with PLOW gets better result for variety of images. But it is suggested that, the proposed algorithm may be extended to color images and video framework, which may further improve video denoising.

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