

AN APPROACH FOR IMAGE DENOISING USING NLM IN TERMS OF ANISOTROPIC DIFFUSION

GANESH NAGA SAI PRASAD V^{#1}, HABIBULLA KHAN^{#2}, E.GOPINATHAN^{#3}

^{#1,2}Department of Electronics and Communication Engineering, K L University, Guntur, AP, India

^{#3} Dean, School of Engineering, Vels University, Chennai, India.

E-mail: ¹vgnsprasad@kluniversity.in, ²habibulla@kluniversity.in,
³dean.se@velsuniv.org

ABSTRACT

In a traditional single view photograph, dynamic objects or cameras cause motion noise. Digital image denoising is a prominent field in signal processing, focusing on improving the quality of images suffering from various degradation effects such as noise. To perform the denoising usually requires modelling the image content in order to separate the true image content from the degradation effects and restoring the degradation-free content. Restoration of image sequences can obtain better results compared to restoring each image individually, provided the temporal redundancy is adequately used. However in denoising of image sequence, the estimation of motion patterns between the frames in order to be able to merge the data from various frames are very complex and as a result motion estimation, a severely under-determined problem, tends to be error-prone and inaccurate. In this paper, for image denoising we are suggesting an algorithm which will give better result than the basic NLM algorithm.

Keywords: Denoising, NLM, Anisotropic Diffusion, Degradation, PSNR.

1. INTRODUCTION

Image denoising is a process of obtaining a faithful image as an output from a noised image without knowing the reason behind the noise. The source of the noise may be a low resolution camera, improper alignment of lens or the camera or object being under out of focus or also under motion. Denoising of an image can be achieved by super resolution in which many frames are overlapped to have an enhanced image. This has also been generalized to Super resolution reconstruction by Matan Protter [1]. As a part of related work few super resolution techniques have also been studied. Other super resolution algorithms [2]-[27] give a clear idea on super resolution through various algorithms. An image can be processed through its frames. This can be done by making use of a single frame [28],[29] and multiple frames [30],[38] and many more new algorithms have also come into existence.

2. NON LOCAL MEANS (NLM)

Having noise in the image is the most common problem in image processing. Non Local Means is one of the methods to denoise the noised image. NLM algorithm is well known for removing

Additive Gaussian Noise by preserving the image structure. In any image, there will be similar pixels in the same image based on the color space and NLM takes of this redundancy in order to denoise. Non Local Means denoising updates the pixel's intensity by averaging the weight of all the pixel intensities in the image with similar neighborhood. Each pixel's weight depends on the distance between its grey level intensity vector and that of the interest pixel.

Let us consider an image I which is discrete, the NLM can be represented as

$$NL[U](x) = \sum_{j \in I} w(x, y) u(y)$$

$w(x, y)$ denotes weight, which will be depending up on the grey level vectors distance at points x and y .

which can be represented as

$$d = \|u(N_x) - u(N_y)\|_{2,a}^2$$

Mathematically weight can be shown as

$$w(x, y) = \frac{1}{Z(x)} e^{-\frac{\|u(N_x) - u(N_y)\|_{2,a}^2}{h^2}}$$

Where, $z(x)$ represents the Gaussian filter weight and is mathematically represented as

$$z(x) = \sum_y e^{\frac{-||u(N_x)-u(N_y)||_{2,a}^2}{h^2}}$$

The main advantage of NLM is it is easy to implement. The disadvantage of NLM is more computational complexity and by using NLM the edge details will be lost.

3. ANISOTROPIC DIFFUSION

Anisotropic diffusion is an art of Image processing which helps to reduce noise in an image without abolishing momentous parts of the image i.e, lines, boundaries and other parts of the image which helps in interpreting the image. This algorithm is a continual process where a comparably elementary set of computations are adopted to calculate each pixel value in the image. Anisotropic diffusion is repeated till a sufficient order of smoothing is obtained. The resulting output image preserves linear structures while performing smoothing at the same time.

Anisotropic diffusion can be stated as

$$\begin{aligned} \frac{dI}{dt} &= \text{div}(C(x,y,t)\nabla I) \\ &= \nabla C \cdot \nabla I + C(x,y,t)\Delta I \end{aligned}$$

where Δ stand for the Laplacian, ∇ stand for the gradient,

$\text{div}()$ is the divergence operator and $C(x,y,t)$ is the coefficient of diffusion, $C(x,y,t)$ controls the rate of diffusion and usually chosen as a function of the image gradient so as to preserve edges in the image. The idea of anisotropic diffusion and the two functions for the diffusion coefficient was stated by Pietro Perona and Jitendra Mailk as

$$C_1(x) = e^{-\left(\frac{x}{\kappa}\right)^2}$$

$$C_2(x) = \frac{1}{1 + \left(\frac{x}{\kappa}\right)^2}$$

where κ function of the noise in the image and controls the sensitivity to the edges. Here κ is called as the acclivity magnitude verge parameter and disciplines the rate of diffusion.

By interpreting Anisotropic Diffusion in terms of robust statistics, Black et al. stated an another function, known as biweight function

$$C_3(x) = \begin{cases} \frac{1}{2} \left[1 - \left(\frac{x}{\kappa\sqrt{2}} \right)^2 \right]^2 & x \leq \kappa\sqrt{2} \\ 0 & \text{otherwise} \end{cases}$$

Anisotropic filtering is highly dependent on biweight function and gradient threshold parameter. The biweight function and the gradient threshold parameter define performance and level of diffusion.

The conductance function C_1 favors for the high contrast edges over low contrast edges. The C_2 conductance function supports wide regions over smaller regions. The C_3 function gives sharp edges enhancing the empirical results of the filtering process. The major disadvantage in this is computational complexity.

4. PROPOSED ALGORITHM

In order to overcome the disadvantages in both NLM and ANISOTROPIC, we are introducing a new algorithm, which is a combination of both these algorithms. In the new algorithm, we are changing the Gaussian filtering parameter in NLM as it is a reason for computational complexity. We are proposing NLM interms of ANISOTROPIC.

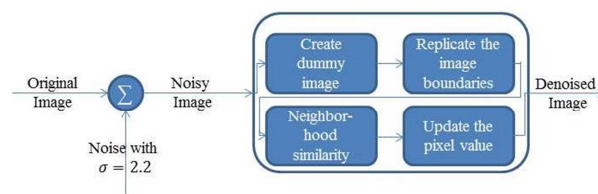


Fig 1 : Image Restoration Block Diagram

The mathematical expression for NLM is

$$NL[U](x) = \sum_{j \in I} w(x,y)v(y)$$

$$\text{Where, } w(x,y) = \frac{1}{z(x)} e^{\frac{-||v(N_x)-v(N_y)||_{2,a}^2}{h^2}}$$

Here, $z(x)$ represents Gaussian equation

In the proposed algorithm, we are replacing $z(x)$ with the biweight function of ANISOTROPIC filter.

The mathematical equation for the proposed algorithm is

$$NL[U](x) = \sum_{j \in I} w(x, y) v(y)$$

$$\text{Where, } w(x, y) = \frac{1}{k_3(x)} e^{\frac{-\|v(Nx) - v(Ny)\|_{2,a}^2}{h^2}}$$

Here, $k_3 = \frac{1}{2} \left[1 - \left(\frac{x}{k\sqrt{2}} \right)^2 \right]^2$, k is the threshold parameter.

By the implementation of this algorithm, we are achieving high PSNR values than the actual algorithms.

5. RESULTS

Proposed algorithm has been implemented on the following five standard MATLAB images, Elaine, Foreman, Lenna, Miss America and Suzie respectively for different standard deviations.

Input



Output



Fig 2a: Results For Proposed Algorithm For $\sigma = 2.2$



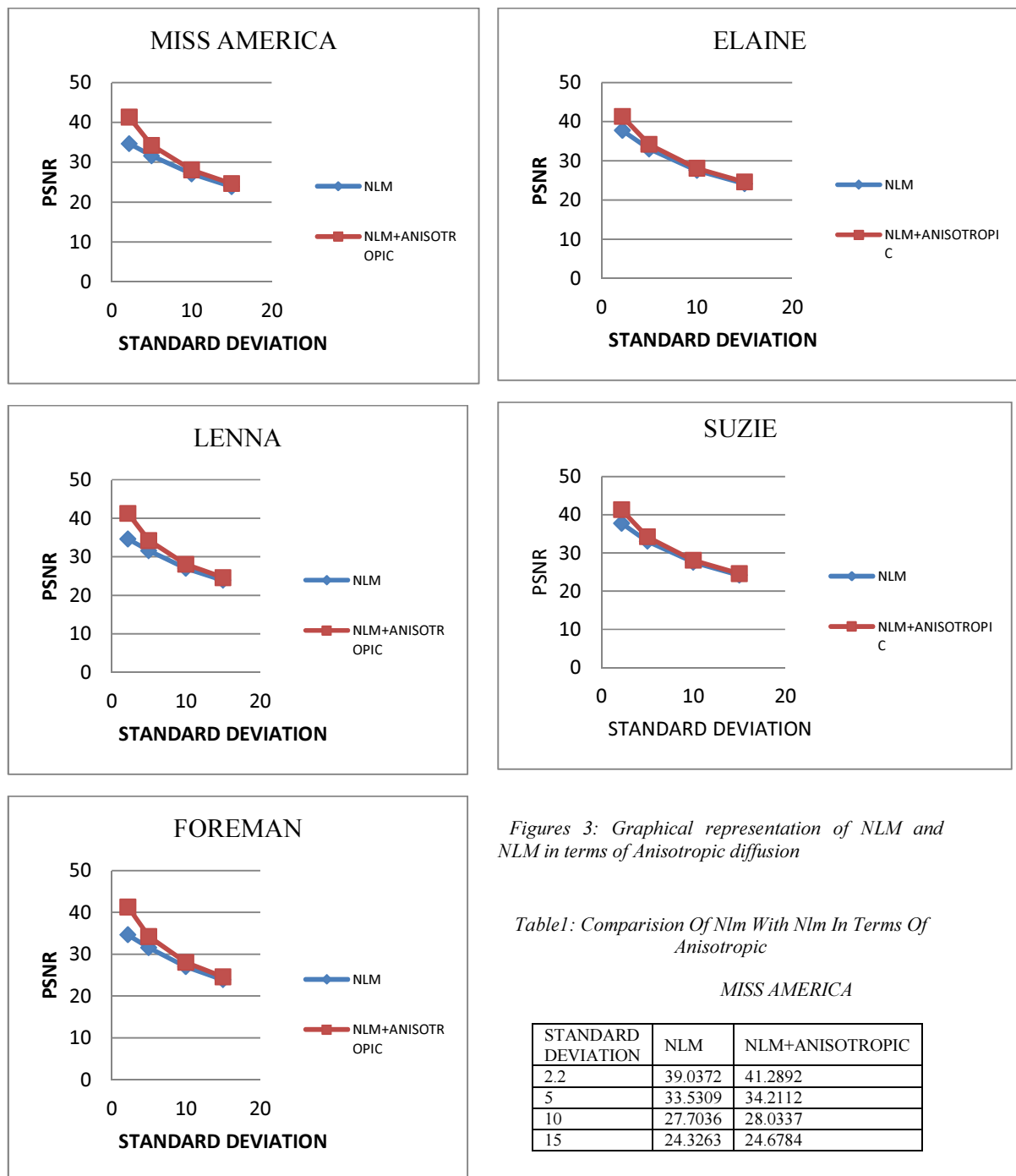
Fig 2b: Results For Proposed Algorithm For $\sigma = 5$



Fig 2c: Results For Proposed Algorithm For $\sigma = 10$



Fig 2d: Results For Proposed Algorithm For $\sigma = 15$



FOREMAN

STANDARD DEVIATION	NLM	NLM+ANISOTROPIC
2.2	34.6303	41.3337
5	31.5639	34.2550
10	27.0308	28.0577
15	23.8771	24.5590

ELAINE

STANDARD DEVIATION	NLM	NLM+ANISOTROPIC
2.2	33.3868	41.2764
5	31.1149	34.0735
10	26.7577	28.1394
15	23.6333	24.7350

SUZIE

STANDARD DEVIATION	NLM	NLM+ANISOTROPIC
2.2	37.7460	41.3319
5	33.0285	34.2085
10	27.5587	28.0795
15	24.1622	24.6016

6. APPLICATIONS

Whenever we try to shot a scene, the primary wish is to get a noise free image. For this the main requirement would be a high resolution camera which will cost very high. And this is the situation where the problem arises. Rather than opting a high resolution camera which costs more, enhancing the image taken from a low resolution camera will be more advisable. This is where the application of image denoising arises. Surveillance cameras cannot take accurate images due to the low quality specifications of the capturing devices, in that case we can make use of the proposed algorithm to make the images look visually good. We can use this algorithm to extend the face detection application to low resolution cameras. In finger print recognition systems we can use this algorithm so that it provides better computational results. Other applications with some modifications include facial reconstruction, multiple descriptive coding and super resolution.

7. CONCLUSIONS

From the results obtained it is clear that the application of the algorithm is successful. And this application is more prominent in de noising the images shot from a camera with low quality specifications. This procedure is successful in obtaining the enhanced images to obtain even the minute details when related to blurred images. We used Non Local Means algorithm in order to denoise the image, but Non Local Means algorithm treats high frequency detail, like edges as noise and removes the high frequency detail which may also be the desired data. So Anisotropic diffusion is adopted which will preserve the edge details. Finally an algorithm is stated by using Non Local Means algorithm in terms of Anisotropic diffusion. The combined use of NLM and Anisotropic diffusion gives the promising applications in denoising the images. With slight proper enhancement in the algorithm can be used in finger print reading, facial reconstruction. The addition of super resolution to the proposed algorithm by using Interpolation technique, specially Bicubic interpolation will help in extracting much more fruitful results. In some real time situations, the images that are of our interest may be visually annoyed because of various reasons. We can apply the proposed algorithm to make the image free from noise.

REFERENCES

- [1] Matan Protter and Michael Elad "Generalizing the Nonlocal-Means to Super-Resolution Reconstruction" *IEEE Transactions On Image Processing*, Vol. 18, NO. 1, January 2009.
- [2] T. S. Huang and R. Y. Tsai, "Multi-frame image restoration and registration," *Adv. Comput. Vis. Image Process.*, vol. 1, pp. 317–339, 1984.
- [3] S. P. Kim, N. K. Bose, and H. M. Valenzuela, "Recursive reconstruction of high resolution image from noisy undersampled multiframes," *IEEE Trans. Acoust. Speech Signal Process.*, vol. 38, no. 6, pp. 1013–1027, Jun. 1990.
- [4] M. Irani and S. Peleg, "Improving resolution by image registration," *CVGIP: Graph. Models Image Process.*, vol. 53, pp. 231–239, 1991.

- [5] S. Peleg, D. Keren, and L. Schweitzer, "Improving image resolution using subpixel motion," *CVGIP: Graph. Models Image Process.*, vol. 54, pp. 181–186, Mar. 1992.
- [6] H. Ur and D. Gross, "Improved resolution from subpixel shifted pictures," *CVGIP: Graph., Models, Image Process.*, vol. 54, pp. 181–186, March 1992.
- [7] R. R. Schultz and R. L. Stevenson, "Extraction of high-resolution frames from video sequences," *IEEE Trans. Image Process.*, vol. 5, no. 6, pp. 996–1011, Jun. 1996.
- [8] A. J. Patti, M. I. Sezan, and M. A. Tekalp, "Superresolution video reconstruction with arbitrary sampling lattices and nonzero aperture time," *IEEE Trans. Image Process.*, vol. 6, no. 8, pp. 1064–1076, Aug. 1997.
- [9] R. C. Hardie, K. J. Barnard, and E. E. Armstrong, "Joint MAP registration and high-resolution image estimation using a sequence of undersampled images," *IEEE Trans. Image Process.*, vol. 6, no. 12, pp. 1621–1633, Dec. 1997.
- [10] M. Elad and A. Feuer, "Restoration of single super-resolution image from several blurred, noisy and down-sampled measured images," *IEEE Trans. Image Process.*, vol. 6, no. 12, pp. 1646–1658, Dec. 1997.
- [11] N. R. Shah and A. Zakhor, "Resolution enhancement of color video sequences," *IEEE Trans. Image Process.*, vol. 8, no. 6, pp. 879–885, Jun. 1999.
- [12] A. Zomet and S. Peleg, "Efficient super-resolution and applications to mosaics," in *Proc. Int. Conf. Pattern Recognition*, Sep. 2000, pp. 579–583.
- [13] N. Nguyen, P. Milanfar, and G. H. Golub, "A computationally efficient image superresolution algorithm," *IEEE Trans. Image Process.*, vol. 10, no. 4, pp. 573–583, Apr. 2001.
- [14] M. Elad and Y. Hel-Or, "A fast super-resolution reconstruction algorithm for pure translational motion and common space invariant blur," *IEEE Trans. Image Process.*, vol. 10, no. 8, pp. 1187–1193, Aug. 2001.
- [15] C. Tom and A. Katsaggelos, "Resolution enhancement of monochrome and color video using motion compensation," *IEEE Trans. Image Processing*, vol. 10, no. 2, pp. 278–287, Feb. 2001.
- [16] Y. Altunbasak, A. J. Patti, and R. M. Mersereau, "Super-resolution still and video reconstruction from MPEG-coded video," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 12, no. 4, pp. 217–226, Apr. 2002.
- [17] S. Baker and T. Kanade, "Limits on super-resolution and how to break them," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 9, pp. 1167–1183, Sep. 2002.
- [18] S. Park, M. Park, and M. G. Kang, "Super-resolution image reconstruction, a technical overview," *IEEE Signal Process. Mag.*, vol. 20, no. 5, pp. 21–36, May 2003.
- [19] S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, "Robust shift and add approach to superresolution," in *Proc. SPIE Conf. Applications of Digital Signal and Image Processing*, Aug. 2003, pp. 121–130.
- [20] Z. Lin and H.-Y. Shum, "Fundamental limits of reconstruction-based superresolution algorithms under local translation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 1, pp. 83–97, Jan. 2004.
- [21] S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, "Fast and robust multiframe superresolution," *IEEE Trans. Image Process.*, vol. 13, no. 10, pp. 1327–1344, Oct. 2004.
- [22] S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, "Advances and challenges in superresolution," *Int. J. Imag. Syst. Technol.*, vol. 14, pp. 47–57, Aug. 2004.
- [23] T. Gotoh and M. Okutomi, "Direct super-resolution and registration using raw CFA images," in *Proc. Int. Conf. Computer Vision and Pattern Recognition*, Jul. 2004, vol. 2, pp. 600–607.
- [24] G. T. Clement, J. Huttunen, and K. Hynynen, "Superresolution ultrasound imaging using back-projected reconstruction," *J. Acoust. Soc. Amer.*, vol. 118, pp. 3953–3960, 2005.
- [25] P. Vandewalle, S. Susstrunk, and M. Vetterli, "A frequency domain approach to registration of aliased images with application to superresolution," *EURASIP J. Appl. Signal Process.*, no. 71459, 2006.
- [26] J. Chung, E. Haber, and J. Nagy, "Numerical methods for coupled super resolution," *Inv. Probl.*, vol. 22, pp. 1261–1272, 2006.
- [27] H. F. Shen, L. P. Zhang, B. Huang, and P. X. Li, "A MAP approach for joint motion estimation, segmentation, and super resolution," *IEEE Trans. Image Process.*, vol. 16, no. 2, pp. 479–490, Feb. 2007.
- [28] W. T. Freeman, T. R. Jones, and E. C. Pasztor, "Example-based super resolution," *IEEE Comput. Graph.*, vol. 22, no. 2, pp. 56–65, Mar./Apr. 2002.

- [29] S. Kanumuri, O. G. Culeryuz, and M. R. Civanlar, "Fast super-resolution reconstructions of mobile video using warped transforms and adaptive thresholding," in *Proc. SPIE*, 2007, vol. 6696, p. 66960T.
- [30] M. Elad and Y. Hel-Or, "A fast super-resolution reconstruction algorithm for pure translational motion and common space-invariant blur," *IEEE Trans. Image Process.*, vol. 10, no. 8, pp. 1187–1193, Aug. 2001.
- [31] S. Farsiu, D. Robinson, M. Elad, and P. Milanfar, "Fast and robust multi-frame super-resolution," *IEEE Trans. Image Process.*, vol. 13, no. 10, pp. 1327–1344, Oct. 2004.
- [32] H. Fu and J. Barlow, "A regularized structured total least squares algorithm for high-resolution image reconstruction," *Linear Algebra Appl.*, vol. 391, pp. 75–98, Nov. 2004.
- [33] B. K. Gunturk, Y. Altunbasak, and R. M. Mersereau, "Multiframe resolution enhancement methods for compressed video," *IEEE Signal Process. Lett.*, vol. 9, no. 2, pp. 170–174, Jun. 2002.
- [34] M. Irani and S. Peleg, "Super resolution from image sequence," in *Proc. 10th Int. Conf. Pattern Recognition*, 1990, vol. 2, pp. 115–120.
- [35] M. M. J. Koo and N. Bose, "Constrained total least squares computations for high resolution image reconstruction with multisensors," *Int. J. Imag. Syst. Technol.*, vol. 12, pp. 35–42, 2002.
- [36] P. Vandewalle, L. Sbaiz, M. Vetterli, and S. Susstrunk, "Super-resolution from highly undersampled images," in *Proc. Int. Conf. Image Processing*, Genova, Italy, Sep. 2005, pp. 889–892.
- [37] N. A. Woods, N. P. Galatsanos, and A. K. Katsaggelos, "Stochastic methods for joint registration, restoration, and interpolation of multiple undersampled images," *IEEE Trans. Image Process.*, vol. 15, no. 1, pp. 201–213, Jan. 2006.
- [38] A. Zomet, A. Rav-Acha, and S. Peleg, "Robust super-resolution," presented at the Int. Conf. Computer Vision and Pattern Recognition(CVPR), 2001.