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Hybrid Transform Based Image Denoising using CT with Wavelet Filters and Thresholding

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Abstract - Image denoising is the essential need of modern image system which facilitates the automatic corrections in the images being processed. Several research are going on to develop new and efficient techniques to reduce noises in the images corrupted by the different environmental noises and distortions affecting images during capture. In this work we have compared the proposed method with the wavelet and found that the images are denoised better with the contourlet transform technique. The experiment performed on different images and on the basis of peak signal to noise ratio (PSNR), root mean square error(RMSE) and Elapsed Time. All the parameters of proposed hybrid transform with contourlet and wavelet decomposition followed by thresholding based technique found better.

Keywords - Denoising, PSNR, contourlet transform, RMSE, Wavelet Filtering Decomposition, Thresholding.

I. INTRODUCTION

The need for image enhancement and restoration is encountered in many practical applications. For instance, distortion due to additive white Gaussian noise (AWGN) can be caused by poor quality image acquisition, images observed in a noisy environment or noise inherent in communication channels. Linear filtering and smoothing operations have been widely used for image restoration because of their relative simplicity. However, since these methods are based upon the assumption that the image signal is stationary and formed through a linear system, their effectiveness is generally acceptable but limited. In reality, real-world images have typically non-stationary statistical characteristics. They are formed through a nonlinear system process where the intensity distribution arriving at the imaging system is the product of the reflectance of the object or the scene of interest and the illumination distribution falling on the scene. There also exist various adaptive and nonlinear image restoration methods that account for the variations in the local statistical characteristic. These methods achieve better enhancement and restoration of the image while preserving high frequency features of the original image such as edges.

The most common type of noise is the additive one. As Figure 1.1 shows, the degradation process is modeled as an additive noise term, w, which operates on an input image, u, to produce a degraded image, U. Given this noisy observation, along with some knowledge of the additive noise term, the restoration technique yields an estimate, U, of the original image. The denoised estimate is desired to be as close as possible to original image.

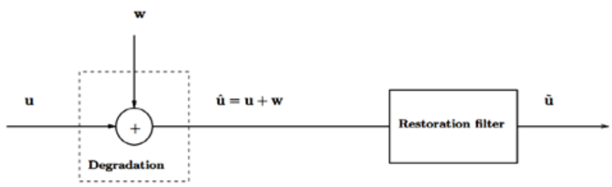


Figure 1.1 degradation and restoration model for an additive noise process.

Besides, the amount of noise usually depends on the signal intensity. Practitioners often consider it to be following a statistical distribution. Generally, when the magnitude of the measured signal is sufficiently high, the noise is supposed to be independent of the original image that it corrupts, and modeled as an additive Gaussian random variable. On the other hand, when the magnitude of the observed signal is relatively low, it is often assumed to follow a Poisson distribution.

Thus, the general goal of this research is to design and implement an efficient image denoising method for Gaussian and Poisson noise, which can satisfy the following requirements.

- Competitive performance

The proposed algorithm should be competitive with other start-of-the-art denoising methods according to certain objective measurements, such as Peak Signal-to-Noise Ratio (PSNR).

- Minimal human interaction

The human interaction should be minimized during the denoising process when applying the proposed algorithm, in other words, the entire denoising process should be totally automatic.

- Low computational burden

The proposed algorithm should not require a very high computing capacity, a regular personal computer should satisfy the hardware requirement and be qualified to Adequate reliability

The proposed algorithm should demonstrate consistent and repeatable experimental results regardless of the sources of images and how many times the denoising process is performed.

II. PROPOSED DENOISING ALGORITHM

In this work, a new contourlet domain image denoising method has been proposed. We have developed a statistical model for the contourlet coefficients using the Bessel k-form distribution that can capture their heavy-tailed property. To estimate the noise-free coefficients, the noisy image is decomposed into various scales and directional subbands via the contourlet transform. A Bayesian estimator has been developed based on the transform prior to remove noise from all the detail subbands. Experiments have been carried out to compare the performance of the proposed denoising method with that provided by some of the existing methods. The simulation results have shown that the proposed scheme outperforms other existing methods in terms of the PSNR values and provides denoised images with higher visual quality.

The block diagram of the Proposed Methodology has been given here in this very firstly the original image is being processed then noise is added with is for analysis purpose after this the combination of contourlet transform followed by wavelet filter decomposition with thresholding is performed and this hybrid technique gives the better results than previous.

Flow graph shows the complete simulation process of Proposed Methodology in this firstly, the grayscale image is taken for loading then generate noise to be added in original image for analysis purpose after that apply contourlet denoising based on filters 9-7 and pkva after that wavelet filter decomposition with thresholding is applied then the calculations of PSNR, and RMSE have been done, at the last outcomes have been displayed.

Process flow chart depicted in figure 2.1 the process start to initialize the system parameters before simulation select the sample input image to demising purposed add Gaussian

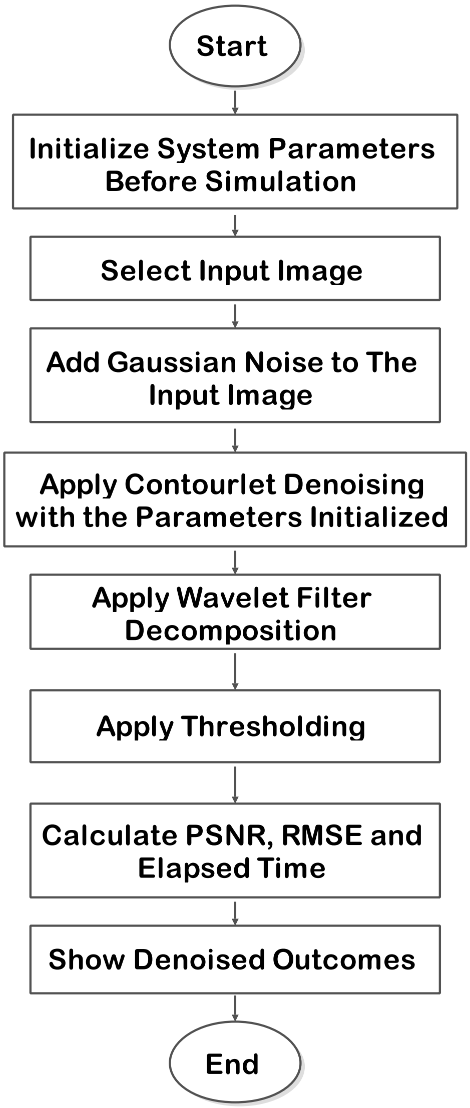


Fig. 2.1: Flow chart of the proposed Methodology.

Noised to the input image just for the testing purpose of the proposed system. apply contourlet denoising with parameter initialized for wavelet filter decomposition with thresholding to calculate PSNR, RMSE and elapsed time show denoised outcome the simulation outcome of the proposed system has give in comparison table 1 table 2 and table 3 for different images and different sizes.

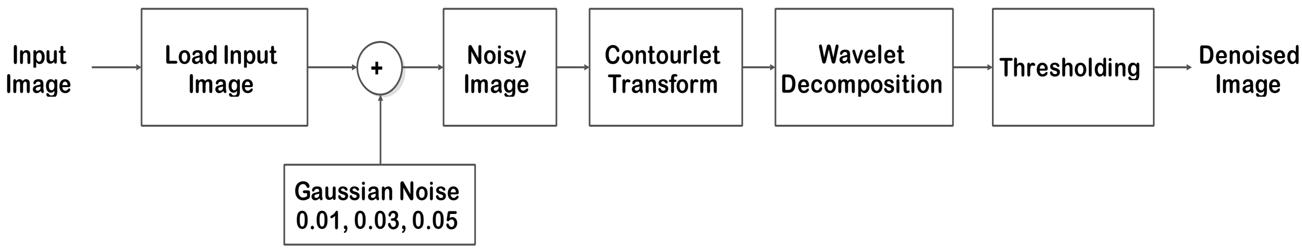


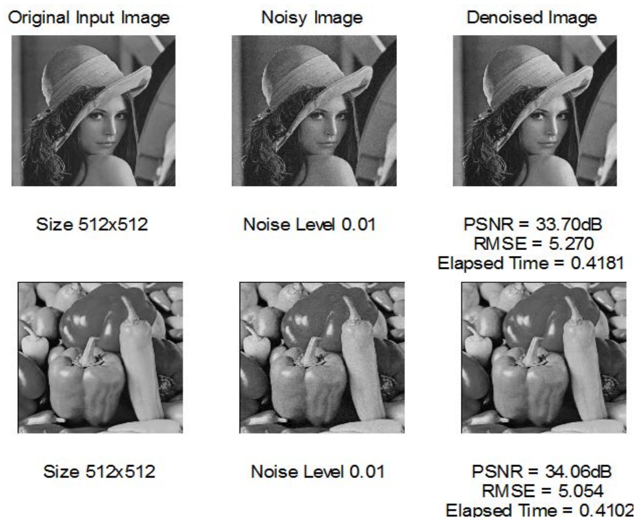
Fig.2.2: Block Diagram of Proposed Methodology

III. SIMULATION OUTCOMES

In the previous section proposed methodology for image denoising is explained with flow chart and block diagram. The simulation done on various image is shown in this section.

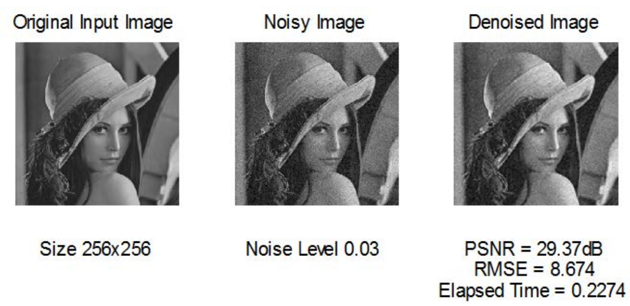
(a) (b) (c)

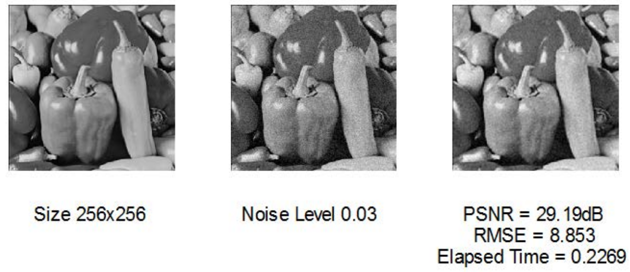
Fig. 3.1 Lena and Peppers Images of 256x256 Size (a) Original Input Image, (b) Noisy Image, (c) Denoised Image with Noise Level 0.01



(a) (b) (c)

Fig. 3.2 Lena and Peppers Images of 512x512 Size (a) Original Input Image, (b) Noisy Image, (c) Denoised Image with Noise Level 0.01





(a) (b) (c)

Fig. 3.3 Lena and Peppers Images of 256x256 Size (a) Original Input Image, (b) Noisy Image, (c) Denoised Image with Noise Level 0.03

(a) (b) (c)

Fig. 3.4 Lena and Peppers Images of 512x512 Size (a) Original Input Image, (b) Noisy Image, (c) Denoised Image with Noise Level 0.03

(a) (b) (c)

Fig. 3.5 Lena and Peppers Images of 256x256 Size (a) Original Input Image, (b) Noisy Image, (c) Denoised Image with Noise Level 0.05

(a) (b) (c)

Fig. 3.6 Lena and Peppers Images of 512x512 Size (a) Original Input Image, (b) Noisy Image, (c) Denoised Image with Noise Level 0.05

Table 1 shows the comparison of peak signal to noise ratio (PSNR), root mean square error (RMSE) and Elapsed Time (Seconds) on noise density 0.01

Images	**Existing Work**			**Proposed Methodology**		
	PSNR	**RMSE**	**Elapsed Time (sec.)**	**PSNR**	**RMSE**	**Elapsed Time (sec.)**
Lena 256x256	32.33 dB	6.11	6.32	32.66 dB	5.936	0.2792
Lena 512x512	33.15 dB	5.39	26.06	33.70 dB	5.270	0.4181
Peppers 256x256	32.39 dB	6.10	2.3	32.42 dB	6.104	0.2593
Peppers 512x512	32.73 dB	5.52	21.99	34.06 dB	5.054	0.4102

Table 2 shows the comparison of peak signal to noise ratio (PSNR), root mean square error (RMSE) and Elapsed Time (Seconds) on noise density 0.03.

Images	Existing Work			Proposed Methodology		
	PSNR	RMSE	Elapsed Time (sec.)	PSNR	RMSE	Elapsed Time (sec.)
Lena 256x256	26.76 dB	12.22	2.44	29.37 dB	8.674	0.2274
Lena 512x512	28.41 dB	9.90	31.48	30.02 dB	8.042	0.4211
Peppers 256x256	26.45 dB	12.57	2.43	29.19 dB	8.853	0.2269
Peppers 512x512	28.95 dB	10.10	29.02	30.12 dB	7.954	0.4080

Table 3 shows the comparison of peak signal to noise ratio (PSNR), root mean square error (RMSE) and Elapsed Time (Seconds) on noise density 0.05.

Images	Existing Work			Proposed Methodology		
	PSNR	RMSE	Elapsed Time (sec.)	PSNR	RMSE	Elapsed Time (sec.)
Lena 256x256	24.95 dB	15.33	8.33	27.69 dB	10.522	0.2249
Lena 512x512	26.76 dB	12.62	39.61	28.17 dB	9.954	0.4071
Peppers 256x256	24.53 dB	17.30	2.66	27.53 dB	10.720	0.2254
Peppers 512x512	26.42 dB	13.03	33.57	28.13 dB	10.006	0.4129

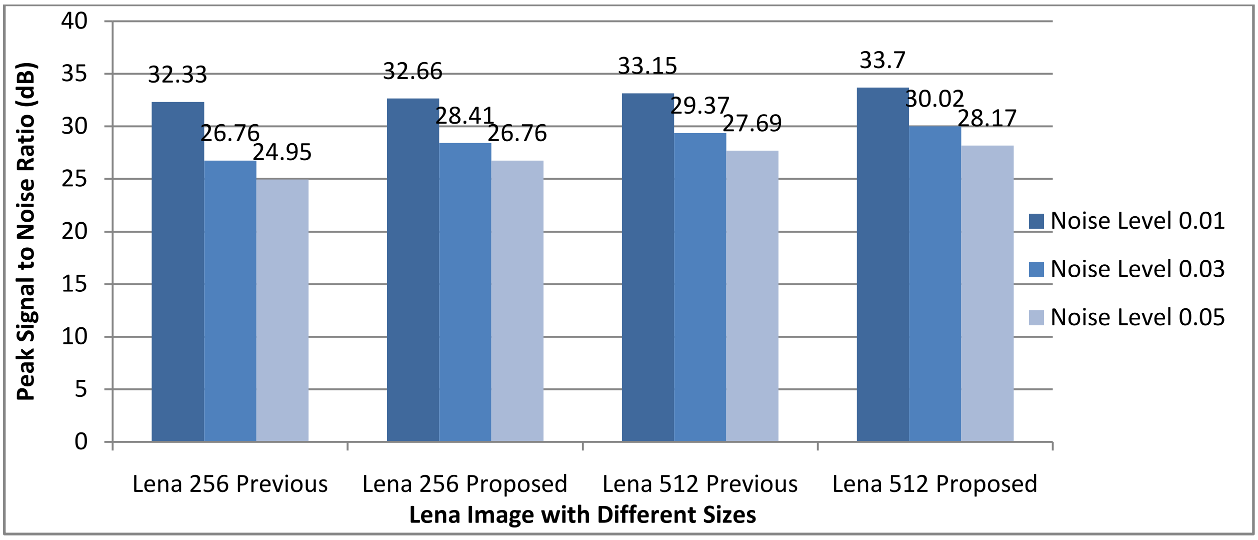


Fig. Peak Signal to Noise Ratio Comparison of Lena Image with Different Sizes and Noise Levels

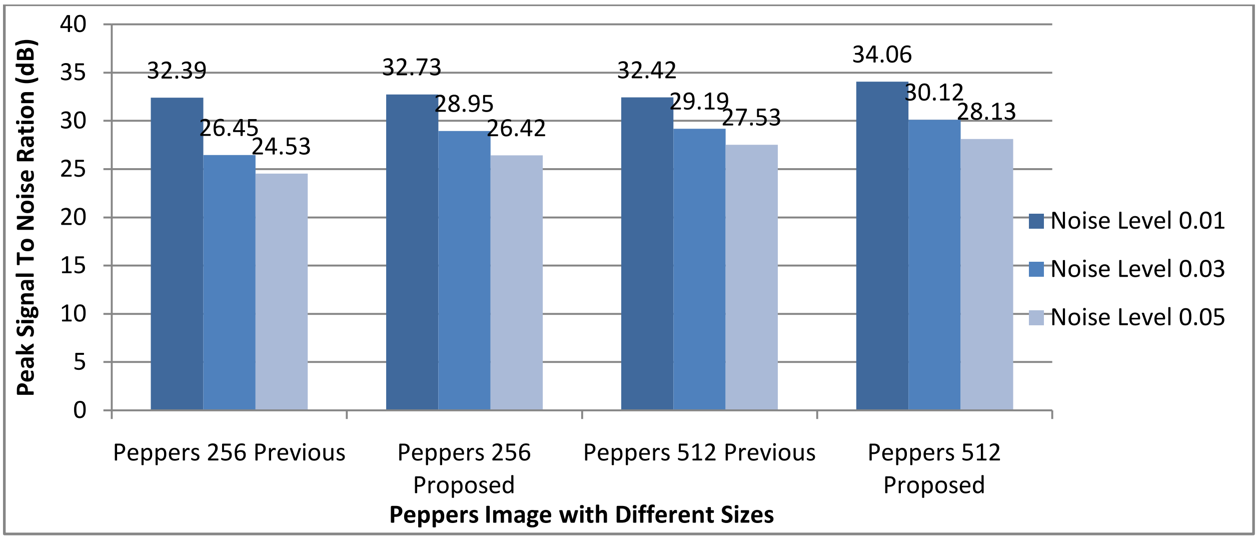


Fig. Peak Signal to Noise Ratio Comparison of Peppers Image with Different Sizes and Noise Levels

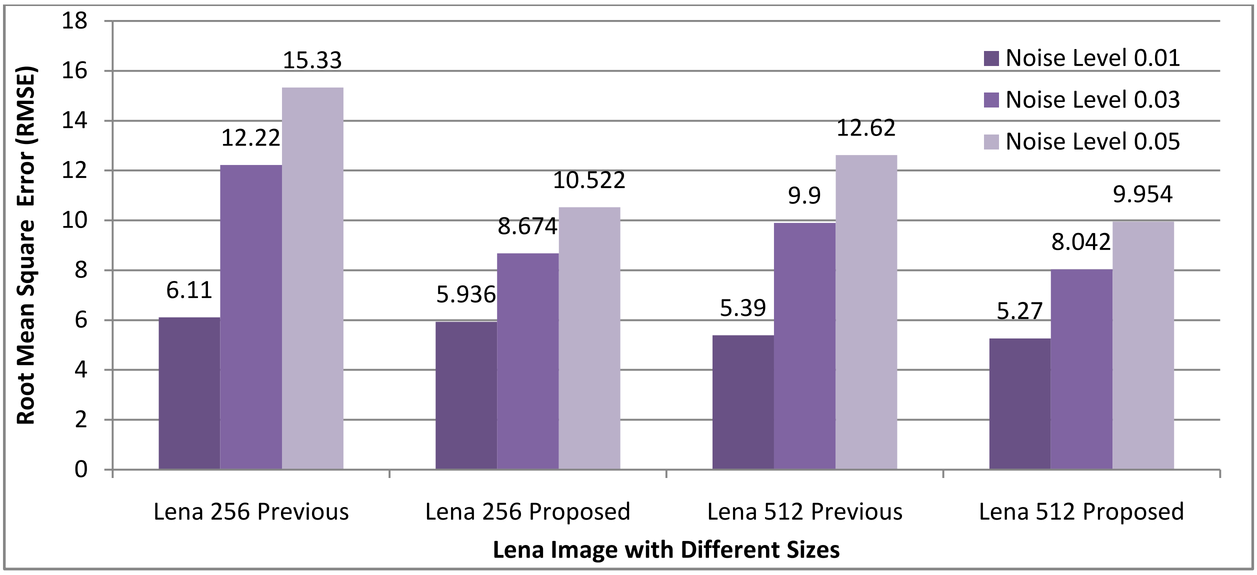


Fig. RMSE Comparison of Lena Image with Different Sizes and Noise Levels

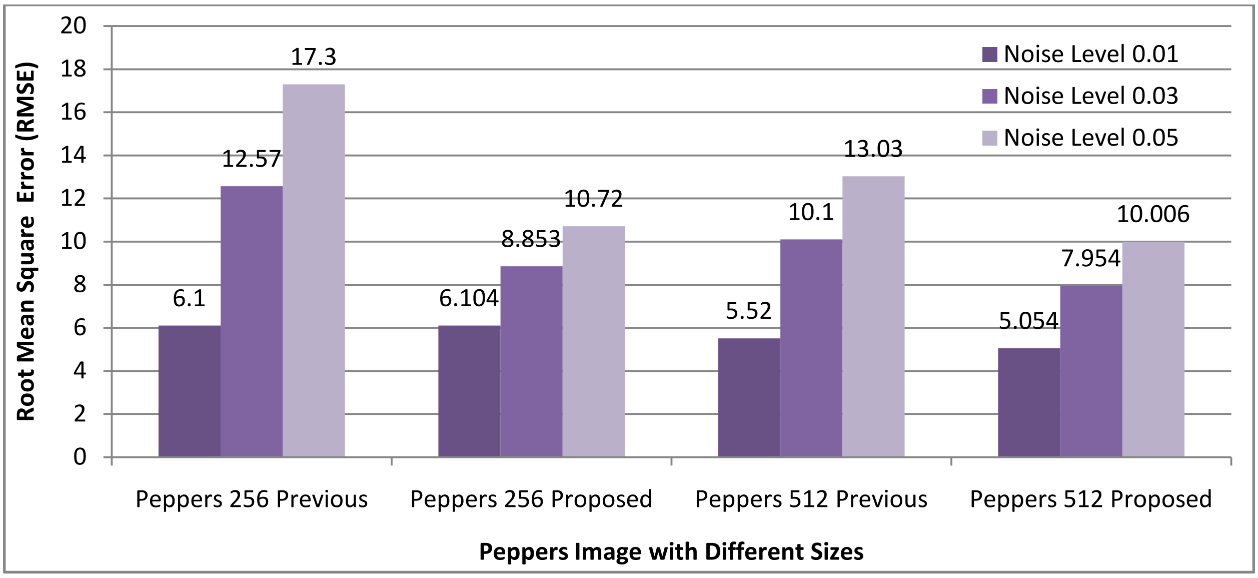


Fig. RMSE Comparison of Peppers Image with Different Sizes and Noise Levels

IV. CONCLUSIONS

This work proved to the pros of the contourlet transform over wavelet transform. The simulation was performed on three images lena, peppers and other different images with three parameters peak signal to noise ratio (PSNR), root mean square error (RMSE) and Elapsed Time found that proposed controurlet transform is better than the wavelet transform based denoising. The proposed methodology integrating with the wavelet filter decomposition and thresholding to enhance the performance of the denoising over wavelet transform. The proposed technique can be integrated with the other denoising algorithms to reduce the level of noise in the input images like wavelet transform, total variation denoising.

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