Proceedings of the Third International Conference on Smart Electronics and Communication (ICOSEC 2022)
IEEE Xplore Part Number: CFP22V90-ART; ISBN: 978-1-6654-9764-0

2022 3rd International Conference on Smart Electronics and Communication (ICOSEC) | 978-1-6654-9764-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICOSEC54921.2022.9951890

Anisotropic Diffusion based Impulse Noise Removal for Remote Sensing Images

Resmi R Nair, Senthamizh Selvi R, Jerusha Beulah, Karthika Sree B.
Department of ECE, Easwari Engineering College, Chennai
Email: resmi.r@eec.srmrmp.edu.in, senthamizhselvi.r@eec.srmrmp.edu.in, jerubeulah2000@gmail.com, karthikasree1584@gmail.com

***Abstract*---In image processing and computer vision, image denoising is a crucial challenge that should be rectified by suppressing the noise-corrupted image and obtaining the image information. The random variation of brightness or colour information in acquired images is referred to as image noise. Image denoising is also useful in a variety of applications, such as image restoration, visual tracking, image registration, picture segmentation, and image classification, where recapturing the original image content is critical to achieving good results. To deal with additive noise, a myriad of image denoising methodologies have been proposed in recent times. Impulse noise, on the other hand, remains a challenging problem to solve using multiple ways. It is a sort of noise with either black or white noise pixels. We propose a novel concept of scale-space in this study, as well as a class of algorithms that implement it via a diffusion process. The primary purpose is to eliminate salt and pepper noise from remote sensing imagery using an anisotropic diffusion median filter. Our method ensures that region boundaries are kept as precise as possible. The findings of the experiments are depicted in a series of images. In terms of visual outcomes and performance metrics, the performance of the algorithm is validated by Structural Similarity Index Metric (SSIM) and Peak Signal to Noise Ratio (PSNR).**

***Keywords*---Image Denoising, Anisotropic Diffusion, Scale-Space Technique, Gaussian kernel, Impulse noise**
.

1. Introduction

Remote sensing is defined as the measurement of object attributes on the earth's surface using data collected by aircraft and satellites. Although remote-sensing data can take the form of discrete point measurements, we are more interested in measurements over a two-dimensional spatial grid, or pictures. Various types of noise can affect these image data during the acquisition and transmission processes. However, noise contains undesirable information, which is a common issue. In digital image processing, reducing noise from remote sensing images is a difficult task. Image denoising has been offered as one possible solution to this problem, to protect information [1].

It preserves the details of an image while removing as much random noise as feasible from the image. Image smoothing seems to be the best way to remove noises. The scale-space theory is a method of representing images on multiple spatial scales. Real-world objects can be seen at multiple scales, which is referred to as the multiscale phenomenon. This phenomenon is entirely reliant on the observation scale. The relevant scales in which a real-world object is depicted cannot be construed. The only way to develop an automatic algorithm would be to depict the objects at all scales concurrently [2].

Scale-space filtering is an important means of image smoothing. Diffusion techniques are used to smooth images via partial differential equations. This approach is based on the diffusion equation:

$$\partial u/\partial t = div(C_{(x,y,t)}.\ \nabla_u),(x,y) \in \Omega \subset R^{2.} \tag{1}$$

$$U_{(0,x,y)} = u_0 \tag{2}$$

In this case, u_0 represents the initial noised image and C is the diffusion tensor. The diffusion process is classified into two types: homogeneous diffusion and inhomogeneous diffusion. If the tensor is constant $C_{(x,\ y,\ t)} = C$ over the entire domain$\Omega \subset R^2$, the diffusion process is said to be homogeneous. Only when the diffusion process is spatially dependent, it is inhomogeneous. Homogenous filtering is referred to as Isotropic Diffusion whereas Inhomogeneous filtering is referred to as Anisotropic Diffusion. The diffusion process that is not entirely reliant on an evolving image is linear, whilst the diffusion process that is entirely reliant on an image's function is non-linear [3].

One of the most significant drawbacks of de-noising is poor edge retention and blurring. These are observed in the technique of linear image smoothing. To address this issue, Persona and Malik devised a nonlinear diffusion method based on partial differential equations. Perona – Malik's anisotropic diffusion filter was a key development in the edge-preserving class of algorithms [2] [4]. The diffusion coefficients in anisotropic diffusion are functions of image intensity gradients between two data points in the same neighbourhood. In each direction, the diffusion coefficient varies. As a result, the amount of flux in a given direction is determined by the gradient in that direction [5].

Smoothing inside a region is preferred over smoothing between regions. Anisotropic diffusion preserves edges while providing effective Gaussian smoothing. As a result, the anisotropic diffusion filter is an excellent choice for suppressing Gaussian noise. For non-Gaussian noises, linear filters are ineffective, whereas nonlinear filters address these difficulties [6]. This study provides an anisotropic diffusion method for reducing impulse noise while preserving significant amounts of image information such as edges, lines, or other image-interpreting elements. Smoothing with edge preservation is a must-have that also functions as denoising [7].

Even though impulse noise reduction is a well-developed field, impulse noise reduction with good smoothing remains a hot research topic, especially in high-noise environments. This noise-reducing technique's basic aim is to remove impulse noise while preserving crucial image features. Our proposed algorithm outdoes the conventional algorithms. It has a low level of complexity, necessitates less arithmetic computation, and is much more efficient.

II. Literature Survey

A real-world object represents in various spatial scales employing scale-space filtering. It has been illustrated that the Gaussian probability density function is the only kernel in which the first-order maxima or minima fluctuate as the filter bandwidth increases [8]. To constrain impulse noise in image data, partial differential equations are used [9]. Witkin pioneered the use of linear partial differential equations to develop coarser high resolution by convolving the original images [10]. This method had a significant limitation except that it did not endorse edge enhancement and had overall smoothing of the image data.

Perona and Malik presented a nonlinear partial differential equation-based diffusion process for Intra region smoothing and edge detection [2]. This form of diffusion is acknowledged as anisotropic diffusion. The objective of this design was to resolve Witkins blurring and dislocation of high-level semantic edges of image data [10]. Unlike many other approaches, images with low SNR are denoised using an anisotropic diffusion filter. This filter has been integrated with the median filter in the diffusion steps to help enhance edge detection [11]. Even though it generated the intended results, it required more arithmetic complexity and computation. The conductance function, the gradient threshold parameter, and the stopping time of the iterative process have all been vital factors in anisotropic diffusion filtering. These parameters define the degree of diffusion, which can consequence in a pixilated, blurry or unfiltered image [12].

To remove multimodal noises, anisotropic diffusion was also formulated with vector median filtering. This contributed to the development of a robust noise removal scheme. The most significant constraint is that it cannot denoise non-Gaussian noises [13]. When the intensity of the noise is high, these methodologies do not function properly. To eliminate these high-intensity noise pixels, the first neighbourhood means the filter is used to remove impulse noise [14]. Our proposed algorithm is used to reduce high-intensity impulse noise with less complexity, less arithmetic computation, and much more efficient outcomes.

III. The Proposed Methodology

The approach is rooted in the idea of scale-space filtering. The basic motivation behind this method is to incorporate the input image I 0(x,y) in a series of generated images I ((x,y,t)) obtained by combining the input image I 0(x,y) with a Gaussian kernel G ((x,y;t)) with variance t[2]:

$$I_{(x,y,t)} = I_{0(x,y)} * G_{(x,y;t)} \tag{3}$$

Increasing t, the scale-space factor, results in images with a finer sharpness. The heat equation, often known as the diffusion equation, is considered a parameter family of generated images. The heat equation outlined in the original PDE filtering model is ineffective and ruins the edges [10].

$$I_t = \Delta I = (I_{XX} + I_{YY}) \tag{4}$$

In terms of image processing, the heat equation is converted. It is the time-dependent derivative of intensity. The intensity of the pixels should change over time in such a way that it is evenly distributed in all directions. It is equal to the change in the gradient of I in *the X* direction and the change in the gradient of *the Y* direction concerning time. T

he intensity should shift in both the X and Y directions as the intensity changes. The use of the heat equation has the benefit because pixel intensities are equivalent to heat. As time passes, the pixel intensities become more evenly distributed, resulting in a coarser resolution and a smoother image. The Gaussian kernel is a heat equation solution.

The image changes over time, as though a Gaussian kernel is being applied. Gaussian blur is the result of applying this equation to every pixel in an image. In other algorithms edges are pushed away from their true places, erasing the most critical feature necessary for edge detection. The natural boundaries of the object are ignored by Gaussian blurring. Instead of being sharp, region boundaries are diffused.

a. Anisotropic Diffusion:

To eliminate image noise while trying to retain critical edges, an anisotropic diffusion method is employed (Ezmahamrul Afreen Awalludin, 2013). Consider the anisotropic diffusion equation,

$$I_t = div\ (c_{(x,y,t)} \nabla I) = c_{(x,y,t)} \Delta I + \nabla c . \nabla I \tag{5}$$

In terms of space variables, the diverging operator is represented by div, and the gradient and Laplacian operators are represented as V and A, correspondingly. The isotropic heat diffusion formula is the result.

$$I_t = C\Delta I \text{ if } c(x,y,t) \text{ is a constant.}$$

The median filter is a nonlinear filter that eliminates impulsive noise and maintains edges intact. In images, row sorting, column sorting, and diagonal sorting are used to execute median operations [15]. Smoothing inside an area is prioritized above smoothing crossing borders in this technique. This may be done by setting the conduction coefficient at 1 within every section and 0 outside. The blur will now occur in each zone independently, with no interaction. The region's borders would be firmly defined.

$$I_{i+j}^{n+1} = I_{i,j}^{n} + \lambda\, G\,\theta(F)\,.\,\theta(F) \quad (6)$$

$$\theta(F) = T\,[\,\nabla_k I\,]\; k = 1 \text{ to } N \quad (7)$$

$$(F) = T[\,(I_{i-1,j}^{n} - I_{i,j}^{n}),\ (I_{i+1,j}^{n} - I_{i,j}^{n}),\ (I_{i,j+1}^{n} - I_{i,j}^{n}),\ (I_{I,j-1}^{n} - I_{i,j}^{n})] \quad (8)$$

θ(F) is the Weighted median Perona–Malik Anisotropic Diffusion for Gaussian Noise + salt and pepper noise [16].

$$I_{i,j}^{n+1} = I_{i,j}^{n} + \beta\,[g\,(I_{i+1,j}^{n} - I_{i,j}^{n})\,(I_{i+1,j}^{n} - I_{i,j}^{n}) + g(I_{i-1,j}^{n} - I_{i,j}^{n})\,(I_{i-1,j}^{n} - I_{i,j}^{n}) + g\,(I_{i,j+1}^{n} - I_{i,j}^{n})\,(I_{i,j+1}^{n} - I_{i,j}^{n}) + g(I_{i,j-1}^{n} - I_{i,j}^{n})\,(I_{i,j-1}^{n} - I_{i,j}^{n})] \quad (9)$$

Our approach is motivated by the concept that an estimate of pixel intensity increment or decrement in measures of directional components concerning neighbour pixels in an empty subset might be used to forecast the intensity of a candidate pixel shortly [17].

Concerning reference to the centre pixel of a 3X3 window, the empty subset contains four neighbouring pixels. Depending on Einstein's stochastic reasoning, the according is a novel mathematical model for Brownian scattering [18]. A candidate pixel, four neighbour pixels, a weighting function, and a control parameter are all part of the problem formulation.

$$I_{i,j}^{n+1} = I_{i,j}^{n} + \lambda g(\nabla_k I_{i,j}^{n}).Median(\nabla_k I_{i,j}^{n}) \quad (10)$$

$$g(\nabla_k I_{i,j}^{n}) = (e^{-\nabla k I i,j\wedge n})^2 / k \quad (11)$$

A code is built using the mathematical formulation. Direction components along the north, south, east, and west directions of the candidate pixel are computed for the mathematical calculation of the technique, and a median calculation of the direction components is obtained.

A value corresponding to the median calculation of the directional derivatives is appended to the candidate pixel intensity. This approach is applied to every pixel in the image. The process is performed n times further until the appropriate signal-to-noise ratio is attained. The approach is put to the test on many test images that have been tainted with different types and levels of noise.

Simulations are run on a computer equipped with a 2.20 GHz Intel (R) Core (TM) i5-5200 U CPU, a computer operating system, 4 GB of RAM, with MATLAB R2018a loaded. Visual findings and performance measurements such as peak signal-to-noise ratio (PSNR) and structural similarity index metric are used to assess the algorithm's performance (SSIM).

Per-pixel computation concerning the centre pixel in a 3x3 mask:

$I_{i,}$ Jn: 5 Numbers

$\nabla_K I_{i,j}^{n}$,K=1,2,3,4:4 Numbers

Median($\nabla_K I_{i,j}^{n}$), α, $I_{i,j}^{n+1}$: 1 Number

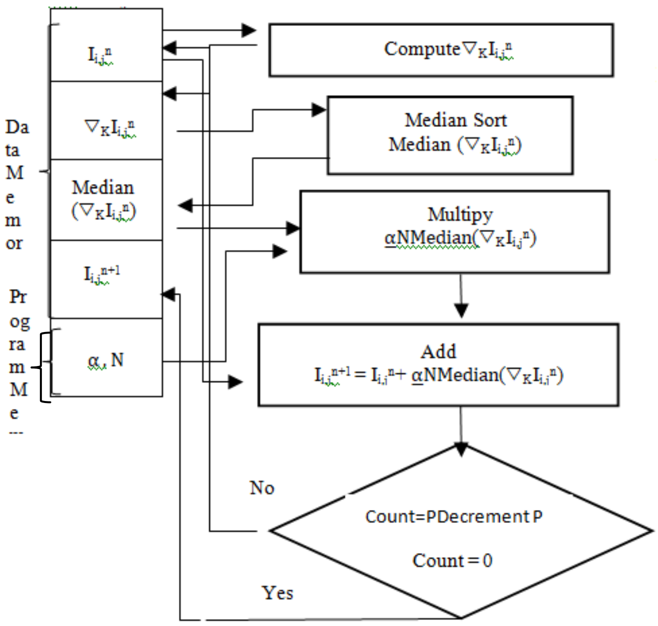
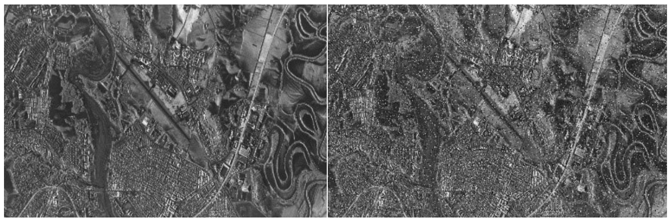


Fig 1: Flowchart of Proposed Algorithm

IV. Results and Discussion

Based on the proposed unified model, the performance of anisotropic diffusion median filters is investigated. The test image is a remote sensing image. The image is corrupted by an Impulse Noise of 70%.



(a) (b)

(c) (d)

Fig 2 (a) Original Grayscale Image, (b) Image with 70% salt & Pepper Noise, (c) Original Colour Image, (d) Colour Image with 70% Salt & Pepper Noise.

Numerical analysis shows that filter provide stable performance for λ = 0.05 (0< λ<0.05) and k = 0.01 (0<k<0.01). A standard value of the minimum number of iterations which provides acceptance performance is chosen as n = 5.

Figure 3 shows the performance of the Anisotropic Diffusion Median filter for grayscale images corrupted by Impulse Noise. Variations in k are made by keeping λ=0.25 and n(iterations)=5.

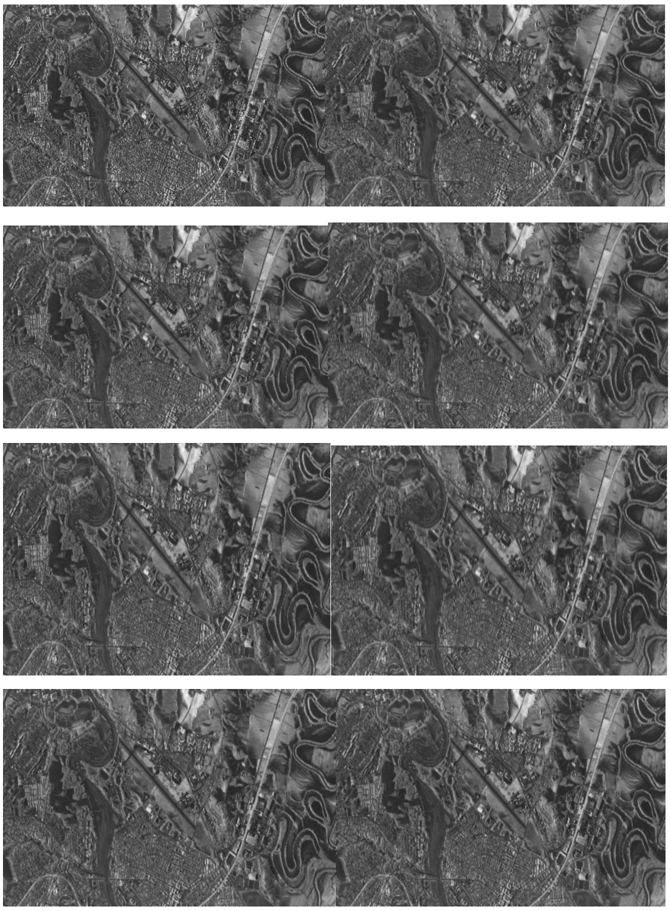


Fig 3 Variations in k (0.01, 1, 2, 4, 8, 10, 50, 100) with λ = 0.25 and n = 5 on grayscale remote sensing imagery.

Figure 4 shows the performance of the Anisotropic Diffusion Median filter for colour images corrupted by Impulse Noise. Variations in k are made by keeping λ=0.25 and n(iterations)=5.

Fig 4 Variations in k (0.01, 1, 2, 4, 8, 10, 50, 100) with λ = 0.25 and n = 5 on colour remote sensing imagery.

Figure 5 shows the performance of the Anisotropic diffusion median filter for grayscale images corrupted by Impulse Noise. Variations in $\lambda$are made by keeping k=2 and n(iterations) = 5.

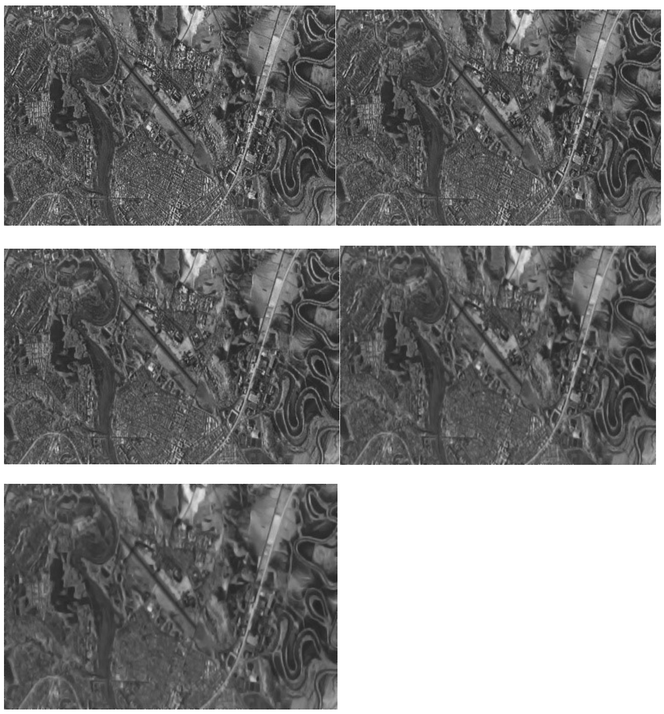
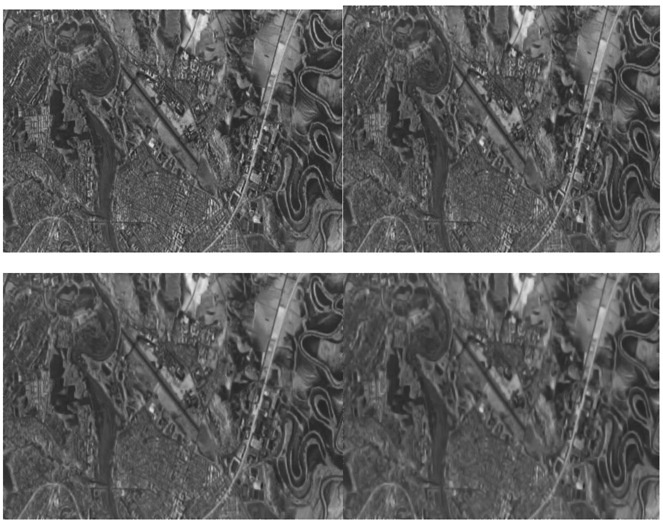


Fig 5 Variations in λ (0.05, 0.2, 0.4, 0.7, 1.0) with k = 2 and n = 5 on grayscale remote sensing imagery.

Figure 6 shows the performance of the Anisotropic Diffusion Median filter for colour images corrupted by Impulse Noise. Variations in λ are made by keeping k=2 and n(iterations)=5.

Fig 6 Variations in λ (0.05, 0.2, 0.4, 0.7, 1.0) with k = 2 and n = 5 on colour remote sensing imagery.

Figure 7 shows the performance of the Anisotropic Diffusion Median filter for grayscale images corrupted by Impulse Noise. Variations in n (iterations) are made by keeping k=2 and λ = 0.25.



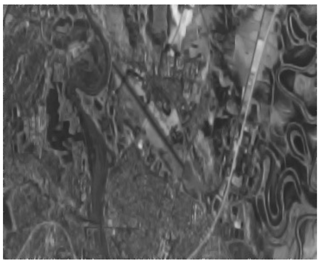


Fig 7 Variations in n (5, 10, 20, 40, 50) with k = 2 and λ= 0.25 on grayscale remote sensing imagery.

Figure 8 shows the performance of the Anisotropic Diffusion Median filter for colour images corrupted by Impulse Noise. Variations in n (iterations) are made by keeping k=2 and λ = 0.25.

Fig 8 Variations in n (5, 10, 20, 40, 50) with k = 2 and λ= 0.25 on colour remote sensing imagery.

The Peak Signal-to-Noise Ratio (PSNR) is an important metric with a concise physical interpretation, but it doesn't always necessarily correlate with the human judgement of quality, whereas Structural Similarity (SSIM) criteria, which are much more closely related to the human visual system. Structural Similarity Index Metric (SSIM) and Peak Signal to Noise Ratio (PSNR) evaluate the algorithm's performance.

TABLE I: PERFORMANCE METRICS (K VARIATIONS)

GAUSSIAN FUNCTION [λ -0.25 & n-5]				
GRAYSCALE IMAGE			COLOUR IMAGES	
K	PSNR	SSIM	PSNR	SSIM
0.01	26.5765	0.9999	27.7188	0.9998
1	23.0732	0.9993	23.1246	0.9995
2	23.0149	0.9993	23.0718	0.9995
4	22.9885	0.9993	23.0670	0.9995
8	23.0027	0.9993	23.0532	0.9995
10	22.9925	0.9993	23.0614	0.9995
50	22.9847	0.9993	23.0619	0.9995
100	22.9741	0.9993	23.0487	0.9995

TABLE II: PERFORMANCE METRICS (λ VARIATIONS)

GAUSSIAN FUNCTION [n-5 & K-2]				
GRAYSCALE IMAGE			COLOUR IMAGE	
λ	PSNR	SSIM	PSNR	SSIM
0.05	26.3963	0.9998	26.9123	0.9997
0.2	23.6465	0.9994	23.7490	0.9996
0.4	21.7014	0.9989	21.6991	0.9993
0.7	20.2622	0.9980	20.1432	0.9988
1.0	19.2726	0.9960	20.1432	0.9988

TABLE III: PERFORMANCE METRICS (n VARIATIONS)

GAUSSIAN FUNCTION [λ-0.25 & K-2]				
GRAYSCALE IMAGE			COLOUR IMAGE	
n	PSNR	SSIM	PSNR	SSIM
5	22.9899	0.9993	24.1856	1.0000
10	21.4448	0.9988	21.9179	1.0000
20	20.2609	0.9981	20.3895	0.9999
40	19.3687	0.9972	19.2524	0.9999
50	19.1280	0.9967	18.9371	0.9999

From figure 9, it is clear that the image denoising is more efficient when k=0.01,=0.05 and n=5.

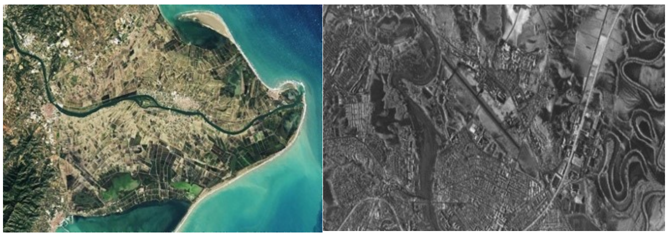


Fig 9 Efficient results of grayscale and colour remote sensing imagery

TABLE IV: PERFORMANCE METRICS (k=0.01,λ=0.05 and n=5)

GAUSSIAN FUNCTION [K-0.01 & L-0.05]			
GRAYSCALE IMAGE		COLOUR IMAGE	
PSNR	SSIM	PSNR	SSIM
26.6337	0.9999	27.7681	0.9997

V. CONCLUSION

Diffusion smoothing of images in a stable environment while retaining edge preservation is a relatively new research area. Existing robust diffusion smoothing filters typically have two or more stages and are mathematically complicated to accomplish. The Median filter is being used in the study to propose a novel method for reducing Impulse noise in image processing systems. This methodology can be used to obtain clear remote sensing imagery. The efficiency of anisotropic diffusion median filters is examined in terms of objective image processing constraints and visual results. The study could serve as a springboard for the systematic development of efficient diffusion image smoothing algorithms and implementation methodologies.

References

1. T. Lindeberg, "Scale-Space," in Encyclopedia of Computer Science and Engineering, vol. 4, Hoboken, New Jersey, Benjamin Wah, ed, 2009, pp. 2495-2504.
2. P. P. A. J. Malik, "Scale-Space and Edge Detection Using Anisotropic Diffusion," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 7, pp. 629-639, 1990.
3. J. Anand, and K. Sivachandar, "An Edge Vector and Edge Map-Based Boundary Detection in Medical Images" International Journal of Innovative Research in Computer and Communication Engineering, Vol. 1, Issue 4, pp. 1050-1055, June 2013.
4. T. Barbu, "Robust Anisotropic Diffusion Scheme for Image Noise Removal," 18th International Conference on Knowledge-Based and Intelligent Information & Engineering System, vol. 35, pp. 522-530, 2014.
5. J. Anand, K. Sivachandar, and M. M. Yaseen, “Contour-based Target Detection in Real-time Videos” International Journal of Computer Trends and Technology, Vol. 4, Issue 8, pp. 2615-2618, August 2013.
6. S. A. D. Ebenezer, "A Non-Linear Decision-Based Algorithm for Removal of Strip Lines, Drop Lines, Blotches, Band Missing and

Impulse in Images and Videos," EURASIP Journal on Image and Video Processing, pp. 1-10, 2008.

7. S. E. Varughese, M. George, and J. Anand, "Content-Based Image Retrieval Technique on Texture and Shape Analysis using Wavelet Feature and Clustering Model", International Journal of Enhanced Research in Science Technology & Engineering, Vol. 3, Issue 8, pp. 224-229, Aug 2014.
8. A. P. M. B. a. R. O. D. Jean Babaud, "Uniqueness of Gaussian Kernel for Scale-Space Filtering," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, no. 1, pp. 26-33, 1986.
9. J. W. A. C. Tang, "PDE-Based Random-Valued Impulse Noise Removal Based on New Class of Controlling Functions," IEEE Transactions on Image Processing, vol. 20, no. 9, pp. 2428-2438, 2011.
10. A. Witkin, "Scale-Space Filtering," International Joint Conference on Artificial Intelligence, pp. 1019-1021, 1983.
11. J. L. A. A. C. Bovik, "Smoothing Low SNR Molecular Images Via Anisotropic Median-Diffusion," February 2002.
12. M. P. Chourmouszios Tsiotsios, "On the Choice of the Parameter for Anisotropic Diffusion in Image Processing," Elsevier Ltd, 2012.
13. G. P. A. P. R. Rajkumar, "Denoising Algorithm Based on Anisotropic Diffusion with Vector Median Filtering," International Journal of Engineering Research & Technology (IJERT), vol. 3, no. 2, pp. 44-47, 2014.
14. U. P. S. A. V. R. Priyanka Shrivastava, "Removal of Impulse Noise using First Order Neighbourhood Mean Filter," International Journal of Computer Application, vol. 87, no. 4, pp. 0975-8887, 2014.
15. M. S. H. Z. B. W. N. J. H. W. Y. Ezmahamrul Afreen Awalludin, "Anisotropic Diffusion Based Edge Detector for Detecting Coral Reefs Edges," IEEE International Conference on Signal and Image Processing Applications (ICSIPA), pp. 226-231, 2013.
16. E. D. A. N. T. Resmi R. Nair, "A Unified Approach to Scale Space Robust Image Smoothing for Mixed Noise," International Journal of Printing, Packaging & Allied Sciences, vol. 4, no. 1, December 2016
17. E. D. A. S. R. Resmi R. Nair, "A Robust Anisotropic Diffusion Filter with Lowarithmetic Complexity for Images," Journal on Image and Video Processing, p. 2019.
18. R. Furth. "R. Nair, "A Robust Anisotropic Diffusion Filter with Lowarithmetic Complexity for Images," Journal on Image and Video Processing, p. 2019.