Improved Image Denoising with Adaptive Filtered-Contourlet Transform using Bessel k-Form Distribution

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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) with structural similarity index (SSIM) proposed contourlet based technique found better.

Keywords - PSNR, contourlet transform, RMSE, Adaptive Filtering.

I. INTRODUCTION

Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality.

There are various methods to help restore an image from noisy distortions. Selecting the appropriate method plays a major role in getting the desired image. The denoising methods tend to be problem specific. For example, a method that is used to denoise satellite images may not be suitable for denoising medical images.

Over the last decade, wavelets have had a growing impact on signal processing, mainly due to their good NLA performance for piecewise smooth functions in one dimension [9, 16, 19]. Unfortunately, this is not the case in two dimensions. In essence, wavelets are good at catching point or zero-dimensional discontinuities, but as mentioned above, two-dimensional piecewise smooth functions resembling images have one-dimensional discontinuities. Intuitively, wavelets in 2-D obtained by a tensor-product of one dimensional wavelets will be good at isolating the discontinuities at edge points, but will not see the smoothness along Beyond Wavelets the contours. This indicates that more powerful representations are needed in higher dimensions.

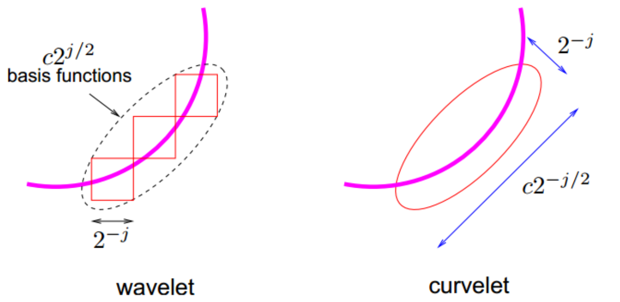

Figure 1.1 Non-linear approximation of a 2-D piecewise smooth function using wavelets and curvelets.

Recently, Candes and Donoho [4, 6] pioneered a new system of representation, named curvelet, that was shown to achieve optimal approximation behavior in a certain sense for 2-D piecewise smooth functions in R2 where the discontinuity curve is a C2 function. More specifically, an M-term non-linear approximation for such piecewise smooth functions using curvelets has L2 square error decaying like O(M-2), and this is the best rate that can be achieved by a large class of approximation processes [14]. An attractive property of the curvelet system is that such correct approximation behavior is simply obtained via thresholding a fixed transform. The key features of the curvelet elements is that they exhibit very high directionality and anisotropy.

The motivation behind the curvelet transform is that by smooth windowing, segments of smooth curves would look straight in sub-images, hence they can be captured efficiently by a local ridgelet transform. Subband decomposition is used to keep the number of ridgelets at multiple scales under control by the fact that ridgelets of a given scale live in a certain subband. The window's size and subband frequency are coordinated such that curvelets have support obeying the key anisotropy scaling relation for curves.

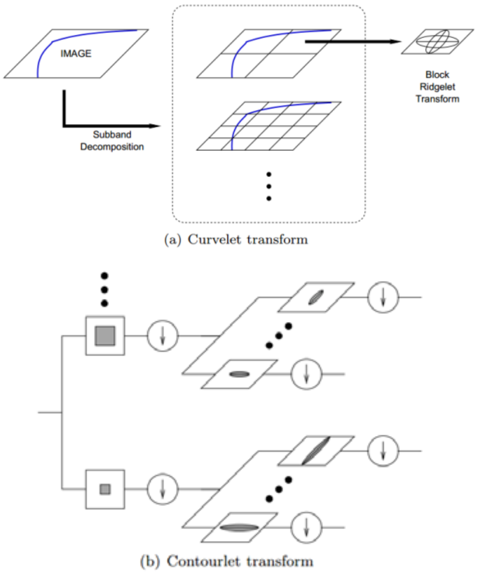

Figure 1.2 Two approaches for dealing with images having smooth contours. (a) Curvelet transform: block ridgelet transforms are applied to subband images. (b) Contourlet transform: image is decomposed by a double filter-bank structure

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 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 Filtering (AF) is used with the combination of contourlet both gives the better results than previous.

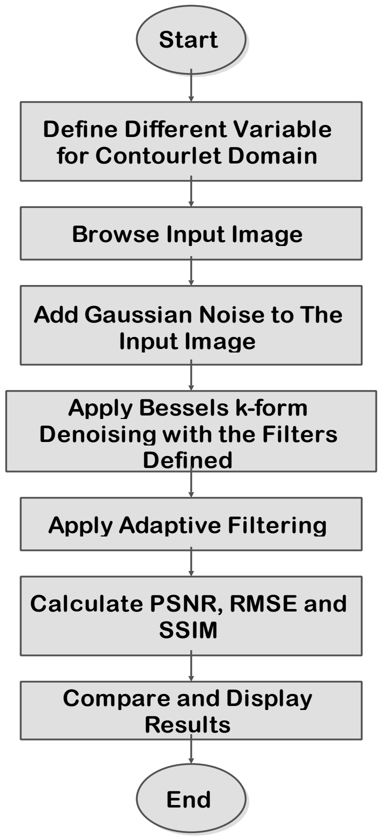

Fig. 2.1: Flow chart of the proposed Methodology

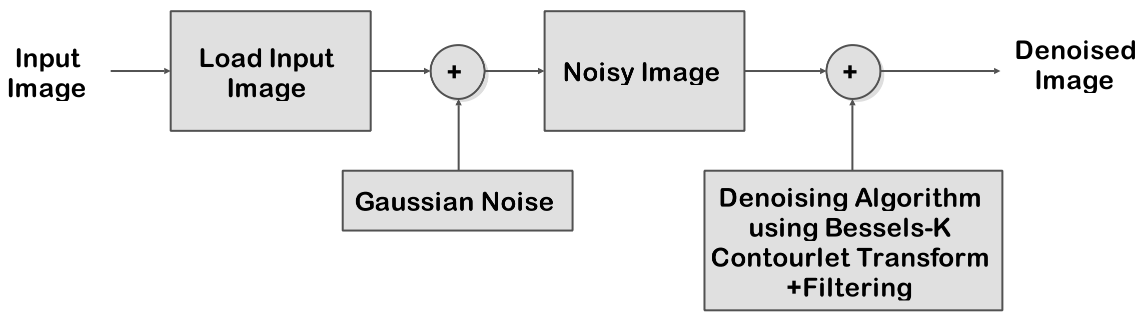

Fig.2.2: Block Diagram of Proposed Methodology

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 it adaptive filtering is applied then the calculations of PSNR, RMSE and SSIM have been done, at the last outcomes have been displayed.

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)

Fig. 3.1 Lena Image (a) Original Input Image, (b) Denoised Image

(a) (b)

Fig. 3.2 Barbara Image (a) Original Input Image, (b) Denoised Image

(a) (b)

Fig. 3.1 Peppers Image (a) Original Input Image, (b) Denoised Image

Table 1 shows the comparison of peak signal to noise ratio (PSNR) with wavelet transform on noise density 50

Image	Wavelet Transform	Proposed Methodology
Lena	30 dB	31.08 dB
Peppers	30.40 dB	31.83 dB
Barbara	27.40 dB	27.99 dB

Table 2 shows the comparison of root mean square error (RMSE) with wavelet transform on noise density 50

Image	Wavelet Transform	Proposed Methodology
Lena	8.10	7.12
Peppers	7.80	6.53
Barbara	10.90	10.17

Table 3 shows the comparison of structural similarity index (SSIM) with wavelet transform on noise density 50

Image	Wavelet Transform	Proposed Methodology
Lena	0.9929	0.9848
Peppers	0.9848	0.9872
Barbara	0.9893	0.9912

CONCLUSIONS

This work proved to the pros of the contourlet transform over wavelet transform. The simulation was performed on three images lena, peppers and barbara with three parameters peak signal to noise ratio (PSNR), root mean square error (RMSE) and structural similarity (SSIM) and found that proposed bessels k-form based controurlet transform is better than the wavelet transform based denoising. The proposed methodology integrating the wiener and median filtering 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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