Filtered Contourlet Transform Based Efficient Image Denoising

Sushma Vishwakarma[1], Prof. Amit Gangoli[2]

[1]*Mtech. Scholar,* [2]*Research Guide*

Department of Computer Science Engineering, SISTEC-R, Bhopal

Abstract: -Image denoising is the interesting examination region among analysts because of utilizations of the images in all over, informal communication destinations, High Definition recordings and stills. The need of it is to upgrade the office to imaging gadgets and the handling gadgets for denoising and improvement of images. In this paper, Adaptive middle sifting (AMF) is utilized to take into consideration exact registration close to such limits. Here we have proposed another definition of AMG with contourlet area to upgrade or denoising of images. The proposed philosophy's outcomes are generally thought about in the term of (PSNR) peak-signal-to-noise ratio and (SSIM) Structural similarity index for the distinctive computerized images of Lena and Barbara.

Keywords - PSNR, Image Denoising, AMF, SSIM.

I. INTRODUCTION

Multiscale image examination is known to be valuable and irreplaceable to the field of image preparing. Contingent upon the prerequisites of an application, an assortment of multiscale and multi-goal transforms have been utilized. Signals can be adequately extended utilizing these transforms. The wavelet transform is by a wide margin the most common transformation in signal preparing offering a multiscale and multi-goal signal portrayal. In numerous applications, for example, arrangement, denoising, surface recovery, restoration and watermarking, it has prompted the improvement of exceptionally proficient calculations, for example, those in JPEG 2000. This transform likewise offers sparsity and limitation highlights to the transformed signals. Notwithstanding, the wavelet transform gives an ideal portrayal just to one-dimensional (1-D) piecewise smooth signals. An immediate expansion of wavelets to higher measurements by the tensor result of 1-D wavelets doesn't give an ideal portrayal to multidimensional signals, for example, images. This is a result of the inborn mathematical structure of regular normal images. As it were, the divisible wavelets are ideal just in speaking to point discontinuities in two-dimensional (2-D) signals, however not ideal in catching line discontinuities, which compare to directional data in images.

The contourlet transform additionally perceives the perfection of the shape in images. There are various other multiscale portrayals, for example, the double tree complex wavelet transform [5], ridgelet transform [6] and curvelet transform [7]-[9] that additionally give multiscale and directional image portrayal. In any case, the contourlet transform can give an adaptable number of bearings in each subband, and in such manner, this transform is better than the intricate wavelet transforms. Contrasted with the curvelet transform, the contourlet transform is liked, since it is characterized on rectangular matrices and offers a consistent interpretation to the discrete world [4]. In addition, the contourlet transform has a 2-D recurrence parceling on concentric square shapes as opposed to on concentric circles as on account of the curvelet, and henceforth, defeats the impeding relic lack of the curvelettransform. Further, because of the utilization of iterated channel banks, the contourlet transform is computationally more effective than the curvelet transform. Taking into account the above properties, the contourlet transform has become an appropriate competitor in many image handling applications.

Images are frequently undermined by noise during the obtaining and transmission measures, prompting critical corruption of image quality for the human understanding and post handling assignments. In this way, denoising is basic for images not exclusively to improve the image quality, yet additionally to continue with additional information examination. It is needed to pre-measure images and eliminate the noise while holding however much as could reasonably be expected the significant image highlights. Along these lines, finding a superior image denoising calculation is absolutely critical. Taking into account the properties of the contourlet transform, an image denoising issue can be adequately tended to in the contourlet space.

Numerous issues in image preparing require an earlier likelihood model of images. This is valid for a wide scope of uses in which estimations and perceptions are viewed as stochastic cycles. In these applications, the hypothetical furthest reaches of a calculation can be overwhelmed by an earlier model of the fundamental signal. For images, a factual model is considered as a specific earlier likelihood model for the basic recurrence area coefficients for catching certain attributes of an image in few boundaries with the goal that they can be utilized as earlier data in image preparing assignments.

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.

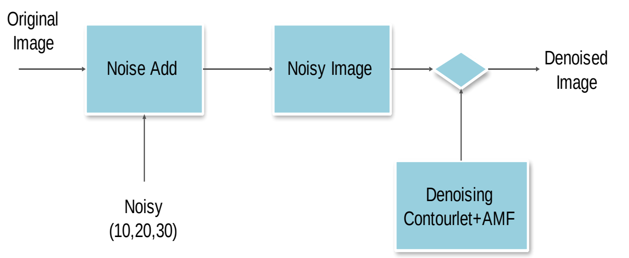


Fig.1.1: Block Diagram of Proposed Methodology

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.

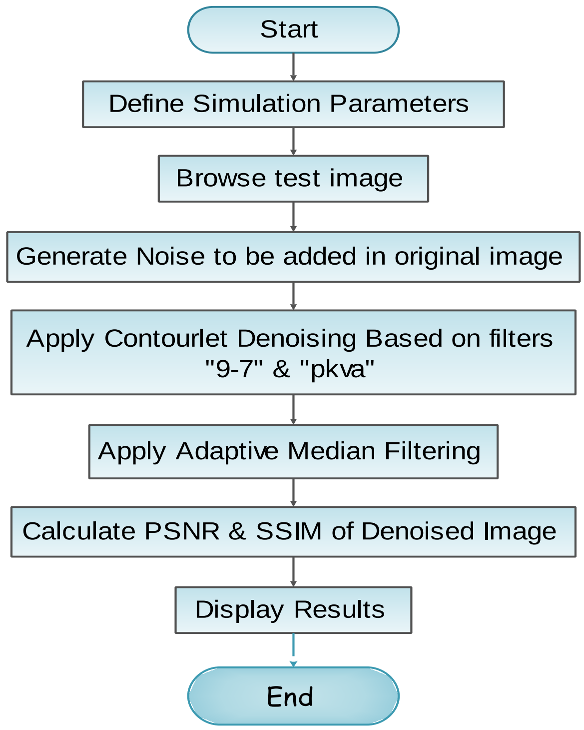


Fig.1.2: Flow chart of the proposed Methodology

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

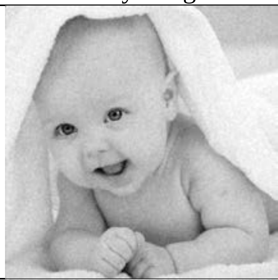
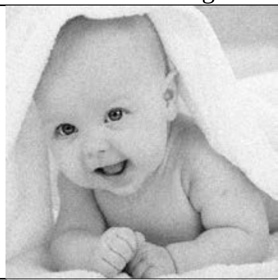
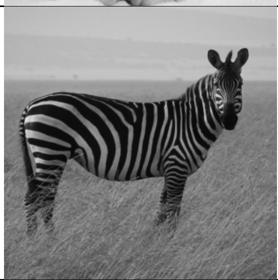
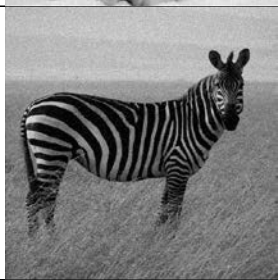
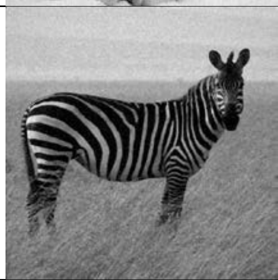
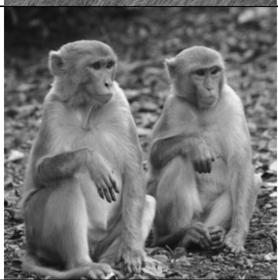
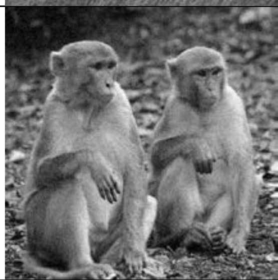
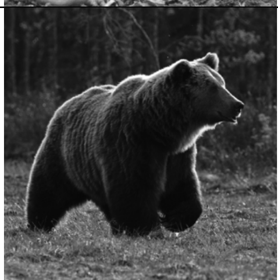
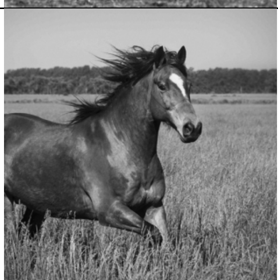
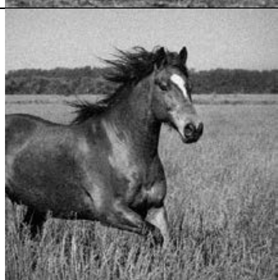
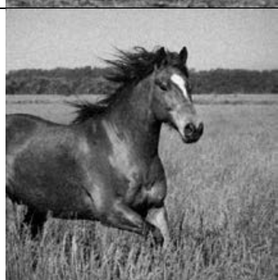
In the previous section proposed methodology for image denoising is explained with flow chart and block diagram. The simulation done on various images are shown in below table with their noisy versions and Denoised versions. The noise level for testing is considered is $\sigma = 30$ which was taken for the purpose of result comparison with previous [1] work.

Results for other level of noises can be evaluated by changing the values of the σ (Noise Level). Here noise level shows the amount of noise being added to the original image to evaluate the performance of the proposed denoising algorithm on images affected by different amount of noises.

Table 1 shows the side by side comparison of the input original image, respective noisy image and Denoised image.

Table 2 shows the peak signal to noise ratio(PSNR) and structural similarity index (SSIM) comparison with the previous work.

Table 1: Denoising Results with σ = 30

Name	Original Image	Noisy Image	Denoised Image
Baby			
Zebra			
Monkey			
Bear			
Horse			
Bridge			

Child			
Seal			

Table 2: Comparison of PSNR and SSIM values for different images with σ = 30 Noise Level

Method	***Parameters***	***Images***								
		Baby	***Zebra***	***Monkey***	***Bear***	***Horse***	***Bridge***	***Child***	***Seal***	***Average***
Previous [1]	***PSNR(dB)***	30.10	27.27	24.66	28.13	25.80	25.61	28.50	25.45	26.96
	SSIM	0.8273	0.7562	0.7034	0.6991	0.6991	0.7131	0.6315	0.7287	0.7198
Proposed [our]	***PSNR(dB)***	***37.13***	***33.02***	***34.87***	***34.07***	***31.18***	***33.27***	***36.35***	***32.83***	***34.09***
	SSIM	***0.9993***	***0.9844***	***0.9946***	***0.9712***	***0.9894***	***0.9841***	***0.9886***	***0.9949***	***0.9883***

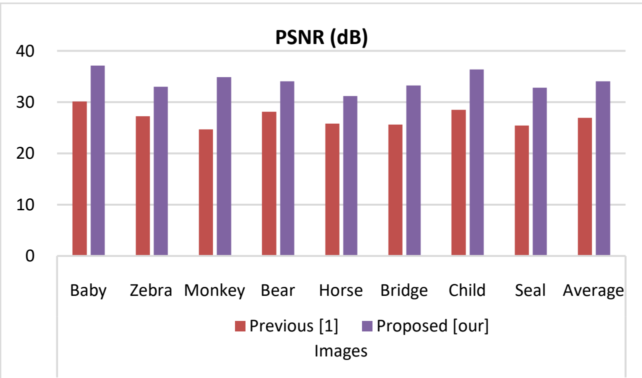


Fig. 4.1 Comparison of PSNR(dB)

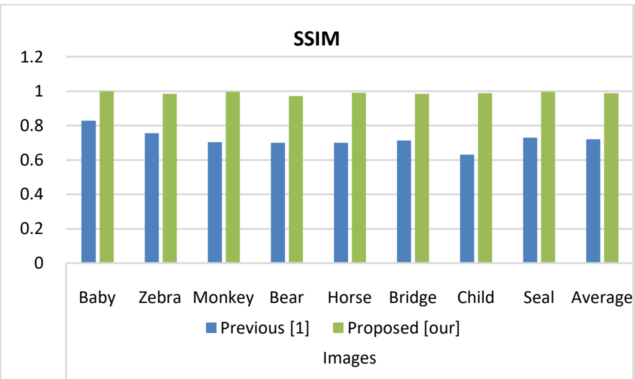


Fig. 4.2 Comparison of SSIM

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 areshown 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.

REFERENCES

[1] J. Yoo and J. Kim, "Enhancing Denoised Image Via Fusion With a Noisy Image," *2019 IEEE International Conference on Image Processing (ICIP)*, Taipei, Taiwan, 2019, pp. 1790-1794.

[2] G. Baloch, H. Ozkaramanli and R. Yu, "Residual Correlation Regularization Based Image Denoising," in IEEE Signal Processing Letters, vol. 25, no. 2, pp. 298-302, Feb. 2018.

[3] J. Zhu, J. Zhang, Y. Cao and Z. Wang, "Image guided depth enhancement via deep fusion and local linear regularizaron," 2017 IEEE International Conference on Image Processing (ICIP), Beijing, 2017, pp. 4068-4072.

[4] P. Riot, A. Almansa, Y. Gousseau and F. Tupin, "Penalizing local correlations in the residual improves image denoising performance," 2016 24th European Signal Processing Conference (EUSIPCO), Budapest, 2016, pp. 1867-1871.

[5] D. Chen, X. He, H. Chen, Z. Wang and Y. Zhang, "Video super-resolution using joint regularization," 2016 IEEE 13th International Conference on Signal Processing (ICSP), Chengdu, 2016, pp. 668-672.

[6] R. Li, C. Li and Y. Guan, "Incremental update of feature extractor for camera identification," 2015 IEEE International Conference on Image Processing (ICIP), Quebec City, QC, 2015, pp. 324-328.

[7] Y. Gan, E. Angelini, A. Laine and C. Hendon, "BM3D-based ultrasound image denoising via brushletthresholding," 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), New York, NY, 2015, pp. 667-670.

[8] A. Scholefield and P. L. Dragotti, "Quadtree Structured Image Approximation for Denoising and Interpolation," in IEEE Transactions on Image Processing, vol. 23, no. 3, pp. 1226-1239, March 2014.

[9] M. Elad and M. Aharon, “Image denoising via sparse and redundant representations over learned dictionaries,” IEEE Trans. Image Process., vol. 15, no. 12, pp. 3736–3745, Dec. 2006.

[10] Y. He, T. Gan, W. Chen, and H. Wang, “Multi-stage image denoising based on correlation coefficient matching and sparse dictionary pruning,” Signal Process., vol. 92, pp. 139–149, 2012.

[11] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Image denoising by sparse 3-D transform-domain collaborative filtering,” IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

[12] D. Zoran and Y. Weiss, “From learning models of natural image patches to whole image restoration,” in Proc. IEEE Int. Conf. Comput. Vision, 2011, pp. 479–486.

[13] M. Aharon, M. Elad, and A. Bruckstein, “K-SVD: An algorithm for de- signing overcomplete dictionaries for sparse representation,” IEEE Trans. Signal Process., vol. 54, no. 11, pp. 4311–4322, Nov. 2006.