Development of Efficient Image Denoising in Contourlet Domain with Adaptive Median Filtering

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Abstract: - Image denoising is the fascinating research area among researchers due to applications of the images in everywhere, social networking sites, High Definition videos and stills. The need of it is to enhance the facility to imaging devices and the processing devices for denoising and enhancement of images. In this paper, Adaptive median filtering (AMF) is used to allow for accurate registration near such boundaries. Here we have proposed a new formulation of AMG with contourlet domain to enhance or denoising of images. The proposed methodology's results are usually compared in the term of (PSNR) peak-signal-to-noise ratio and (SSIM) Structural similarity index for the different digital images of Lena and Barbara.

Keywords - PSNR, Image Denoising, AMF, SSIM.

I. INTRODUCTION

Multiscale image analysis is known to be useful and indispensable to the field of image processing. Depending on the requirements of an application, a variety of multiscale and multi-resolution transforms have been used. Signals can be effectively projected using these transforms. The wavelet transform is by far the most prevalent transformation in signal processing offering a multiscale and multi-resolution signal representation. In many applications such as classification, denoising, texture retrieval, restoration and watermarking, it has led to the development of very efficient algorithms, for instance, those in JPEG 2000. This transform also offers sparsity and localization features to the transformed signals. However, the wavelet transform provides an optimal representation only to one-dimensional (1-D) piecewise smooth signals. A direct extension of wavelets to higher dimensions by the tensor product of 1-D wavelets does not provide an optimal representation to multidimensional signals such as images. This is because of the intrinsic geometrical structure of typical natural images. In other words, the separable wavelets are optimal only in representing point discontinuities in two-dimensional (2-D) signals, but not optimal in capturing line discontinuities, which correspond to directional information in images.

The contourlet transform also recognizes the smoothness of the contour in images. There are a number of other multiscale representations such as the dual-tree complex wavelet transform [5], ridgelet transform [6] and curvelet transform [7]-[9] that also provide multiscale and directional image representation. However, the contourlet transform can provide a flexible number of directions in each subband, and in this regard, this transform is superior to the complex wavelet transforms. Compared to the curvelet transform, the contourlet transform is preferred, since it is defined on rectangular grids and offers a seamless translation to the discrete world [4]. Moreover, the contourlet transform has a 2-D frequency partitioning on concentric rectangles rather than on concentric circles as in the case of the curvelet, and hence, overcomes the blocking artifact deficiency of the curvelet transform. Further, due to the use of iterated filter banks, the contourlet transform is computationally more efficient than the curvelet transform. In view of the above properties, the contourlet transform has become a suitable candidate in many image processing applications.

Images are often corrupted by noise during the acquisition and transmission processes, leading to significant degradation of image quality for the human interpretation and post processing tasks. Therefore, denoising is essential for images not only to improve the image quality, but also to proceed with further data analysis. It is required to pre-process images and remove the noise while retaining as much as possible the important image features. Therefore, finding a better image denoising algorithm is of the utmost importance. In view of the properties of the contourlet transform, an image denoising problem can be effectively addressed in the contourlet domain.

Many problems in image processing require a prior probability model of images. This is true for a wide range of applications in which measurements and observations are regarded as stochastic processes. In these applications, the theoretical limits of an algorithm can be overcome by a prior model of the underlying signal. For images, a statistical model is considered as a particular prior probability model for the underlying frequency domain coefficients for capturing certain characteristics of an image in a small number of parameters so that they can be used as prior information in image processing tasks.

II. ADAPTIVE FILTER

An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm. Because of the complexity of the optimization algorithms, almost all adaptive filters are digital filters. Adaptive filters are required for some applications because some parameters of the desired processing operation (for instance, the locations of reflective surfaces in a reverberant space) are not known in advance or are changing. The closed loop adaptive filter uses feedback in the form of an error signal to refine its transfer function.

Generally speaking, the closed loop adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration. The most common cost function is the mean square of the error signal. As the power of digital signal processors has increased, adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment.

III. PROPOSED METHODOLOGY

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 Bessel k-form 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 Adaptive Median Filtering (AMF) is used with the combination of contourlet both gives the better results than previous.

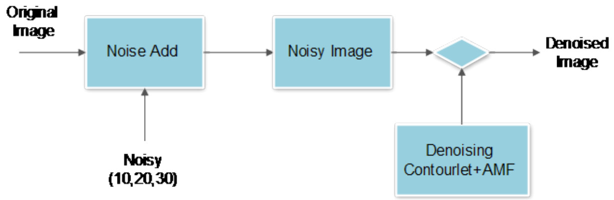


Fig.1.1: Block Diagram of Proposed Methodology

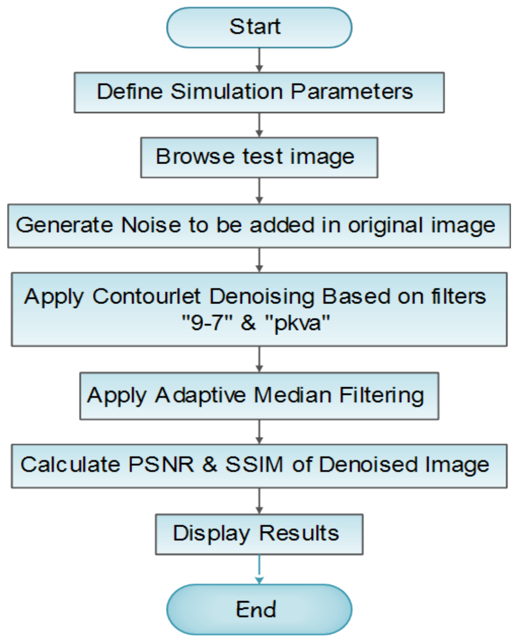


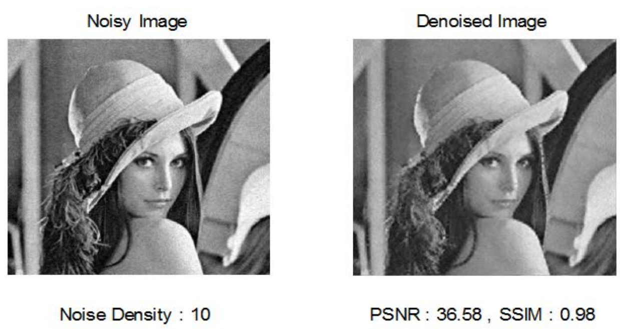
Fig.1.2: Flow chart of the proposed Methodology

Above flow graph shows the complete simulation process of Proposed Methodology in this firstly, the colour 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 it adaptive median filtering is applied then the Calculations of PSNR, and SSIM have been done, at the last outcomes have been displayed.

IV. 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.

Lena Image (PSNR/SSIM)



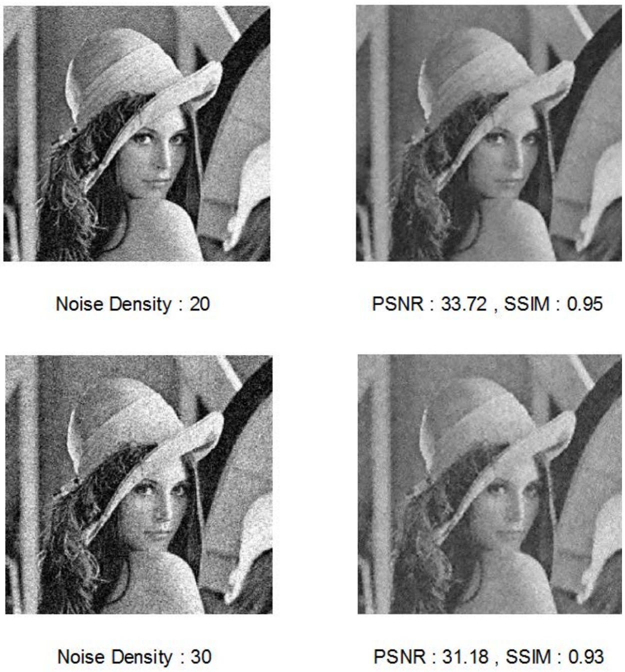


Fig.1.3: Lena Images with different PSNR and SSIM values

Table 1: Lena Images PSNR and SSIM values with Different Noises

Noise Density	**10**	**20**	**30**
Noisy Image	28.12 / 0.71	24.62 / 0.44	22.13 / 0.32
Proposed Methodology	**36.57 / 0.9756**	**33.67 / 0.9545**	**31.20 / 0.9310**
Existing Methodology	33.95 / 0.91	31.49 / 0.83	29.65 / 0.76

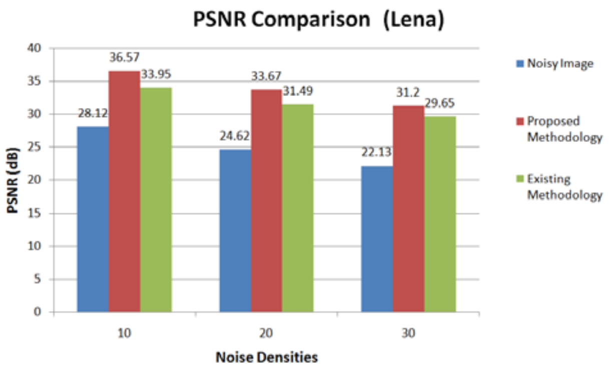


Fig.1.4: PSNR Comparison of Lena Image

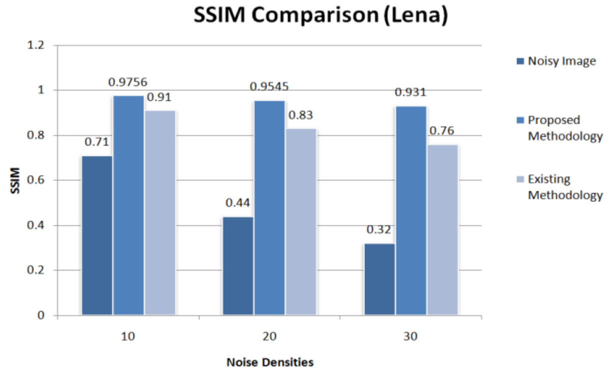


Fig.1.5: SSIM Comparison of Lena Image

Barbara Image (PSNR/SSIM)

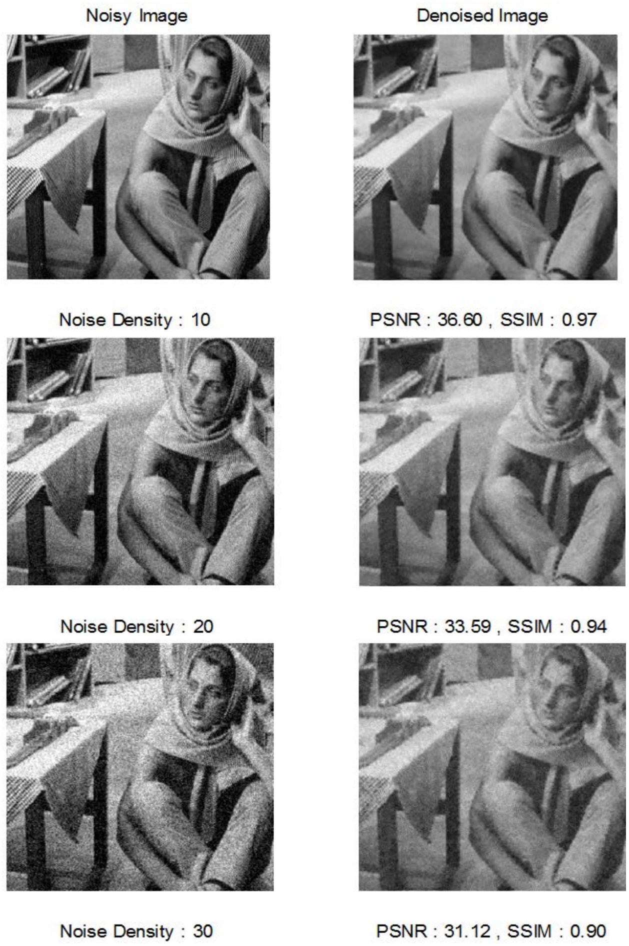


Fig. 1.6: Barbara Images with different PSNR and SSIM values

Table 2: Barbara Images PSNR and SSIM values with Different Noises

Noise Density	**10**	**20**	**30**
Noisy Image	28.12 / 0.71	24.62 / 0.44	22.13 / 0.32
Proposed Methodology	**36.49 / 0.96**	**33.61 / 0.93**	**31.15 / 0.9037**
Existing Methodology	32.01/0.87	29.17/0.83	27.87/0.71

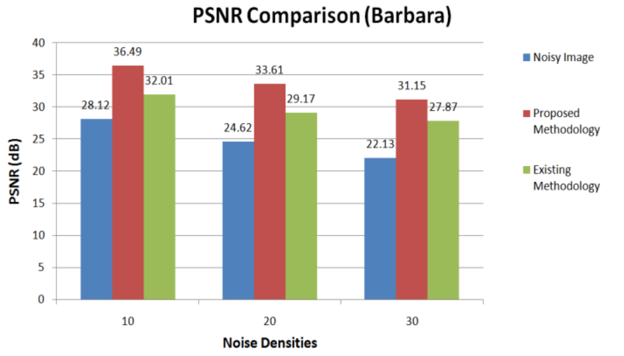


Fig.1.7: PSNR Comparison of Barbara Image

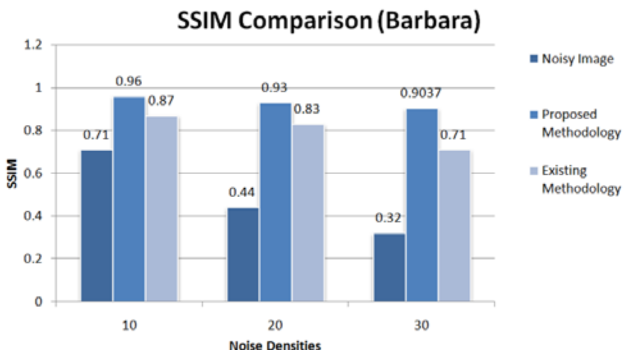


Fig.1.8: SSIM Comparison of Barbara Image

Table 3: Other Images Image (PSNR/SSIM)

Noise Density	10	20	30
Cameraman (Proposed)	34.83 / 0.95	32.83 / 0.90	30.72 / 0.86
Peppers (Proposed)	38.23 / 0.98	34.44 / 0.96	31.64 / 0.94

V. CONCLUSION AND FUTURE SCOPES

The image denoising approach shown in this paper is proved efficient for various images and also for various noise densities of Gaussian Noise. The Effectiveness of the proposed approach is compared with the existing work in terms of Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM). The improvements from previous work is shown in the previous tables such performance is appreciable. The adaptive median filtering in proposed algorithms can be more efficient with some other filters like Daubechies, Symlet, Haar and Bi-Orthogonal filters with different thresholding and filter levels.

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