

# Anisotropic Image Restoration Based on Image Inpainting with Diffusion Enhancement



Marlapalli Krishna, V Naga Bushanam, Bandlamudi S B P Rani, K Rakesh, V Pranav

**Abstract**— Reconstructing the damaged images and improving the quality of an image, results in image restoration. Here anisotropic diffusion based iterative inpainting developed to minimise the noise level in the colour images and enhancing the image boundaries, this approach observed on speckle, Gaussian and shot noise. To reduce noise and topological defects from images, 3D- anisotropic diffusion used to decompose the image into high frequencies and low frequencies and protects the image from losing the information, to enhance the image quality, image inpainting was used. In this process most of the high frequency decomposed sections got damaged with noise and appears as there is information available at those pixels, therefore the complete restoration process was done on all the high frequency decomposed components so this results in achieving better restored images in mean time. The two effects on images can be reduced by the mixed fusion algorithm i.e., noise reduction by using anisotropic diffusion and distance based neighbourhood image inpainting for restoring the damaged parts. So, this results in reconstructing the damaged image and enhancing the boundaries of the image.

**Index Terms**— Noise Enhancement, Image Restoration, Anisotropic Diffusion, Boundaries, Image Inpainting.

## I. INTRODUCTION

Enhancing/ removing distortion/ reconstructing a degraded image were comes in the process of restoration. For this various process were approached namely homomorphed filters [12, 13], pseudo inverse filters, wiener filter and notch filters were used to reduce the image and reconstructing the degraded image [1].

The problem observed here is a blurry reconstructed image and loss of information [10-12]. Therefore to rectify these problems many iterative techniques were followed and these were also listed. Many of these were used to suave the images which are noised [11,13,14] these results in blurring the image.

So, to reduce the effect of blurring inverse of the transform or filtration approach needs to be more minimised [7]. This is only possible by diffusion approach, because in diffusion all the grouped values tuned to scatter. So here inpainting technique can be used to reduce the damage of the image, but for filtration we need to access 3D filtration technique.

Now, Image Inpainting is combination of mask image that was restricted to create a new image and now we are accessing texture based image Inpainting for restoration of colour images [9]. In a large part of the photo coping with [3] methods pics are sifted in a -dimensional flag through making use of widespread flag preparing strategies thereto. Picture making ready or Image Restoration [15, 18] now and then alludes to automatic photo coping with structures, anyway optical and easy photograph making ready likewise are potential. This record is with appreciate to fashionable techniques that follow to every considered one of them. The securing of snapshots (handing over the info photograph in the number one spot) expressed as imaging a few packages, for instance, restorative imaging, space technology and far off detecting located photos are typically debased by using bending [6, 7].

Twisting could emerge from climatically choppiness, relative motion between an object and moreover the digital camera and an out-of-centre digital camera. Reclamation of debased photographs is normally required for all of the greater handling or translation of the snapshots. Since barriers at the debasement and furthermore the primary photo shift with the equipment, numerous optional calculations exist to disentangle the issue. At times, the underlying photograph, this is formed as both a settled is obscured by using a celebrated carryout. Numerous option commonplace methodologies are created to make up for haze works after they're celebrated [2, 4].

## II. PROPOSING SCHEME

More usually the blur perform isn't famed. In this case the model of the blur is commonly assumed, for example, a linear space- invariant filter. In some applications, many blurred versions of an equivalent original image return from completely different blurring channels, or several blurred pictures are accessible from however highly correlated original pictures and channels, as in short exposure image sequences, multispectral pictures and microwave radiometric pictures. Restoration of this image or pictures known as Image Restoration[5, 8, 15].

The equation (1) describes the formula for Gaussian mixture distribution.

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$$f(x_s) = \sum_{i=1}^k p_i N(x_s | \mu_i, \sigma_i) \quad (1)$$

Where

$$N(x_s | \mu_i, \sigma_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp[-\frac{1}{2\sigma_i^2} (x_s - \mu_i)^2]$$

Assume an image classified into  $C_i$ ,  $i = 1, 2, \dots, k$  class that the number of class's  $k$  is known.

The parameters  $\mu_i, \sigma_i^2$  and  $p_i$  are respect to mean, variance and the probability of a pixel belongs to the class  $C_i$ . It means

$$p_i = p(x_s \in C_i), \quad 0 < p_i < 1, \quad \sum_{i=1}^k p_i = 1$$

The white noise (WN) is random process which is uncorrelated random variables with zero mean and constant variance. The Gaussian white noise (GWN) also has the Gaussian distribution is written by the equation (2),

$$N(n | 0, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} \exp(-\frac{1}{2\sigma^2} n^2) \quad (2)$$

Let us consider the GWN adds the true image and makes the observed image as follows

$$Y_s = X_s + n_s$$

If the true image supposes to be constant then the probability distribution of  $Y_s$  for given  $X_s = x_s$  is the form by

$$N(y_s | x_s, \sigma) = \frac{1}{\sigma \sqrt{2\pi}} \exp[-\frac{1}{2\sigma^2} (y_s - x_s)^2] \quad (3)$$

The frequency domain and spatial domain of the image is calculated by the evaluation parameter Energy and is defined by using the equation in continuous and discrete modes.

### III. WAVELET 3D TRANSFORM

#### 3D Wavelet Malicious Tree Decomposition

The following sub-band decomposition of and image can be given as

$$N(m, n, c) = \begin{pmatrix} X_{j0}(m) \\ X_{j1}(m) \end{pmatrix} \otimes \begin{pmatrix} X_{k0}(n) \\ X_{k1}(n) \end{pmatrix} \otimes \begin{pmatrix} X_{l0}(c) \\ X_{l1}(c) \end{pmatrix} \quad (4)$$

Where  $N(m, n, c)$  is three dimensional noised image equation (3) and is sub-band decomposition is observed in the equation (4), sub-scripts  $j, k, l$  are stands for temporal direction. From the above equation we can find 8 sub-bands. The 3D Wavelet Decomposition is show in Fig. 1.



Fig. 1. 3D Wavelet Decomposition

All the 11 frequency ranges from Fig.1 is plotting as 3D decomposition and is shown in the Fig.2.

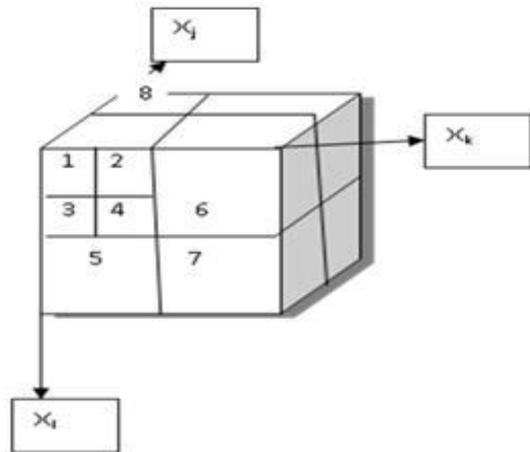


Fig. 2. Sub band regions in spatial temporal format.

### IV. IMAGE INPAINTING

Inpainting is stock-still within the restoration of pictures. The block diagram for Image Inpainting is show in Fig. 3. Historically, Inpainting has been done by skilled restorers. Working procedure is followed below

- Step-1: The global image determines a way to fill within the gap. The aim of Inpainting is to revive the unity of the work.
- Step-2: The structure of the gap surroundings is meant to be continued into the gap. Contour lines that hit the gap boundary square measure prolonged into the gap.
- Step-3: The different regions within a spot, as outlined by the contour lines, square measure stuffed with colours matching for those of its boundary.
- Step-4: The small details square measure painted, i.e. "texture" is another

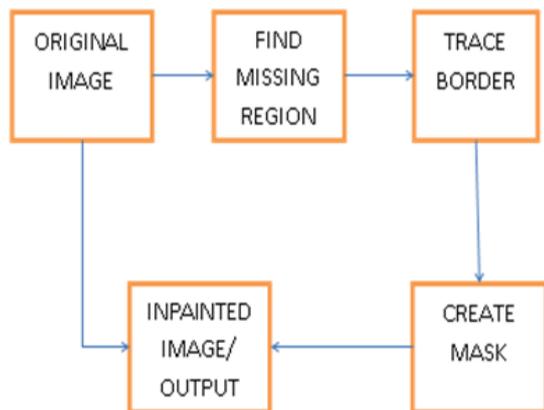


Fig. 3. Block diagram for Image Inpainting.

For the analysis of Texture image Inpainting mask is considered which is a similar. So, this helps removing the additional steps of creating mask and damaged region identification. Process of restoration of a damaged image is identified using normal Inpainting approach and to enhance this for noise damaged image a texture Inpainting is used for our process. This represents using the following mathematical function.

Adaptive values were occupied such as  $\lambda$  and space discretization  $h$ . These were extended and updated on iteration with a complete loop of 100, extension is doing by calculating the distance between the texels(textural pixels) using eculidean distance and is given by the equation (5) below and this is considered for all the colors in the image i.e., Red, Green and Blue. Color is carried out by using  $i = [R \ G \ B]$ .

$$D_i = \sqrt{(I_i(x_t, y) - I_i(x_{t+1}, y))^2 + (I_i(x, y_t) - I_i(x, y_{t+1}))^2} \quad (5)$$

The place  $D_i$  represents the gap between gift pixel and next neighbouring pixel and the difference is determined on the photo  $I_i$ .

Let  $I_0(i, j): [0, M] \times [0, N] \rightarrow R$ , with  $[0, M] \times [0, N] \subset R^n$ , be a discrete second grey degree picture. The inpainting system will construct a family of snap shots  $I(i, j, n): [0, M] \times [0, N] \times [0, \infty) \rightarrow R$  such that  $I(i, j, zero) = I_0(i, j)$  and  $\lim_{n \rightarrow \infty} I(i, j, n) = I_R(i, j)$ , where  $I_R(i, j)$  is the output of the algorithm (Inpainted photo). Let  $\Omega$  represent the neighborhood to be inpainted and  $\partial\Omega$  be the boundary of the vicinity to be inpainted.

The proposal of Bertalmio's inpainting algorithm is as follows. First, decrease the impact of noise on the estimation of the course of the isophotos arriving at the boundary  $\partial\Omega$ . For that, the entire long-established photograph undergoes anisotropic diffusion smoothing. Then, the photo enters the inpainting loop the place handiest the values throughout the lacking neighbourhood  $\Omega$  are modified making use of the next evolution equation (6).

$$I^{n+1} = I^n(i, j) + \Delta t * I_t^n(i, j) \quad (6)$$

Where  $n$  denotes the inpainting time,  $\Delta t$  is the expense of improvement and  $I_t(i, j)$  is the replace of the photo  $I(i, j)$ . As instructed by means of guide inpainting strategies, we need to easily propagate understanding from outside  $\partial\Omega$  into  $\Omega$ . Let  $L(i, j)$  being the information that we want to propagate and  $N(i, j)$  is the propagation path. Given the know-how and propagation path, the value of the current pixel to be

inpainted is:  $I_t(i, j) = \delta L^-(i, j) \cdot N^-(i, j)$ .  $\delta L^-(i, j)$  is a measure of the alternate within the information.  $L(i, j)$  is laplacian photograph smoothness estimator, it may be written as:  $L(i, j) = I_{xxn}(i, j) + I_{yy n}(i, j)$ .  $N^-(i, j) = \nabla^\perp(I, j) = [-I_y \ I_x]$  is the smallest spatial change, it's the 90° of the gradient (Gradient  $\nabla I_n(i, j)$  offers us the largest spatial change).

#### ALGORITHM for 3D image restoration

- Step-1:** Consider a 3-D image.  
**Step-2:** Separating and obtaining the colour modes of 3-D image.  
**Step-3:** Decomposing the image into 3 level images.  
**Step-4:** Zero DWT (Discrete Wavelet Transform) is applied for different threshold levels.  
**Step-5:** For  $R = 1$ : length (D4);  
**Step-6:** If  $C_i(R) < \text{Threshold value}$ , then  
**Step-7:**  $C_i(R) = 0$  & count zeros++.  
**Step-8:** end  
**Step-9:** end  
**Step-10:**  $I_t(i, j) = C(i, j) \cdot C1(i, j)$
- $I_t(i, j)$  updating image intensities
  - $C(i, j)$  is the information to propagate
  - $C1(i, j)$  is the propagation direction
  - $dL(i, j) \cdot N(i, j)$  information direction changes

This algorithm raised to restore the image from all consecutive steps of decomposing image using wavelet transform for reduction of noise effect and the topological effect which is on all direction is minimised by using neighbourhood image inpainting based on distance approach is observing.

## V. RESULTS

Results were considered under different noises and showing using the simulating results. These results were obtained after 100 iterations of the Inpainting approach after wavelet 3D de-noising approach.



Fig. 4. Input Image

Here input image size is 256X256 colour image as shown in Fig. 4 is considered in the pre-processing phase and applied with different noises for experimental results speckle noise and Gaussian noise is applied on the input image as shown in the Fig. 5A and Fig. 7A.



Fig. 5A. Speckle Noise image



Fig. 5B. Restored image



Fig. 7A. Gaussian Noise image



Fig. 7B. Restored image

The images were restored by using wavelet combined Inpainting and helps in finding the reduction of noise and restoring the damaged parts of the image due to noise in the image. While considering Fig. 5A and 5B showcases the Speckle noise and restored image after the DWT\_II process. Here DWT helps in filtering the image using multi-resolution analysis and image Inpainting as a repetitive process helps in improving the restoration part. This completely observed in diffusion process with parameter Energy which was calculated for all restoration iterations and plotted in Fig. 6. The frequency domain and spatial domain of the image is calculated by the evaluation parameter Energy and is defined by using the equation in continuous and discrete modes.

In conventional terms spatial domain is equivalent to multiplication and frequency domain is represented by vice versa.

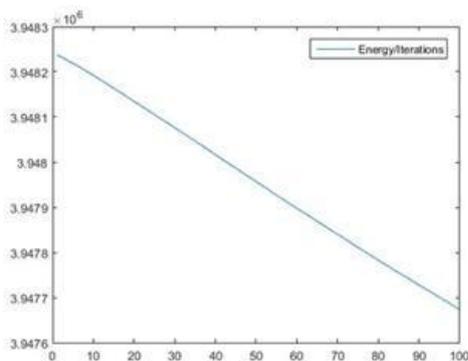


Fig. 6. Energy / Iterations for speckle noise

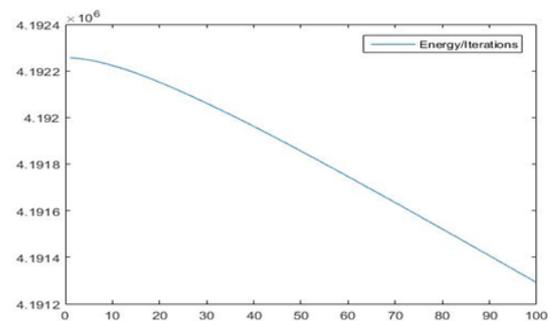


Fig. 8. Energy / Iterations for Gaussian noise

Therefore in Fig. 6 energy/iteration is provided with a graphical representation, in each iteration there is minuet change in the energy but not with a great level of variation. Therefore while the image reconstructing will not going to lose any information from the image.

The similar is explained for the Fig. 7 and Fig. 8 as above and the energy is approximately @  $4.19 \times 10^6$ .

## VI. CONCLUSION

Restoration of image is carried out by means of any filtration approaches and decomposing techniques, inpainting observations also. But here restoration made possible by anisotropic diffusion and neighbourhood inpainting approach. The local energy as a performance parameters observed on all iterations of restoration and observed the image degrading or restored by the graphical values.

In the results section Speckle noise and Gaussian noises were observed and proposing minimising energies, noise effect along with restoring the images.

## REFERENCES

1. R. C. Gonzales, R. E. Woods, *Digital Image Processing* 2nd Edition. New Jersey: Prentice-Hall Inc., 2002.
2. S. Hashemi, S. Kiani, N. Noorozi, M. E. Moghaddam, "An image enhancement method based on genetic algorithm," in Proc. of 2009 *IEEE International Conference on Digital Image Processing*, March 2009, pp. 167–171.
3. C. Munteanu, A. Rosa, "Towards automatic image enhancement using genetic algorithms," in Proc. of 2000 *IEEE Congress on Evolutionary Computation*, vol. 2, 2000, pp. 1535–1542.
4. C. Chen, M. K. Ng and X. L. Zhao, "Alternating direction method of multipliers for nonlinear image restoration problems" in *IEEE Transactions on Image Processing*, vol. 24, No. 1, pp. 33-43, Jan. 2015.
5. J. Zhang, D. Zhao, R. Xiong, S. Ma and W. Gao, "Image restoration using joint statistical modeling in a space-transform domain" in *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 24, no. 6, pp. 915-928, June 2014
6. Y. Xu, J. Wen, L. Fei and Z. Zhang, "review of video and image defogging algorithms and related studies on image restoration and enhancement" in *IEEE Access*, vol. 4, No. , pp. 165-188, 2016.
7. X. Shen, Q. Yan, L. Xu, L. Ma and J. Jia, "Multispectral joint image restoration via optimizing a scale map" in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 37, No. 12, pp. 2518-2530, Dec. 1 2015.
8. R. Wang and D. Tao, "Non-local auto-encoder with collaborative stabilization for image restoration" in *IEEE Transactions on Image Processing*, vol. 25, No. 5, pp. 2117-2129, May 2016.
9. M. Niknejad, H. Rabbani and M. Babaie-Zadeh, "Image restoration using gaussian mixture models with spatially constrained patch clustering" in *IEEE Transactions on Image Processing*, vol. 24, No. 11, pp. 3624-3636, Nov. 2015.
10. Dr.Marlapalli Krishna, V Devi Satya Sri, Bandlamudi S B P Rani and G. Satyanarayana. "Edge based reliable digital watermarking scheme for authorized ownership" *International Journal of Pure and Applied Mathematics* pp. 1291-1299, Vol-119, No-7, 2018.
11. Dr.Marlapalli Krishna, Bandlamudi S B P Rani, V Devi Satya Sri and Dr. Rama Rao Karri. "Filter based jpeg compression for noisy images" *Journal of Advanced Research in Dynamical and Control Systems*, pp: 1233-1248, Vol-9, Issue-18, 2017.
12. Dr. Marlapalli Krishna, Gunupusala Satyanarayana and V. Devi Satya Sri. "Digital image processing techniques in character recognition - a survey", *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, pp: 95-101, Vol-2, Issue-6, Nov-Dec 2017.
13. Marlapalli Krishna, Prasad Reddy PVGD, G. Srinivas and Ch. Ramesh."A smoothening based jpeg compression for an objective image quality of regular and noisy images", *International Journal Of Applied Engineering and Research*, pp: 3799-3804, Vol:11, No:6, 2016.
14. Marlapalli Krishna, G. Srinivas and Prasad Reddy PVGD. "Image smoothening and morphological operator based jpeg compression", *Journal of Theoretical and Applied Information Technology*, pp: 252-259, Vol: 85, No: 3, Mar-2016.
15. M.Krishna, V.Devi Satya Sri and B S B P Rani. "EDGE Based Image Steganography for Data Hiding", *International Journal of Research*, pp: 1689-1694, Vol.03, Issue.13, Oct-2017.
16. Dr. M. Krishna. "The VLIW Architecture for Real-Time Depth Detection in Image Processing", *International Journal of Computer Science & Mechatronics*, pp: 1-9, Vol.2.Issue.VI, Dec-2016.
17. Dr. M. Krishna. "An Efficient Multi Dimensional view for vehicles by Patch memory management in image processing", *International Journal of Computer Science & Mechatronics*, PP:1-10, Vol.1.Issue.V, Dec-2016.
18. Kavitha Paravathaneni and M. Krishna. "Unadulterated Image Noises and Discrepancy Estimation", *International Journal for Technological Research in Engineering*, 3(7), pp: 1501-1503, Mar-2016.