A Novel Image Denoising Based on Local Geometry Encoding

Thoti Saravana [1], B.Ramesh Naick [2]
[1]Dept of ECE
[2]Assistant Professor, Dept of ECE
[1, 2] Seshachala Institute Of Technology,Puttur

Abstract- *Generally the speckle noise occurred in images of different modalities due to random variation of pixel values. To denoise these images, it is necessary to apply various filtering techniques. So far there are lots of filtering methods proposed in literature which includes the Wiener filtering and Wavelet based thresholding approach to denoise such type of noisy images.This thesis analyze exiting Wiener filtering for image restoration with variable window size. However this restoration may not exhibit satisfactory performances with respect to standard indices like Structural Similarity Index Measure (SSIM), Signal-to-Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), and Mean Square Error (MSE). Literature indicates that Curvelet transform represents natural image better than any other transformations. Therefore,curvelet coeffcient can be used to segment true image and noise. The aim of the thesis to characterize the multiplicative noise in Curvelet transform domain.Subsequently a threshold based denoising algorithm has been developed using hard and MCET thresholding techniques.*

Finally, the denoised image was compared with original image using some quantifying statistical indices such as SSIM, MSE, SNR and PSNR for different variances the experimental results were developed.

Keywords- Multiplicative Noise, Wiener filtering, Curvelet transform, Image thresholding techniques, Statistical parameters.

I. INTRODUCTION

1.1 BACK GROUND:

Image denoising is one of the most essential tasks in image processing for better analysis and vision. There are many types of noise which can decrease the quality of images. The Speckle noise which can be modeled as multiplicative noise, mainly occurs in various imaging system due to random variation of the pixel values. It can be defined as the multiplication of random values with the pixel values. Mathematically this noise is modeled as:

$$\text{Speckle noise}=I*(1+N)$$

Where 'I' is the original image matrix and 'N' is the noise, which is mainly a normal distribution with mean equal to zero. This noise is a major problem in radar applications. Wiener filtering comes under the non-coherent type of denoising method, which is mainly used as a restoration technique for all type of noisy images .

However this filter do not giving promising result in terms of various quality performance measuring indices such as Structural Similarity Index Measure (SSIM), Mean-Square-Error (MSE), Signal-to-Noise Ratio (SNR) and Peak-Signal-to-Noise Ratio (PSNR) between original and restored image. Curvelet transform was introduced by E. J. Candes . It is a higher version of image representation at fine scales, and it is developed from Wavelet as multi-scale representation. Curvelet transform based algorithms are widely used for image denoising. In Curvelet domain the large coeffcients value are shown as original image signal and the small coeffcients value shown as noise signal. In this research, we propose first discrete Curvelet transform with different thresholding methods such as Hard-thresholding and Minimum Cross Entropy Thresholding (MCET) for removal of speckles from image. The proposed method consist of three parts, Curvelet transform(FDCT), Curvelet coeffcients processing and inverse transform(IFDCT). image was compared with original image using SSIM, MSE, SNR and PSNR. An entropy based thresholding has been implemented in Curvelet domain for better result. The next modification can be use of clustering-based thresholding methods. Curvelet denoising technique is applied to any type of images like natural, satellite, medical like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Ultrasonic images, etc.

1.2 MOTIVATION:

Image processing has got wide varieties of applications in computer vision, multimedia communication, television broadcasting, etc. that demand very good quality of images. The quality of an image degrades due to introduction of additive white Gaussian noise (AWGN) during acquisition, transmission/ reception and storage/ retrieval processes. It is very much essential to suppress the noise in an image and to preserve the edges and fine details as far as possible. In the present research work, efforts are made to develop efficient spatial-domain and transform-domain image filters that suppress noise quite effectively.

1.3 IMAGE DENOISING:

Digital Image Processing usually refers to the processing of a 2-dimensional (2-D)picture signal by a digital hardware. The 2-D image signal might be a photographic image, text image, graphic image (including synthetic image), biomedical image (X-ray, ultrasound, etc.), satellite image, etc. In a broader context, it implies processing of any 2-D signal using a dedicated hardware, e.g. an application specific integrated circuit (ASIC) or using a general-purpose computer implementing some algorithms developed for the purpose. An image is a 2-D function (signal), f (x ,y) where x and y are the spatial (plane) coordinates. The magnitude of f at any pair of coordinates f(x,y) is the intensity or gray level of the image at that point. In a digital image, f(x,y), and the magnitude of f are all finite and discrete quantities. Each element of this matrix (2-D array) is called a picture element or pixel. Image processing refers to some algorithms for processing a 2-D image signal, i.e. to operate on the pixels directly (spatial domain processing) or indirectly (transform-domain processing). Such a processing may yield another image or some attributes of the input image at the output. It is a hard task to distinguish between the domains of image processing and any other related areas such as computer vision.

Robotics, and computer aided manufacturing (CAM) and automated quality control in industries depicts a typical image processing system . Most of the image-processing functions are implemented in software. A significant amount of basic image processing software is obtained commercially. Major areas of image processing are :

(i) Image Representation
(ii) Image Transformation
(iii) Image Enhancement
(iv) Image Restoration
(v) Color Image Processing
(vi) Transform-domain Processing
(vii) Image Compression
(viii) Morphological Image Processing
(ix) Image Representation and Description
(x) Object Recognition

Image processing begins with an image acquisition process. When illumination energy is incident upon an object, it reflects some part of it depending on its surface-reflectance. Thus, the image created, f(x,y), is a 2-D planar projection of a 3-D object, in general, and os directly proportional to the illumination energy, i(x,y), incident on the object and the reflectance, r(x,y), of the object. Mathematically, it may be expressed as:

$$f(x, y) = K \,.\, i(x, y) \,.\, r(x, y)$$

where, $0 < i(x, y) < \alpha$
$0 < r(x, y) < 1$
K is a constant for the physical acquisition process.

Under perfect ideal conditions, the process-constant, K, is space-invariant and the whole process of image acquisition is noise-free. In fact, both the assumptions are invalid in any practical acquisition system. Therefore, a practical image contains some distortion and noise and hence needs to undergo a process of restoration.

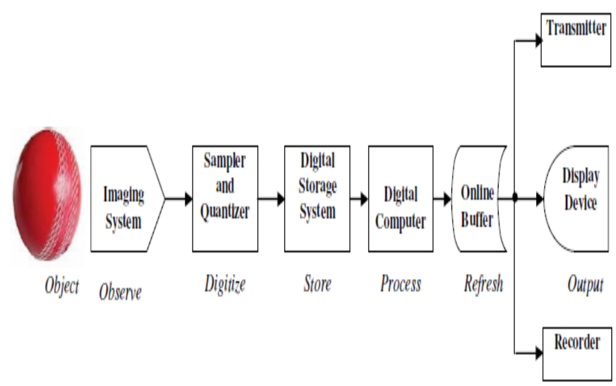

Fig.1.1: A typical digital image processing system

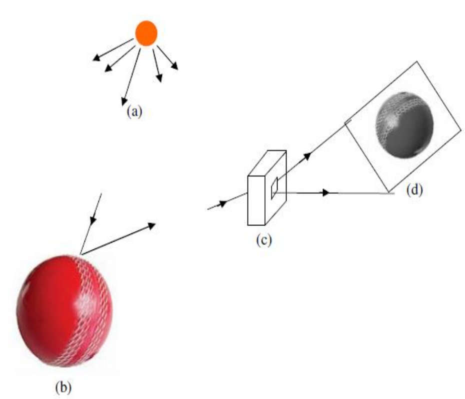

Fig. 1.2: An example of image acquisition process

(a) Illumination energy source
(b) an object
(c) Imaging system
(d) 2-D planar image

Image processing may be performed in the spatial-domain or in a transform domain. To perform a meaningful and useful task, a suitable transform, e.g. discrete Fourier transform (DFT) , discrete cosine transform (DCT) , discrete Hartley transform (DHT) , discrete wavelet transform (DWT) etc., may be employed. Depending on the application, a suitable transform is used.

It is difficult to suppress AWGN since it corrupts almost all pixels in an image. The rithmetic mean filter, commonly known as Mean filter can be employed to suppress AWGN but it introduces a blurring effect. Efficient suppression of noise in an image is a very important issue. Denoising finds extensive applications in many fields of image processing. Image denoising is usually required to be performed before display or further processing like texture analysis object recognition image segmentation etc.

Conventional techniques of image denoising using linear and nonlinear techniques have already been reported and sufficient literature is available in this area. Recently, various nonlinear and adaptive filters have been suggested for the purpose. The objectives of these schemes are to reduce noise as well as to retain the edges and fine details of the original image in the restored image as much as possible. However, both the objectives conflict each other and the reported schemes are not able to perform satisfactorily in both aspects. Hence, still various research workers are actively engaged in developing better filtering schemes using latest signal processing techniques. In this doctoral research work, efforts have been made in developing some novel filters to suppress AWGN quite efficiently.

1.4 Noise in Digital Images

In this section, various types of noise corrupting an image signal are studied; the sources of noise are discussed, and mathematical models for the different types of noise are presented.

1.4.1 Sources of Noise

During acquisition, transmission, storage and retrieval processes an image signal gets contaminated with noise. Acquisition noise is usually additive white Gaussian noise (AWGN) with very low variance. In many engineering applications, the acquisition noise is quite negligible. It is mainly due to very high quality sensors. In some applications like remote sensing, biomedical instrumentation, etc., the acquisition noise may be high enough. But in such a system, it is basically due to the fact that the image acquisition system itself comprises of a transmission channel. So if such noise problems are considered as transmission noise, then it may be concluded that acquisition noise is negligible.

1.4.2. Mathematical Representation of Noise

The AWGN, SPN, and RVIN are mathematically represented below. The Gaussian noise is given by,

$$n_{AWGN}(t) = \eta_G(t)$$

$$\Rightarrow \; f_{AWGN} = f(x,y) + \eta_G(x,y)$$

where, $G(t\ )$ h is a random variable that has a Gaussian probability distribution. It is an additive noise that is characterized by its variance, 2 s , where, s represents its standard deviation. In (1.5), the noisy image is represented as a sum of the original. uncorrupted image and the Gaussian distributed random noise G h . When the variance of the random noise G h is very low, N_G (x, y) is zero or very close to zero at many pixel locations. Under such circumstances, the noisy image *AWGN* *f* is same or very close to the original image $f(x, y)$ at many pixel locations (x, y) .

Let a digital image $f(x, y)$, after being corrupted with SPN of density *d*, be represented by *SPN* *f* (x,y). Then, the noisy image *SPN* *f* (x,y) is mathematically represented as:

$$f_{SPN}(x,y) = \begin{cases} f(x,y) & \text{with probability,} \quad p = 1-d \\ 0 & \quad\quad\quad\quad\quad\quad\quad\; p = d/2 \\ 1 & \quad\quad\quad\quad\quad\quad\quad\; p = d/2 \end{cases} \qquad 1.6$$

The impulse noise occurs at random locations (x, y) with a probability of *d*. The SPN and RVIN are substitutive in nature. A digital image corrupted with RVIN of density *d*, *RVIN* *f* (x,y), is mathematically represented as:

$$f_{RVIN}(x,y) = \begin{cases} f(x,y) & \text{with probability,} \quad p = 1-d \\ \eta(x,y) & \text{with probability,} \quad p = d \end{cases} \qquad 1.7$$

Here, h (x, y) represents a uniformly distributed random variable, ranging from 0 to 1, that replaces the original pixel value $f(x, y)$. The noise magnitude at any noisy pixel location (x,y) is independent of the original pixel magnitude. Therefore, the RVIN is truly substitutive.

Another type of noise that may corrupt an image signal is the *speckle noise* (SN). In some biomedical applications like ultrasonic imaging and a few engineering applications like synthesis aperture radar (SAR) imaging, such a noise is encountered.

III. LITERATURE SURVEY

Noise introduced in an image is usually classified as substitutive (impulsive noise: e.g., salt & pepper noise, random-valued impulse noise, etc.) and additive (e.g., additive white Gaussian noise) noise. The impulsive noise of low and moderate noise densities can be removed easily by simple denoising schemes available in the literature. The simple median filter works very nicely for suppressing impulsive noise of low density. However, many efficient filters have been developed for removal of impulsive noise of moderate and high noise densities. Chen *et al.* have developed a nonlinear filter, called tri-state median filter, for preserving image details while effectively suppressing impulsive noise. The standard median filter and the center weighted median (CWM) filter are incorporated into noise detection framework to determine whether a pixel is corrupted before applying the filtering operation. A nonlinear noniterative multidimensional filter, the *peak-and-valley* filter, is developed for impulsive noise reduction. The filter consists of a couple of conditional rules that identify the noisy pixels and replace their gray level values in a single step. F. Russo has developed an evolutionary neural fuzzy system for noise cancellation in image data . The proposed approach combines the advantages of the fuzzy and neural paradigms. The network structure is designed to exploit the effectiveness of fuzzy reasoning in removing noise without destroying the useful information in input data.

Farbiz *et al*. have proposed a fuzzy logic filter for image enhancement. It is able to remove impulsive noise and smooth Gaussian noise. Also, it preserves edges and image details. H-L Eng and K-K Ma have proposed a noise adaptive soft-switching (NASM) filter . A soft-switching noise-detection scheme is developed to classify each pixel to be uncorrupted pixel, isolated impulsive noise, non-isolated impulsive noise or image object's edge pixel. 'No filtering', a standard median filter or the proposed fuzzy weighted median filter is then employed according to respective characteristic type identified. T. Chen and H.R. Wu have developed a scheme for adaptive impulse detection using CWM filters. In addition to the removal of noise from gray images, some color image denoising filters are also developed for efficient removal of impulsive noise from color images.

IV. IMAGE DENOISING BASED ON LOCALGEOMETRY ENCODING

4.1. IMAGE DECOMPOSITION IN A MOVING FRAME:

A. The Gray-Level Case

Let $I : \subset \mathbb{R}^2 \longrightarrow \mathbb{R}$ be a gray-level image, and (x , y) be the standard coordinate system of $\mathbb{R}^2$. We denote by I_x resp. I_y the derivative of I with respect to x resp. y, and by ∇I the gradient of I . Our image decomposition model for I is a two-stages approach: first, we construct an orthonormal moving frame $(\boldsymbol{Z_1}, \boldsymbol{Z_2}, \boldsymbol{N})$ of $(\mathbb{R}^3, {}_2)$ over that encodes the local geometry of I . Then, we compute the components (J^1, J^2, J^3) of the $\mathbb{R}^3$-valued function $(0, 0, I)$ in that moving frame. More precisely, we consider a scaled version μI of I , for μ]0, 1], and its graph, which is the surface S in $\mathbb{R}^3$ parameterized by

$$\psi : (x , y) \longrightarrow (x , y, \mu I (x , y)) \qquad (4.1$$

PSNR-1

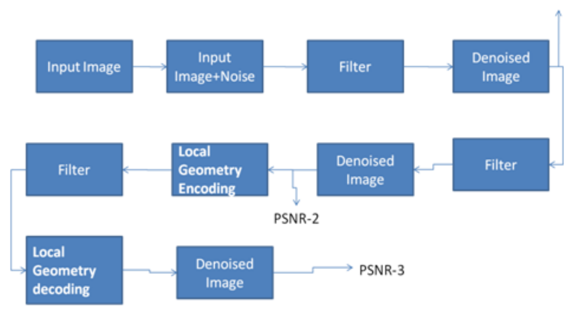

Fig4.1:Image Denoising Based on Local Geometry Encoding

The orthonormal moving frame $(\boldsymbol{Z_1}, \boldsymbol{Z_2}, \boldsymbol{N})$ we consider is the following: the vector field $\boldsymbol{Z_1}$ is tangent to the surface S and indicates the direction of the steepest slope at each point of S; the vector field $\boldsymbol{Z_2}$ is tangent to S and indicates the direction of the lowest slope at each point of S. It follows that $\boldsymbol{N}$ is normal to the surface since we require $(\boldsymbol{Z_1}, \boldsymbol{Z_2}, \boldsymbol{N})$ to be orthonormal.

The moving frame $(\boldsymbol{Z_1}, \boldsymbol{Z_2}, \boldsymbol{N})$ can be constructed as follows. Let $\boldsymbol{z_1}$ be the gradient of μI and $\boldsymbol{z_2} = (-\mu I_y , \mu I_x)^T$ indicating the direction of the level-lines of μI . On homogeneous regions of I , i.e. at pixel locations (x , y) where $I_x (x , y) = I_y (x , y) = 0$, we define $\boldsymbol{z_1} = (1, 0)^T$ and $\boldsymbol{z_2} = (0, 1)^T$. Then, $\boldsymbol{Z_1}$ and $\boldsymbol{Z_2}$ are given by the following expressions

$$Z_i = \frac{d\psi(z_i)}{\|d\psi(z_i)\|_2}, \quad i = 1, 2 \qquad 4.2$$

where $d\psi$ stands for the differential of ψ, which maps vector fields on _ to tangent vector fields of S. The expression of the unit normal ***N*** is then obtained as the vectorial product between ***Z1*** and ***Z2***. The explicit expressions of the vector fields ***Z1, Z2, N*** are given by the matrix field

$$P = \begin{pmatrix} \frac{I_x}{\sqrt{|\nabla I|^2(1+\mu^2|\nabla I|^2)}} & \frac{-I_y}{|\nabla I|} & \frac{-\mu I_x}{\sqrt{1+\mu^2|\nabla I|^2}} \\ \frac{I_y}{\sqrt{|\nabla I|^2(1+\mu^2|\nabla I|^2)}} & \frac{I_x}{|\nabla I|} & \frac{-\mu I_y}{\sqrt{1+\mu^2|\nabla I|^2}} \\ \frac{\mu|\nabla I|^2}{\sqrt{|\nabla I|^2(1+\mu^2|\nabla I|^2)}} & 0 & \frac{1}{\sqrt{1+\mu^2|\nabla I|^2}} \end{pmatrix}$$

where the coordinates of the vector field ***Z1*** are given in the first column, the coordinates of ***Z2*** in the second column, and the coordinates of ***N*** in the third column.

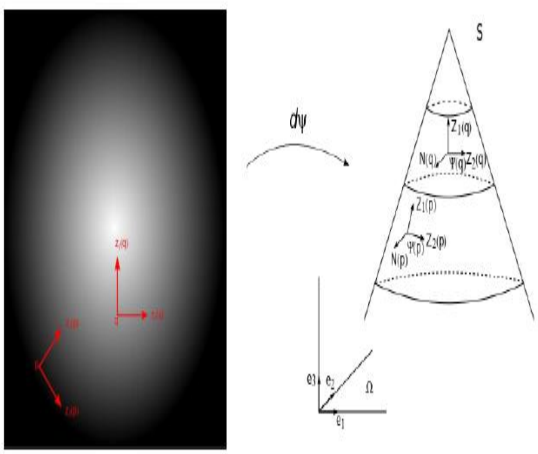

Fig.4.2:Moving frame encoding the local geometry of a gray-level image.

Left: original gray-level image and a moving frame ***(z*1, *z*2*)*** indicating the direction of the gradient and the level-line of the image at two points *p* and *q* of the image domain.

B .Image Denoising

The framework we propose for denoising an image while systematically taking into account its local geometry is based on applying image denoising techniques to the components of the image in the moving frame constructed above instead of applying the technique to the image itself. This methodology has already been used in [2]–[4] with local regularization/ denoising methods, but it can actually be extended to any denoising technique. In this section, we give more details about our approach dealing with gray-level and color images.

1) Gray-Level Images: In the experiments performed throughout this article, the strategy on gray-level images I : _ ⊂ R2 −→ R is the following:

1) Process *I* with some denoising technique *F* and call the output image *Iden*.
2) Compute the components *(J* 1*, J* 2*, J* 3*)* of *I* in the moving frame (3), for some scalar μ, with formula (4). Apply the same denoising technique *F* to the components to obtain the processed components *(J* 1 *den, J* 2 *den, J* 3 *den)*.
Then, apply the inverse frame change matrix field to the processed components, i.e. and denote by *IdenMF* the third component *I* 3 *denMF*.

$$\begin{pmatrix} I^1_{denMF} \\ I^2_{denMF} \\ I^3_{denMF} \end{pmatrix} := P \begin{pmatrix} J^1_{den} \\ J^2_{den} \\ J^3_{den} \end{pmatrix}$$

3) Compare *Iden* and *IdenMF* with the metrics PSNR and SSIM.

2) Color Images: The extension to color images is not straightforward because of the flexibility of the choice of color space and the way in which the moving frame approach can be applied (channel-wise, only to selected channels, or vectorially). We will see in the next two sections that the color space and manner in which the approach is applied both depend on the image denoising technique. However, in all of the experiments performed throughout this article, our approach for color images I : _ ⊂ R2 −→ R3 is of the form:

1) Process *I* with an image denoising technique *F* and call the output image *Iden*.
2) Apply the same image denoising technique *F* to the components in some moving frame related to the channels of the image or the full image itself. Then apply the inverse frame change matrix field to the processed components, from which a color image *IdenMV* is reconstructed.
3) Compare *Iden* and *IdenMV* with the metrics PSNR and SSIM. Note that SSIM has been originally designed for gray-level images, and we define the SSIM Index for color images as the mean of the SSIM Index of each color channel.

VI. RESULTS AND DISCUSSIONS

6.1 OUTPUTS OF FIRST IMAGE:

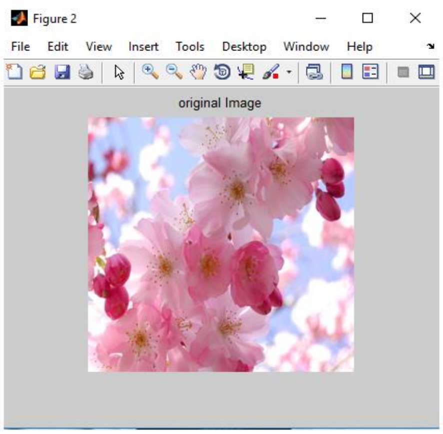

Fig:6.1.1:Input image

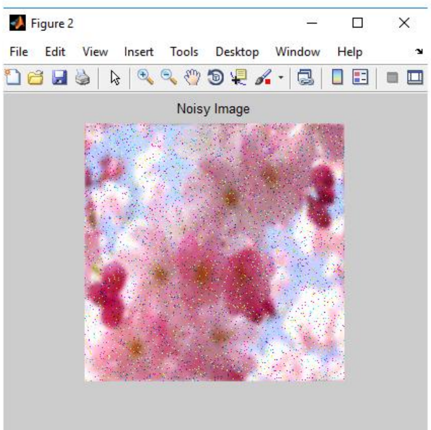

Fig:6.1.2:Noisy image

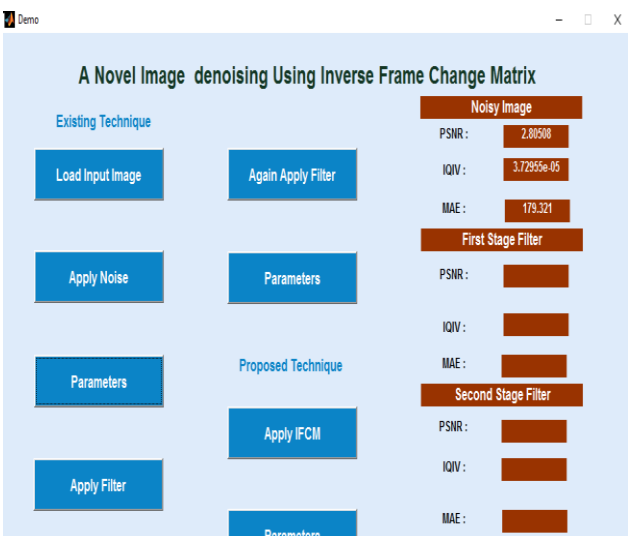

Fig: 6.1.3:Parameters of the noisy image

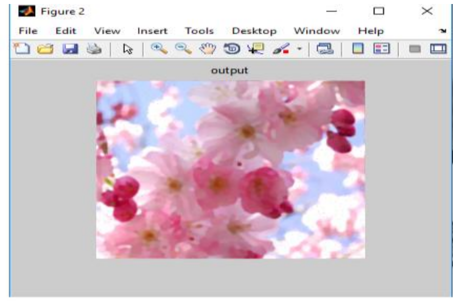

Fig: 6.1.4:First stage filtered image

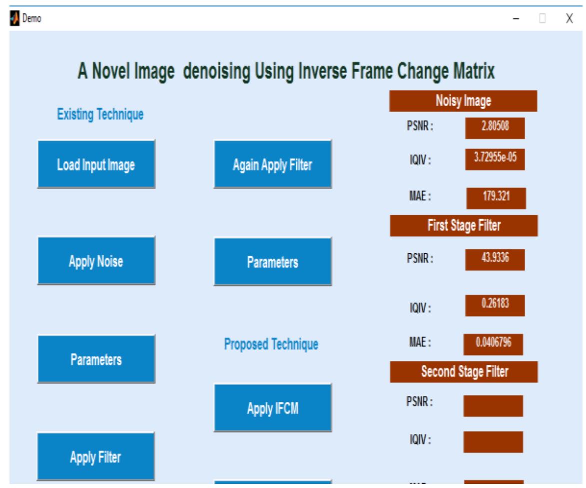

Fig :6.1.5:Parameters of the first stage filter

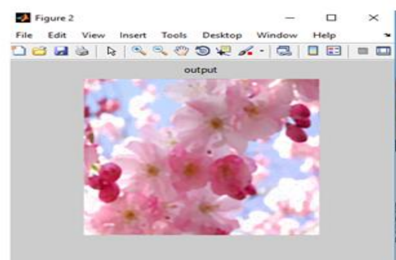

Fig6.1.6:Second stage filtered image

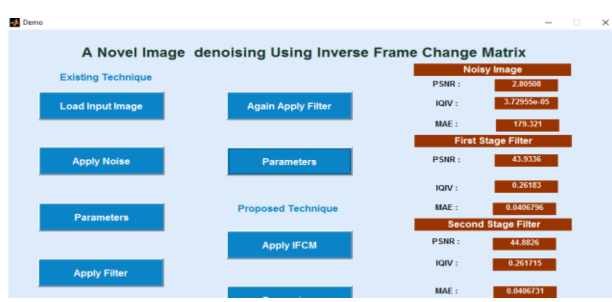

Fig 6.1.7:Parameters of the second stage filter

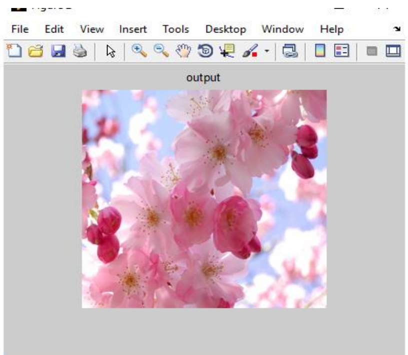

Fig 6.1.8:Output image

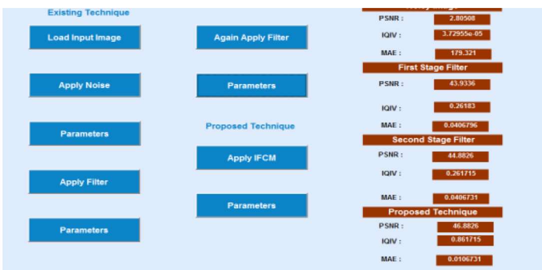

Fig 6.1.9: Parameters of the output image

6.2 OUTPUTS OF SECOND IMAGE:

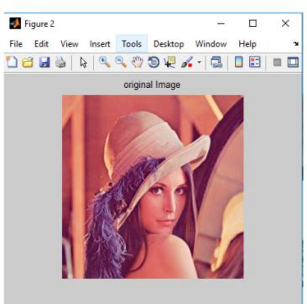

Fig: 6.2.1:Input image

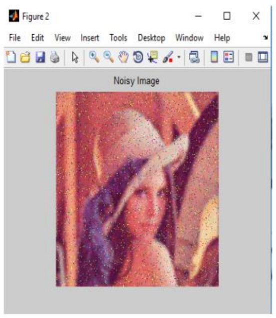

Fig 6.2.2:Noisy image

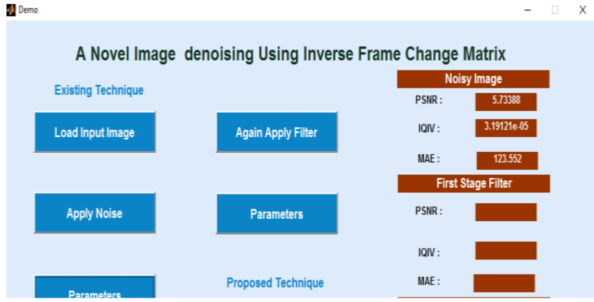

Fig 6.2.3:Parameters of noisy image

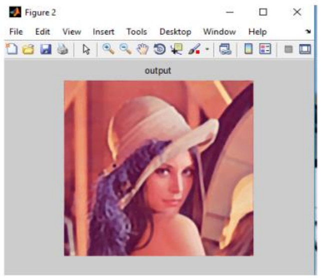

Fig 6.2.4:First stage filtered image

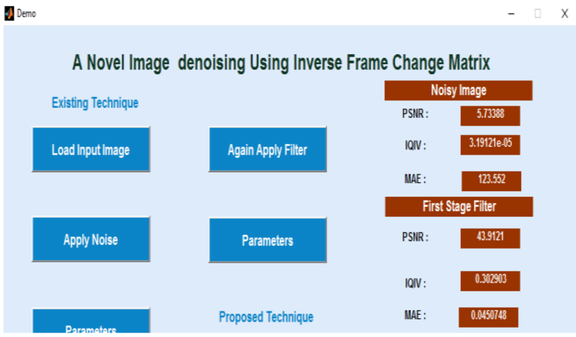

Fig 6.2.5:Parameters of first stage filter

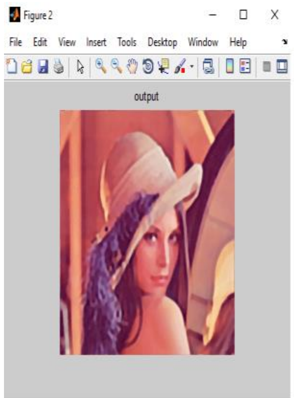

Fig 6.2.6:Second stage filtered image

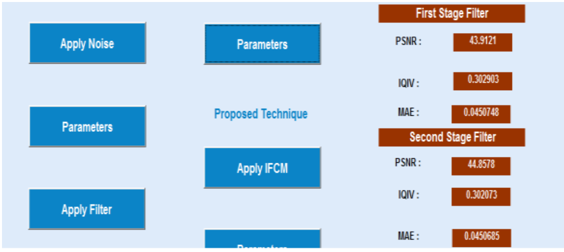

Fig 6.2.7:Parameters of second stage filter

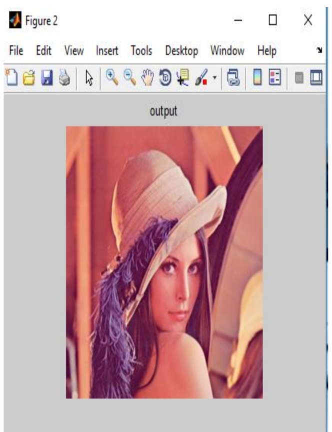

Fig 6.2.8: Output image

VII. CONCLUSION

In this thesis an attempt has been made to develop denoising methods for images under multiplicative noise. The performance of this method is evaluated and compared with that of existing state-of-the-art. In the first section of this chapter an overview of contributions of the thesis and the conclusions are summarized.

A Curvelet domain based approach with different thresholding technique has been developed. The thresholding on Curvelet coefficient is determine by an hard and entropy based thresholding method developed in [8]. The algorithm is applied to several standard images and performance is evaluated using statistical indices like SSIM, MSE, SNR, PSNR. Experimental results exhibits improvement over the exiting stat-of-art for denoising such as Wiener filtering.

VIII. FUTURE SCOPE

The current research work indicates the ability of the proposed denoising method. However, further investigations may improve the recovered images under multiplicative noise condition. During the research work a few directions for further research have been identified. These are stated below:

- Exploring various thresholding techniques in sparse domain.
- Developing restoration technique in real-time embedded platform.

REFERENCES

[1] S. P. Awate and R. T. Whitaker, "Higher-order image statistics for unsupervised, information-theoretic, adaptive, image filtering," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2. Jun. 2005, pp. 44–51.

[2] T. Batard and M. Berthier, "Spinor Fourier transform for image processing," *IEEE J. Sel. Topics Signal Process.*, vol. 7, no. 4, pp. 605–613, Aug. 2013.

[3] T. Batard and M. Bertalmío, "Generalized gradient on vector bundle— Application to image denoising," in *Scale Space and Variational Methods in Computer Vision* (Lecture Notes in Computer Science), vol. 7893. Berlin, Germany: Springer-Verlag, 2013, pp. 12–23.

[4] T. Batard and M. Bertalmío, "On covariant derivatives and their applications to image regularization," *SIAM J. Imag. Sci.*, vol. 7, no. 4, pp. 2393–2422, 2014.

[5] M. Bertalmío, *Image Processing for Cinema*. Boca Raton, FL, USA: CRC Press, 2014.

[6] M. Bertalmío and S. Levine, "Denoising an image by denoising its curvature image," *SIAM J. Imag. Sci.*, vol. 7, no. 2, pp. 187–201, 2014.

[7] P. Blomgren and T. F. Chan, "Color TV: Total variation methods for restoration of vector-valued images," *IEEE Trans. Image Process*, vol. 7, no. 3, pp. 304–309, Mar. 1998.