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Denoising of Digital Images Using Spatial Domain Edge Detection Approach

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Abstract

Better results can be produced by the Hybridization of the Wavelet-based image denoising technique and sparse representation of edges. A novel method for spatial domain edge identification that produces a denoised image that has been tainted by additive white Gaussian noise without sacrificing the image's detail information. By combining bivariate shrinkage and local profile edge detection, a denoised image is produced. In this paper, the hybridization method is proposed by modifying the existing Wavelet Transform for image denoising leading to an increase in the PSNR and SSIM as compared to that given by existing Wavelet denoising techniques, maintaining the visual quality of an image. To modify the wavelet coefficients Bivariate Wavelet Shrinkage is used. The quality assessment is evaluated in terms of SSIM value and PSNR value.

Keywords: *Spatial Domain, Bivariate Wavelet Shrinkage, PSNR, SSIM, Discrete Wavelet Transform*

INTRODUCTION

Nowadays, visual methods are primarily used for communication. Almost all data is communicated using digital graphics or video. However, the acquired information is frequently distorted by noise after transmission. Finding effective image-denoising techniques remains a difficult task, leading to the proposal of several denoising algorithms, including NL means and BM3D. to denoise digital images [1] [2] [3] [4] [5]. This work describes a novel method for reducing noise from a wide range of photographs, both in terms of types and intensities. If an image is $I(x, y)$ and the noise is $N(x, y)$. Noise expression will be defined by the following equation 1

$$Y(x, y) \square I(x, y) \square N(x, y) \quad (1)$$

Where $Y(x, y)$ is a noisy image affected by additive noise. Image denoising is simply minimizing the factor $N(x, y)$ so that the image will be denoised. Here we present a new image-denoising algorithm based on the combined effect of Discrete Wavelet Transform [6] and Spatial domain edge preservation. The algorithm removes most of the noisy parts from the image and maintains the quality. The goal of this paper is to present the improved method of denoising which is a purely digital and performance-based approach using wavelet transform.

Additionally, a novel approach is suggested in this work for spatial domain edge detection and preservation of these edges. So, by hybridization of the Wavelet-based image denoising technique and sparse representation of edges, better results are achieved. Thresholding the coefficients obtained by a standard wavelet transform is typically used to remove the noise. The wavelet transform's success is mostly attributable to its capacity to characterize certain signal classes with a fairly small number of transform coefficients. 2D wavelet transform is a separable transform that is given by the product of two 1D wavelets along the horizontal and vertical directions i.e. the lines and columns are treated independently in wavelet transform and the basis function is simply the product of these two. Despite being computationally simple, it does not capture all the characteristics

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of an image. So, in this work, a new truly separable discrete multidirectional transform is given with the edge preservation and

denoising using the Local Profile Edge detection method. This provides very good results for denoising by preserving the fine details and sharp edges. In this method also, simplicity and low computational complexity are maintained.

In this paper, we prove the denoising capabilities of the Discrete Wavelet Transform by using bivariate shrinkage and also spatial domain edge preservation. A computationally efficient set of accurate and elegant denoising algorithms has been presented. The proposed algorithms offer much better numerical performance and comparable visual performance at less computational overhead compared to other contemporary algorithms.

LITERATURE SURVEY

This literature survey explores several image-denoising methodologies [5], comparing them across the spatial domain, transform domain and learning-based style approach[1].

Through this survey we found that the methods incorporating non-local grouping were performing significantly better compared to those that didn't apply nonlocal grouping, the importance of this aspect in denoising techniques was discovered [1]. Additionally, this study highlights the effectiveness of dictionary learning-based methods, especially in achieving denoising results that are on par with the most computationally complex approaches[4].

One paper in particular [2] demonstrates the highly effective performance of NL-means using non-local averaging over the other denoising methods, thus being a valuable asset for image restoration across various applications.

By capitalizing on a 2D quincunx sub-lattice, NL-means optimizes the image quality while also effectively suppressing the noise and facilitating local image reconstruction capabilities [5]. Furthermore, Sure Shrink, achieves noise suppression with computational efficiency by adapting to wavelet smoothness [7]. Bayesian denoising techniques [8] and new and coming techniques like Neigh Shrink [10] have contributed to the image denoising performance by taking advantage of the mathematical properties of wavelet coefficients and incorporating neighbouring coefficients. More details into noise types, sources, and models [15] with a comparative analysis of various denoising methods [16] help to provide us with valuable data for further research. They help in critical decision-making to select the best denoising techniques required according to the specific applications. The combination of such methodologies emphasized the ongoing development of image-denoising techniques to address more real-world problems. The in-depth study of spatial and transform domain methods with the rapid development in the field of image edge detection, further helps in understanding effective noise reduction techniques. Hence, we made the final decision to use the Hybridization of Transform and Spatial domain denoising techniques to use the strengths of various methods to address the challenges faced in image denoising.

A DCT-based watermarking technique is introduced based on block-wise embedding into the images to protect the copyright of the images [18]. An embedding technique is used to block the noise and crop the images by embedding and also calculate the gain factor [19].

PROPOSED METHOD

Transform-Based Techniques

Wavelet Transform-Based Denoising

Here the work is focused on the separable wavelet transform filtering method. All wavelet transform denoising algorithms involve the following three steps in general as shown in Figure 1.

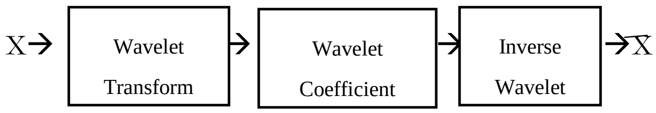

Figure1: Denoising Based on Wavelet Transform

Forward Wavelet Transform: The wavelet transformation is used to calculate wavelet coefficients.

Estimation: Noisy coefficients are used to estimate clean coefficients.

Inverse Wavelet Transform: By using the inverse wavelet transforms, a clear image is produced.

Robust Median Estimator-based Noise Variance Estimation

An estimation of the noise level is necessary for the thresholding technique used here. Unless the function is sufficiently flat, the typical standard deviation of the delta values is not a suitable estimator. When estimating in the wavelet domain, Donoho and Johnstone [7] proposed a reliable estimate that is based solely on the empirical wavelet coefficients at the highest resolution level. Because the related empirical wavelet coefficients typically consist primarily of noise, only the finest level is taken into consideration. Donoho and Johnstone offered a robust estimate of the noise level based on the median absolute deviation provided as shown in equation 2.

$$\sigma_n = \frac{median\left\{|W_j|:j=1,2,\ldots\ldots,\frac{k}{2}\right\}}{0.6745} \qquad (2)$$

Here W_0, W_1……. etc. are the detail coefficients at the finest level.

Bivariate Shrinkage

Coefficients that are close to one another are very dependent on one another. A parent coefficient (near coarser scale places), and its siblings are all highly dependent on one another (adjacent spatial locations). Here in this algorithm, the dependencies between a coefficient and its parent are being carefully taken into account. A linear Bayesian estimator is provided that requires the estimation of neighbouring coefficients [9], [10] [11], [12] and it is argued in [8] that a coefficient's pdf, conditional on its neighbours, is Gaussian. The Bayesian estimation model is defined to find the statistical dependence between a coefficient and its parent[13]. So, the modified Wavelet Coefficient by Bivariate shrinkage is given by

$$\widehat{w_1} = \frac{\left(\sqrt{y_1^2+y_2^2}-\frac{\sqrt{3}\sigma_n^2}{\sigma}\right)_+}{\sqrt{y_1^2+y_2^2}} \cdot y_1 \qquad (3)$$

Where w_2 is the wavelet coefficient within the level whereas w_1 at the next coarser scale. y_1 and y_2 are noisy observations of w_1 and w_2 , defined in equation 1 and Equation 2.

$$y1=w1+n1 \qquad (4)$$

$$y2=w2+n2 \qquad (5)$$

When estimating each coefficienty1 in denoising methods derived from the independence assumption, the parent value y2 is ignored. For instance, in scalar soft thresholding, if a coefficient is below the threshold value, we set it to zero. The threshold value is fixed and independent of other coefficients for all coefficients. Our findings, however, unequivocally demonstrate that the projected value should be dependent on the parent value. The shrinking increases as the parent value decreases. This outcome is intriguing since it demonstrates the impact of accounting for parent-child dependency. So, we have decided the threshold for estimating the wavelet coefficients as

$$T = \sqrt{N}\frac{\sigma_n^2}{\sigma_s} \qquad (6)$$

Where N is the size of the search area taken. If the search area is a 3X3 tile, then N is taken as 3. So, by using the Bivariate Shrinkage function the wavelet coefficients are modified.

Wavelet Coefficient Modification

1. An efficient and simple locally adaptive image denoising technique is created using the bivariate shrinkage function. The noise variance and the signal variance for each wavelet coefficient must be known in advance for this shrinking function to work. As a result, the method first calculates the parameters:

2. First calculate the noise variance using robust median estimator

3. Then for each wavelet coefficient

a) Calculate the signal variance using the neighboring coefficients of selected window size.

b) Calculate the threshold value from the estimated signal variance and noise variance by the modified bay shrink formula as given in eq (6).

c) Estimate each coefficient using Bivariate Shrinkage function.

The following algorithm is used for image denoising using 2D-DWT.

1. *Take Noisy Image*
2. *Apply 2D DWT to an image by setting the number of levels*
3. *Modify the wavelength coefficient using Bivariate shrinkage*
4. *Take inverse discreate wavelength transform from modified wavelength coefficients*
5. *Denoised Image*

Techniques Based on Local Profile Edge Detection

The proposed algorithm for the spatial domain edge detection and denoising of corrupted image. By using this algorithm, the details can be preserved by preserving the fine edges. This denoising algorithm has been seen to cause edges in noisy photos to become blurry. Here, we make the premise that, if the original image contains any fuzzy edges, those edges will be further blurred during the denoising process but may not be very obvious. Sharp edges, on the other hand, could lose their visual appeal if they are blurred. Thus, we may identify the edges in the spatial domain using some fuzzy techniques. There are numerous established edge detection techniques available. Edges of an image can be detected by the use of domain-specific transformations or direct spatial processing. Numerous edge-detection methods, including Sobel and Prewitt edge detectors, are already in use in the spatial domain. But in this instance, we're adding a new technique to find edges in the spatial domain without using Sobel and Prewitt operator. To detect the edges, we use the Local Profile Detection algorithm. Using the Local Profile Detection technique, we can identify rising and falling edges in the image shown in Fig. 2. And according to the edge detected we process that part of the image further to denoise the image. The algorithm for the Local Profile Edge Detection is given as

1. *3x3 tile of noise corrupted image is taken.*
2. *Use the formula provided to determine the threshold*

   $t = mode(\delta)$ --(7)

   where δ is the distance vector between each pixel. The horizontal edge can be obtained by following steps:

   a) *By taking sum of the shaded area of Fig.2 (a) U and D are calculated.*
   b) *If $|U - D| < t$ then there is a horizontal edge.*
3. *By applying the above steps to Fig. 2 (b), (c) and (d) respectively, the vertical, falling, and rising edges are obtained.*
4. *Calculate the distance between the edges and their adjacent ray sums. Replace the ray sum having the minimum distance and edge by the potential average of the edge.*
5. *If there is no edge, replace each pixel of a 3X3 tile with its mean.*

Thus, it is clear from the above discussion that the edges in a small tile in spatial domain can be detected using this fuzzy algorithm and be subsequently classified as 'tiles with edges' and 'tiles without edges. The tiles without edges will be processed using the 3x3 mean filter. The tiles with edges will be skipped from the processing using the 3x3 tile size mean filter to protect the edges. However, if there is an edge in the 3x3 tile we are replacing the edge and the closest surrounding ransom with the average of the edge pixels. Hence the process of locating such edges in real images must be based on fuzzy descriptions of edges.

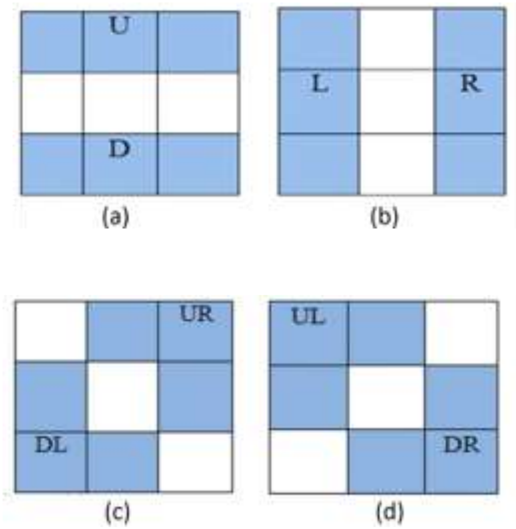

Figure 2: *Different types of edges (a) Horizontal edge, (b) Vertical edges, (c) Falling edge, (d) Rising edge*

As shown in Fig. 3 (a), H is the average sum of horizontal edge pixels. If |U-H| < |D-H| then we replace U by H as shown in Fig. 3 (b) else we replace D by H as shown in Fig. 3 (c). So, by replacing the neighboring pixels with the edge potential it helps in denoising as well it protects the edges. Similarly, for Vertical, Falling and Rising edges we use the same method to replace the neighboring pixels with edge pixel potentials.

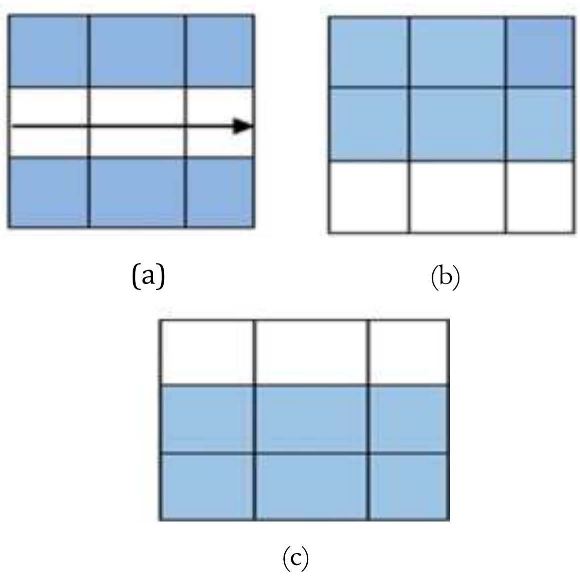

Figure3: Representation of Denoised tile for horizontal edge.

Similarly, the representation of 3x3 tile for vertical, falling and rising edges can be obtained by applying the above procedure. In this way by replacing the neighboring pixels to an edge by the average sum of edge potentials we can get the final denoised image. This helps in denoising the image as we are replacing the pixels by the average of the edge potentials. Thus, edges are also preserved. In this way we have detected the edges in an image and also denoised the image using Local Profile Edge Detection algorithm. It can be seen that the edges can be detected easily from spatial domain image tile. Thus, the detection of edges from spatial domain will be more robust and computationally easy. The effect of this edge detection is that the noise present in the close vicinity of edges is less suppressed as the tiles containing edges are not mean filtered completely. However, the blurring of the straight sharp edges is completely avoided. This results in a further increase in PSNR and also SSIM especially in the case of images containing a large number of sharp edges.

METHOD

Hybridization of Transform and Spatial Domain Denoising

Bivariate shrinkage is used to enhance the image performance during denoising. The crisp details of an image are lost during DWT denoising, though. In an image, edges often appear where two distinct parts meet. Often, the initial step in extracting information from photos is edge detection. Edge detection is still a topic of current research due to its significance. Image denoising with edge preservation is covered in this section. Thus, if we combine the Wavelet Shrinkage algorithm for denoising with the Local Profile Edge Detection approach, the crisp details of a picture are also retained.

Algorithm

1. *Take Noisy Image*
2. *Find the edges in the noisy image by applying the DWT-based denoising method using bivariate Shrinkage, as well as the denoising technique.*
3. *If there is an edge present in the 3 x 3 Search area of the image, then replace that tile by the corresponding result obtained by local profile edge detection algorithm.*
4. *If there is no edge present in the 3 x 3 search area, then replace that tile by the corresponding result obtained from DWT based denoising algorithm.*
5. *So, we get the resultant image which contains. the preserved detail information compared to DWT based denoising algorithm. Also, it gives improvement in the denoising result compared to both the algorithms previously used.*

We have estimated each pixel value in this technique nine times. These nine estimations were obtained by row- and column-shifting the image's original matrix. For example, the first estimate will be the algorithm applied on the original matrix only. Then for second estimate the original matrix is shifted by one column to the right and the last column is replaced by all zeros and applied the same algorithm on resultant matrix. In this way for first column we have got only one estimate but for the second row onwards we have got 2 estimates of every pixel. In this way, the nine estimates for each pixel are calculated by shifting the original matrix two times column-wise, two times row-wise. Then one row one column, one row two columns, two rows one column and two rows two columns combination. So, we get different estimates by averaging the estimated pixels to get the final result. This result is visually much better than if we had applied the same algorithm only on the original matrix. As well as the PSNR is also improved by these nine estimates.

EXPERIMENTAL RESULTS

Experimentation has been carried out on various test images. In this section, a few representative outcomes have been shown. It has been noted that the suggested techniques outperform published state-of-the-art denoising algorithms both visually and numerically. The earlier images and zero mean Gaussian noise of various variances have been added. Peak signal-to-noise-to-noise ratio (PSNR) and structural similarity index (SSIM) are two measurements used in this suggested work to analyze the denoised image's performance [14] objectively.

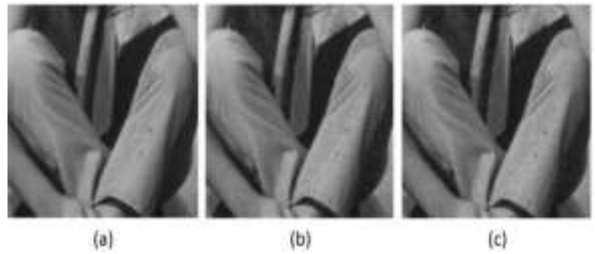

Figure 4: *(a)Original Barbara zoomed, (b)Noisy image, standard deviation20, PSNR 22.15 dB, (c) Denoised Images with Algorithm2 i.e. Local Profile edge detection algorithm, PSNR 27.63dB*

The original Barbara zoomed image is shown in Figure 4 (a). The corresponding image is shown in Fig. 4(b) with zero mean Gaussian noise and a standard deviation of 20. Denoising results from the Local Profile Edge Detection technique are shown in Figure 4(c). The results demonstrate that the method preserves the edges of an image. Denoising is carried out in the spatial domain itself to some extent as well. Figures 5(a) and 5(b), respectively, display the original zoomed images of Barbara's trouser and Lena's eye The quantitative results of method 3 are depicted in the corresponding figures after adding zero mean Gaussian noise with a standard deviation of 25 to the corresponding images. Since it is visually challenging to see the entire image's

true denoising in this instance, it is evident that the results are superior to the first algorithm in terms of PSNR, as well as the visual quality of an image and the preservation of the edges.

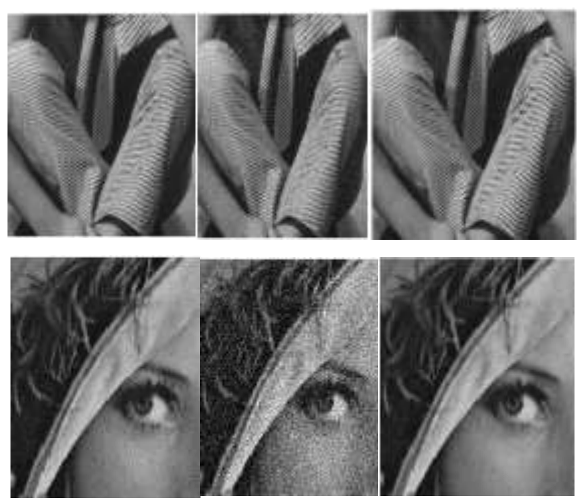

Figure 5: *(a) Original, Noisy and Denoised images of Barbara Trouser respectively, (b) Original, Noisy and Denoised images of Lena.*

The suggested algorithm 3's de-noising performance is shown in Table 1 along with BM3D and Baudes NL means. Cameraman, Peppers, and Lena's original 512x512 greyscale images have been swapped as per the standard deviation shown in Table 1 and considering zero mean Gaussian. It can be observed that the PSNR and SSIM values of the images when de-noised by Baudes NL means. The performance of both approaches decreased as expected as the noise standard deviation grew. In comparison to Baudes NL means and BM3D, the edges are protected to a great amount in our suggested algorithm employing 9 estimations. Higher SSIM values are retrieved as compared to Baudes NL means and the BM3D technique. The suggested approach also keeps the image's visual quality intact throughout all of the testing. The graph in Figure 6(a) and (b) displays the PSNR of the relevant photos on various standards respectively. The graph makes it evident that the suggested algorithm's PSNR produces results that are comparable to those of BM3D and that are superior to those of NL-means. The experimental outcomes of the suggested algorithm on the Lena image are shown in Figure 7. Taken is a noisy image that has additive white Gaussian noise with standard deviations of

Table 1: Benchmarking of the outcomes from the proposed algorithm on grayscale images

Sr No	Image Type	Standard Deviation	Image with noise		Buades Algo.		BM3D		Proposed Algorithm (9estimates)	
		σ	*PSNR*	*SSIM*	*PSNR*	*SSIM*	*PSNR*	*SSIM*	*PSNR*	*SSIM*
1	Cameraman	15	24.61	0.72	32.99	0.91	35.76	0.95	34.82	0.93
		25	20.23	0.54	30.52	0.86	33.18	0.92	31.95	0.90
		35	17.22	0.43	28.8	0.83	31.52	0.90	30.19	0.86
		50	14.75	0.34	26.63	0.78	29.94	0.86	28.13	0.79
		80	11.45	0.20	23.82	0.66	27.74	0.81	25.71	0.70
		100	10.19	0.15	22.67	0.60	26.62	0.78	24.48	0.65
2	Peppers	15	24.61	0.76	34.34	0.93	36.42	0.95	35.92	0.96
		25	20.23	0.58	31.57	0.90	33.91	0.92	33.16	0.92
		35	17.22	0.46	29.44	0.87	32.16	0.90	31.18	0.89
		50	14.75	0.34	27.17	0.83	30.47	0.87	28.44	0.82
		80	11.45	0.20	24.28	0.74	27.98	0.82	25.88	0.74
		100	10.19	0.15	23.26	0.69	26.77	0.78	24.60	0.69
3	Lena	15	24.61	0.77	32.51	0.92	34.3	0.95	33.24	0.94
		25	20.23	0.59	29.84	0.88	32.07	0.92	31.09	0.90
		35	17.22	0.47	28.20	0.84	30.6	0.89	29.34	0.87
		50	14.62	0.35	26.45	0.79	29.03	0.86	27.52	0.81
		80	11.42	0.22	24.38	0.69	26.94	0.80	25.36	0.72
		100	10.15	0.16	23.46	0.64	25.94	0.76	24.30	0.67

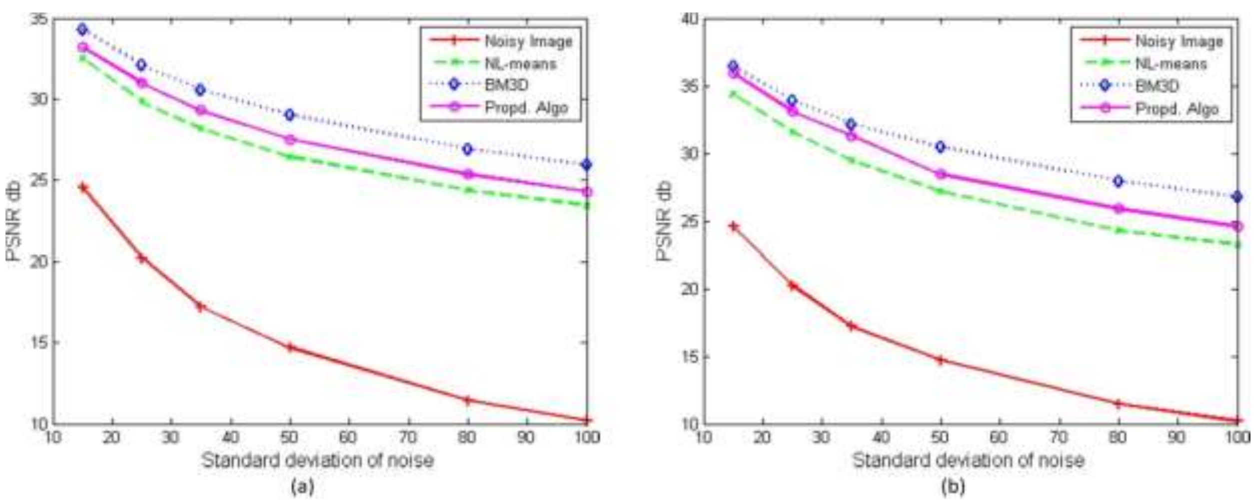

Figure 6: PSNR vs. standard deviation (Noise) (a)Lena Image (b)Peppers Image

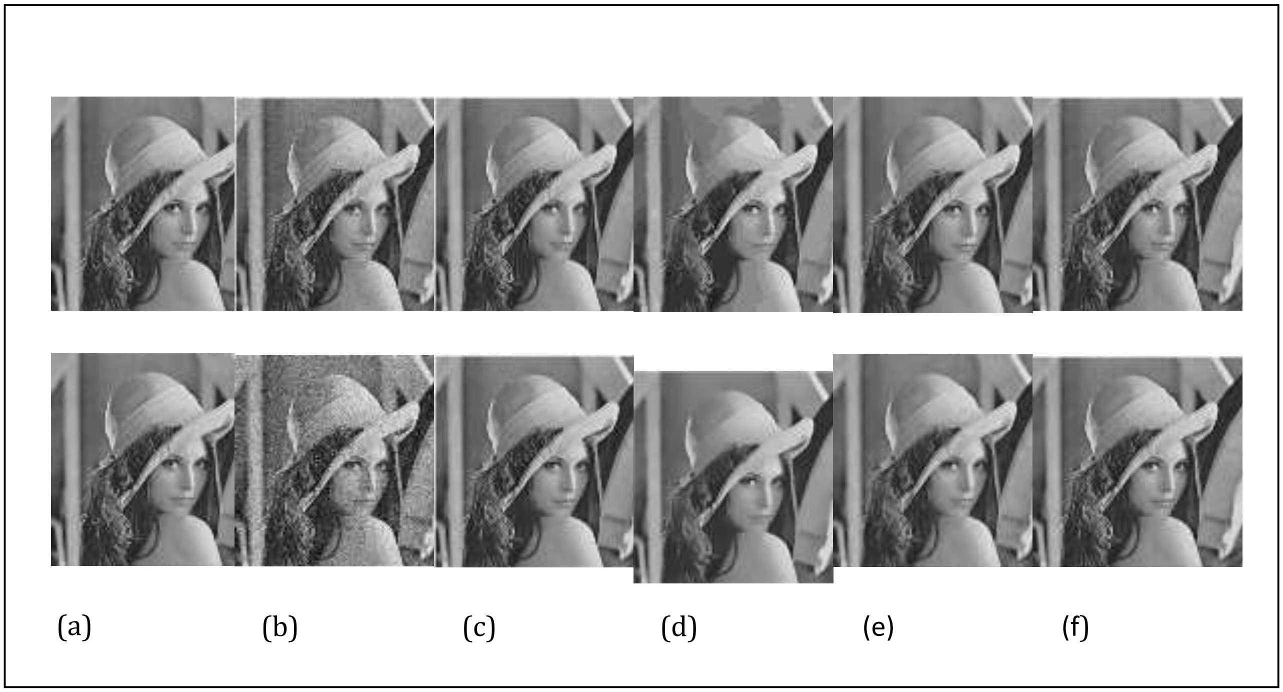

Figure 7: (a)Original Image (b)Noisy Image (c)BM3D (d)NL-means (e)Bivariate (f)Proposed Algorithm

CONCLUSION

Although the PSNR results from the denoising technique utilizing DWT and Bivariate shrinkage are good, the fine features of a picture are not preserved. The suggested technique has superior edge preservation and denoising capabilities as a result of the merger of the attributes of two techniques, Discrete Wavelet transform and Local Profile edge detection. By averaging each estimate to produce the final denoised output, estimate calculation significantly enhances the capabilities of denoising. For zero mean Gaussian noise with low and moderate magnitudes, the suggested technique produces improved PSNR. This paper presents a novel denoising method for reducing Gaussian noise using the separable wavelet transform and spatial domain edge preservation. Unlike conventional algorithms, the suggested ones don't call for any prior knowledge of the noise characteristics.

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