A Comparative Analysis of Edge-Preserving Approaches for Image Filtering

Niveditta Thakur, Nafis Uddin Khan, and Sunil Datt Sharma

Abstract Noise removal while sustaining the integrity of important details is a pedantic problem in image enhancement and reclamation. The vital stage to improve image quality which is needed for quantitative imaging study is filtering. Edges preserving filtering techniques are used extensively in computer vision to serve denoising efficiently in prominent research areas for enhancing the quality of low-level vision images, medical images, industrial images, geological images, and so on. This review paper is presenting the popular edge-preserving approaches for the enhancement of speckle contaminated images and to enhance peak signal-to-noise ratio (PSNR) of images. Various image quality metrics for proving the worth of these approaches are discussed. The main challenges in these filtering approaches are also covered along with how those challenges are inscribed by researchers. This review contributes to research problems to other fellow researchers who are keen to work in this area.

Keywords Anisotropic diffusion (AD) · Guided filtering · Image quality assessment (IQA)

1 Introduction

Real-world limitations lead to image quality degradations including noise, blurring, low contrast, etc. Image filtering [1] is a vital topic in image processing that is used to do denoising. Goyal et al. [2] conclude that lack of expertise of operator, adverse external and environmental conditions at the time of capture, and bad quality of used

N. Thakur · N. U. Khan (✉) · S. D. Sharma
Jaypee University of Information Technology, Waknaghat, Solan, India
e-mail: nafisuddin.khan@juit.ac.in

N. Thakur
e-mail: niveditta.thakur06@gmail.com

S. D. Sharma
e-mail: sunildatt.sharma@juit.ac.in

H. Sharma et al. (eds.), *Intelligent Learning for Computer Vision*,
Lecture Notes on Data Engineering and Communications Technologies 61,
https://doi.org/10.1007/978-981-33-4582-9_34

imaging device is the principal cause of noise in medical images which lead to false diagnosis. Speckle and additive Gaussian noise are dominant in ultrasound images (US), remote sensing images, and computed tomography (CT) scans.

Speckle noise is extensively found in the real-world image which has a more consequential result on performance and structural detail. Inaccurate characterization and loss of relevant information during the diffusion process called over-filtering are major problems in speckle reducing filter.

Cardiac US images are used to assess cardiac physiological indicators, coronary heart diseases, and diagnosing heart failure covering a wide range of clinical applications. Detection of a brain tumor using magnetic resonance imaging (MRI) shows the detailed image of the attacked brain position, and noise removal from an image is challenging. Identification of potential tumors on CT images for the early stage oral cavity cancer detection requires suitable filtering algorithms. In biometrics, fingerprint identification using anisotropic diffusion is popular since fingerprint has a systematic texture with well-ordered local inclination and frequency. Mineralogy, surveillance, agriculture, and astronomical areas use hyper-spectral images. Remote sensing image helps in detecting vehicles, buildings, road-linked objects, and the acquisition of transportation data.

In the linear filtering approach, output pixel values are linear combinations of the pixels in the input pixel's neighborhood. Linear filters do well at emphasizing edges, and they have the disadvantage of also emphasizing noise, inevitably blur edges, and fail to protect the details of the image well. Spatial nonlinear filters reduce noise without blur edges and thus conserve edges. But, the generation of factitious features distorts subsisting features of images because meaningful edges in a coarse image would be smudged so much so that it is hard to determine where the real meaningful edge is originally located. Another class of filter is the isotropic diffusion filter where isotropic means the same in all directions and this behaves in the same way as Laplacian filtering. Desirable filtering along with edge preservation is achieved using a guided filter and anisotropic diffusion filter which are discussed in Sects. 2 and 3, respectively. Section 4 is about implementation and observation along with a brief discussion on challenges and future research directions. Section 5 concludes this paper.

2 Guided Filter

Enhancement algorithms inspired by the guided filter possess edge-preserving property. In guided image filter (GIF) [3], each output pixel is computed locally as a linear transform of the guidance image. Low computational complexity and high efficiency make GIF well-liked. But, GIF when applied to edge-aware smoothing results in halo artifacts near edges. Also, the guided filter approach performs inefficiently on structural discontinuities due to lack of anisotropy.

Efficient adaptive guided image filtering (EAGIF) [4] does image sharpening and denoising at the same time. EAGIF algorithm has low computational requirements in comparison with adaptive bilateral filtering. Weighted guided image filter (WGIF) [5] makes a regularization parameter adaptive by executing edge-aware weighting. Non-consideration of edge direction, in WGIF, leads to blurred edges in the averaging process. Inconsistent structure occurrence in image results in failure of guided filtering due to the lack of anisotropy. Chen and Wu [6] introduced weighted aggregation GIF (WAGIF) to reduce halo artifacts and to get sharp edges. But, the small scaling parameter η makes WAGIF suffer from over-sharpening and gradient reversal artifacts. Sun et al. [7] proposed steering kernel inspired filtering (SKWGIF), by utilizing the steering kernel to fully use edge direction by adaptively learning direction and including the learning results into the filtering process. SKWGIF suppresses halo artifacts better along with edge conservation.

Edge preservation results of SKGIF found better than GIF and WGIF as shown in resulting Fig. 1, and comparative PSNR results are in Fig. 2.

Anisotropic guided filter (AnisGF) [8] is a derivative of a guided filter which has been used in edge-preserving along with noise removal [9–13]. Weighted averaging helps achieve maximum diffusion along with strong edge preservation. Summary of the varying properties of the family of guided filter design is specified in Table 1.

Family of guided filters compared in Table 1 include GIF [3], AGF [4], WGIF [5], GGIF [14], WAGIF [6], SKWGIF [7], and AnisGF [8]. 'P' = Present, 'A' = Absent, 'L' = Low, 'H' = High, 'M' = Medium.

Steering kernel [7] learning process complexity is required to be reduced which is very challenging and needs further surveyed. With AnisGF [8], there is fine extraction

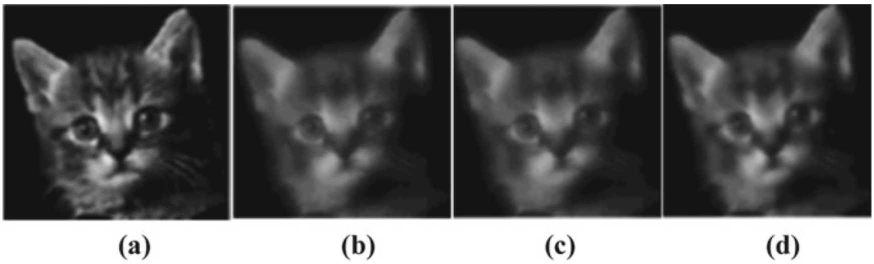


Fig. 1 **a** Reference image. **b–d** Filtered output of GIF, WGIF, and SKWGIF [7]

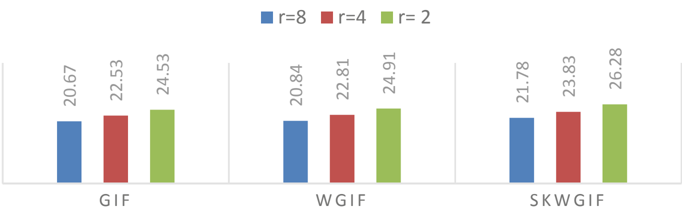


Fig. 2 PSNR values of different guided filters [7]

Table 1 Comparative analysis of guided filter designs

Property	GIF	AGF	WGIF	GGIF	WAGIF	SKWGIF	AnisGF
Adaptive regularization	A	P	P	P	P	P	P
Adaptive weighting	A	A	A	A	P	P	P
Inconsistent structure handling	A	A	A	A	P	P	P
Computational complexity	L	L	L	L	L	H	L
Time consumption	L	L	L	L	–	H	M

of textures, making certain that very little color and structural information are eliminated. But, AnisGF is not found immune to the formulation of density-dependent artifacts, so there is a need to extend this filter to multiple scales.

3 Speckle Reducing Anisotropic Diffusion Filter

Classical divergence-based anisotropic diffusion (AD) has received considerable attention to serving denoising efficiently. Traditional approaches include Weickert's edge-enhancing diffusion (WAD), Cho's dictionary-based anisotropic diffusion (DAD), and extended anisotropic diffusion (EAD) which overcome undesirable effects of linear smoothing filter such as blurring and misinterpretation of meaningful edges, but actual noise present in the image is not considered. A set of parameters that determine the success of anisotropic diffusion-based enhancement are the threshold parameter, conduction function, and stopping parameter [15].

Efficient enhancement of noisy image follows causality, piecewise smoothing, and immediate localization as described by Perona and Malik (PM) [16] along with anisotropic diffusion equations as represented by Eqs. (1) and (2) for filtering along with the preservation of edges. The anisotropic diffusion equation using four nearest neighbors is given by Eq. (1):

$$I_{t+1} = I_t + \frac{1}{4}\sum_{i=1}^{4}[C_t.\nabla I_t] \tag{1}$$

Equation 1 is rewritten as:

$$\partial_t I = \mathrm{div}(C.\nabla I) \tag{2}$$

$$C = \frac{1}{1 + \left(\frac{|\nabla I|}{k}\right)^2} \tag{3}$$

where

t Iteration.
I Input image.
∇I Image gradient.
C Diffusivity coefficient.
k Edge threshold parameter.

Equation (1) shows that the diffusion model is dependent on C. Equation 2 shows that C is a function of the gradient of image and k.

Here, the parameter to be controlled is diffusion coefficient C by changing k for the specific image used in an application and the type of noise present in the image. Regular anisotropic diffusion reaches a steady-state solution for a large number of iterations which result in longer computational time along with loss of sharpness at edges. But for large noise content image and more variation of noise across the image, the scheme proves insufficient to get correct multi-scale segmentation, and it proves an ill-posed problem [17]. Local contrast and noise can be considered for correct enhancement.

The problem of inaccurate speckle statistical modeling and issue of poor formulation of edges in classical filters, e.g., Lee, Frost, Kuan, and Gamma, is solved by using non-homogeneous diffusive heat phenomenon in speckle reducing AD filter (SRAD) [18]. Detail preserving AD filter-oriented speckle reducing AD filter and optimized Bayesian non-local means method came out as an improved despeckling method.

Fuzzy AD algorithm is suggested by Puvanathasan and Bizheva [19], for OCT images specifically, corresponding to various features and biological tissue types, by considering uncertainty in the calculated diffusivity coefficient. This proves the best edge preserver in comparison of Type-I fuzzy AD algorithm, Wiener, and adaptive Lee filter for fairly short processing time. New fuzzy rules can be added further to refine speckle noise reduction performance for different images. Probability-driven OSRAD [20] uses tissue-based statistical models and got good results. But the structural loss of details is still there. Wu and Tang [21] suggested an anisotropic method for speckle noise removal considering two functions, fidelity and speed function based upon ENI (edge, noise, interior pixels). If $p = (i, j)$ is pixel under consideration and $N_P^0(w)$ are neighbor pixels centered at p with window $= (2w + 1) \times (2w+1)$. For each $q \in N_P^0(w)$, $d(p, q)$ is the difference in intensity of pixel p and q.

$$\mathrm{ENI}_P = \sum_{q \in N_P^0(w)} I_p(q) \tag{4}$$

$$I_P(q) = \begin{matrix} 1 & \text{when } d(p,q) \le T \\ 0 & \text{when } d(p,q) > T \end{matrix} \tag{5}$$

Controlling speed function is:

$$g_n(\mathrm{ENI}_P) = \frac{1}{2} + \frac{1}{2}\cos\left(\frac{2\pi \mathrm{ENI}_P}{N}\right) \tag{6}$$

Controlling fidelity function is:

$$\lambda_n(\mathrm{ENI}_P) = \frac{1}{4} - \frac{1}{4}\cos\left(\frac{\pi \mathrm{ENI}_P}{N}\right) \tag{7}$$

where $N = (2w + 1)^2 - 1$.

The value of g_n at edge minimum, at noise intermediate, and at an interior is maximum. The value of λ_n at the edge intermediate, at noise minimum, and at the interior is maximum. There is no explicit formula or method to determine the parameters w and T. Results are checked on standard test images; however, it can be extended to SAP contaminated medical images.

Fabbrini et al. [22] proposed a novel anisotropic diffusion filter, improved edge-enhancing diffusion (IEED) filter to minimize noise on homogeneous regions while keeping weak edges. IEED does not use any noise model, also mathematically less complex, but the method is checked for speckle noise only.

The over-filtering problem of classical filters is resolved by ADMSS [23] by extending the formulation to perform selective diffusion so that diffusion structures and textural regions reduced, and in this way, visibility of important structures is enhanced. K-means clustering-based AD filter [24] uses a cluster-based speckle scale function, and the homogeneous sample region is chosen based on the clustering results. To control and guide the diffusion process, Mishra et al. [25] use the probability density function of edge and pixel relativity information (EPPR-SRAD). Diffusion equation theory is used by the doubly degenerate nonlinear diffusion (DDND) model [26] to promote the denoising process given by:

$$\partial_t I = \mathrm{div}\left(b(\mathrm{I})\frac{1}{\left(1 + |\nabla I|^2\right)^{(1-\beta)/2}}\nabla I\right) \tag{8}$$

$b(I)$ gray level indicator function.

New despeckling diffusion model:

$$\partial_t I = \mathrm{div}\left(\frac{\nabla I}{1 + (|\nabla I|/k)^{\beta(I)}}\right) \tag{9}$$

$\beta(I) = 1 - b(I)$ is the region indicator function.

Gao et al. [27] found that in ADMSS, erroneous pixels appear in homogeneous background, so they developed an improved DDND model (IDDND). Xu et al. [28] suggested Gabor-based AD (GAD-LBM), supporting advantages of GAD on edge preservation and the advantages of the lattice Boltzmann method (LBM) on rapid parallel implementation. GAD-LBM provides excellent noise reduction, detail preservation, and computational efficiency. Goyal et al. [29] proposed an SGS-SRAD filter for the despeckling of US images which is a combination of Savitzky-Golay smoothing (SGS) filter and SRAD.

4 Image Quality Assessment (IQA)

IQA is used to quantitative and statistical performance analysis which is used to benchmark or to validate the performance of various image enhancement algorithms. Here, IQA techniques for ADF-based enhancement methods are presented.

Despeckling on homogeneous regions is calculated by ENL index [22] given as:

$$\mathrm{ENL} = \left(\frac{4}{\pi} - 1\right)\frac{\mu_{\tilde{I}}^2}{\sigma_{\tilde{I}}^2} \tag{10}$$

where $\tilde{I}$ = despecled image, $\mu_{\tilde{I}}^2$, $\sigma_{\tilde{I}}^2$ are mean, and variance of $\tilde{I}$ on the homogenous region.

Contrast measure [24] is used to check the performance of despeckling algorithms:

$$C_m(i) = \frac{1}{n}\sum_m |c(i)|.\log(1 + |c(i)|) \tag{11}$$

where

n number of pixels,
m number of edge points,
$c(i)$ local contrast at pixels i

where

$c(i) = \sum_p (i - i^{'})$, p denotes neighbor pixels around i.

Contrast-to-noise ratio (CNR) [19] is the difference between particular image features relative to the background. Edge preservation (η) which shows edge degradation is occurring in the image.

$$\mathrm{CNR} = \frac{1}{R}\left(\sum_{r=1}^{R}\frac{(\mu_r - \mu_\mathrm{b})}{\sqrt{\sigma_r^2 + \sigma_\mathrm{b}^2}}\right) \tag{12}$$

where $\mu_\mathrm{b}, \sigma_\mathrm{b}^2$ = mean and variance,of background noise. μ_r, and σ_r^2 is mean and variance of rth region of interest that includes Pratt's figure of merit (FOM) [18, 25, 28, 30] calculates edge preservation in denoised images. FOM range is between 0 and 1 where 1 means best edge detection. FOM score decreases with an increase in the noise level.

$$\text{FOM} = \frac{1}{\max\{\hat{n}, n\}} \sum_{i=1}^{\hat{N}} \frac{1}{1 + d_i^2 \gamma} \tag{13}$$

$\hat{n}$ detected edge pixel and
n reference edge pixel.
d_i Euclidean distance between $\hat{i}_{th}$ edge and its nearest neighbor.
γ 0.9.

Perceptual fog density is calculated by fog-aware density evaluator (FADE) [6] where low FADE is desired. Structural degradation-oriented mean structural similarity index (MSSIM), MSE, and PSNR are simple and popular error sensitivity metrics.

5 Discussions and Observations

Image smoothing with edge conservation is a growing field of research. The experiments are performed on standard test images of Lena which are speckle contaminated for different level of noise (10% and 20%) as shown in Figs. 3b and 4b. Implementations are done on MATLAB R2020a software, and then PSNR is calculated. Table 2 summarizes various edge-preserving filtering techniques on the basis of the type of image and IQA method used. Anisotropic and guided filtering is applied on standard test images, and anisotropic techniques analyzed here are Frost [18], PM [16], DPAD [31], OBNLM [32], and ASMSS [23].

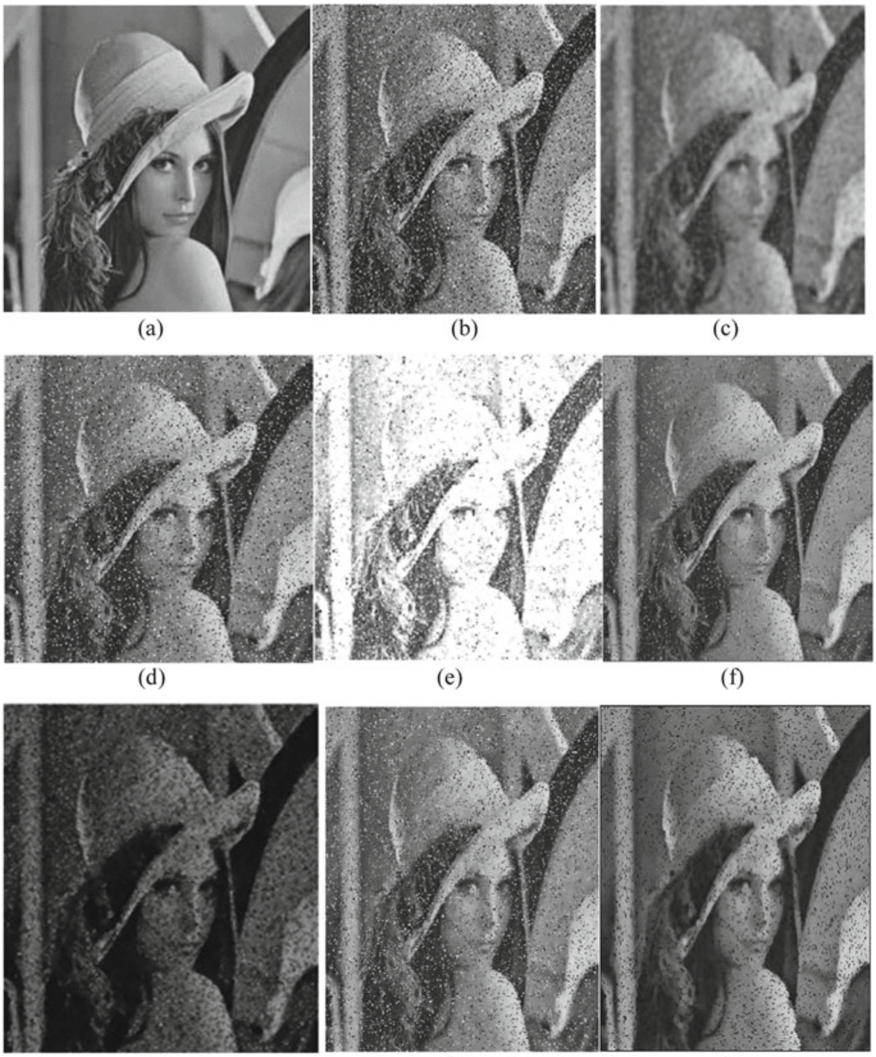
From Table 3, it is clear that with an increase in noise, PSNR is decreasing for each method. Guided filter results in Figs. 3h and 4h which is showing the highest PSNR values; however on seeing visual results, this filter fails on speckle noise. However, anisotropic diffusion methods OBNLM and ADMSS result in Figs. 3f, g and 4f, g which show effective filtering of speckle noise. Frost and DPAD result in Figs. 3c, e and 4c, e which show that speckle removal is not achieved properly. PM achieves speckle removal, but edge information is severely affected in Figs. 3d and 4d. DMF which is a directional median filter fails in completely removing speckle noise as shown in Figs. 3i and 4i.

(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 3 **a** Original Lena image. **b** Noisy image (speckle noise = 10%). **c** Frost filtered image. **d** PM filtered image. **e** DPAD results. **f** OBNLM. **g** ADMSS. **h** Guided filter. **i** DMF

6 Conclusion

Guided filter and partial differential equation (PDE) based anisotropic diffusion methods are capable of smoothing noise in the image along with edges preservation. Anisotropic diffusion filters are the best option for speckle contaminated images where guided filter does not work effectively. The optimal diffusion coefficient function can be explored to discriminate the isolated impulsive noisy pixels from edge



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 4 **a** Original Lena image. **b** Noisy image (speckle noise = 20%). **c** Frost filtered image. **d** PM filtered image. **e** DPAD results. **f** OBNLM. **g** ADMSS. **h** Guided filter. **i** DMF

pixels. Whereas traditional intensity transformation, Histogram Processing, directional median filtering, Edge detection, and Edge filtering smooth important gradient information along with noise. Medical images require such anisotropic technique by proper formulation of the diffusion equation since the presence of even small artifacts leads to false diagnosis. However, the computational load of various AD methods needs to be reduced. Anisotropy can be combined with a guided filter which can be exploited for various contaminated images. Further to benchmark,

Table 2 Summary of various edge-preserving filtering techniques

Filtering technique	IQA technique	Image type
WAGIF [7]	FADE	Fog image
SKWGIF [8]	PSNR, SSIM	Barbara, Pirate, Baboon, Hazy image
SRAD [13]	FOM	US and SAR images
DPAD [25]	MSSIM	US image
OSRAD [26]	FOM	2D and 3D synthetic image
OBNLM [27]	Despeckling assessment index	2D and 3D synthetic image, real US image
Type-II fuzzy AD [14]	PSNR, ENL, CNR	OCT fingertip and retina images
POSRAD [15]	FOM	Cardiac US image
NSDD [16]	PSNR	Standard test images (Lena and Pepper)
IEED [17]	ENL index	SAR image
ADMSS [18]	Despeckling assessment index, PSNR, SSIM	US image
CDAD [19]	Contrast measure	US image
EPPR-SRAD [20]	SSIM, MSE, FOM	Synthetic and real US cardiac and liver images
IDDND [22]	PSNR, SSIM, MAE	Real ultrasound and RGB color images
GAD-LBM [23]	SSIM, PSNR, FOM	Synthetic and clinical images
SGS-SRAD [24]	SSIM, PSNR, MSE	Real and synthetic US images

Table 3 PSNR results for speckle contaminated Lena image

Filter method	PSNR (in dB)	
	Speckle noise (10%)	Speckle noise (20%)
FROST	26.30	24.16
PM	18.92	16.05
DPAD	8.52	8.33
OBNLM	23.86	19.88
ADMSS	28.68	28.51
Guided filter	31.58	29.74
Directional median filter (DMF)	28.46	27.67

various anisotropic diffusion technique, more advanced neural-based image quality metric can be explored depending upon the type and availability of image under processing. The filtering model must be power efficient, less time-consuming, robust, and uncomplicated in hardware and operational complexity. Fuzzy logic and neural network are emerging approximation tools which may be employed for optimizing the edge threshold parameter needed in the diffusion filters. Some other decomposition and transform techniques may also be used in conjunction with diffusion filters and guided filters for image denoising.

References

1. Gonzalez RC, Woods RE (2018) Digital image processing, 4th edn. Pearson Education India, pp 140–188, 318–337
2. Goyal B, Agrawal S, Sohi BS (2018) Noise issues prevailing in various types of medical images. Biomed Pharmacol J 11(3):1227
3. He K, Sun J, Tang X (2012) Guided image filtering. IEEE Trans Pattern Anal Mach Intell 35(6):1397–1409
4. Pham CC, Jeon JW (2014) Efficient image sharpening and denoising using adaptive guided image filtering. IET Image Proc 9(1):71–79
5. Li Z, Zheng J, Zhu Z, Yao W, Wu S (2014) Weighted guided image filtering. IEEE Trans Image Process 24(1):120–129
6. Chen B, Wu S (2019) Weighted aggregation for guided image filtering. Sig Image Video Process 1–8
7. Sun Z, Han B, Li J, Zhang J, Gao X (2019) Weighted guided image filtering with steering kernel. IEEE Trans Image Process 29:500–508
8. Ochotorena CN, Yamashita Y (2019) Anisotropic guided filtering. IEEE Trans Image Process 29:1397–1412
9. Khan N, Arya KV (2018) Two stage image de-noising and edge enhancement by SVD on large scale heterogeneous anisotropic diffused image data. Multimedia Tools Appl 77:22543–22566
10. Khan N, Arya KV, Pattanaik M (2013) Histogram statistics based variance controlled adaptive threshold in anisotropic diffusion for low contrast image enhancement. Signal Process 93:1684–1693
11. Khan N, Arya KV, Pattanaik M (2014) Edge preservation of impulse noise filtered images by improved anisotropic diffusion. Multimedia Tools Appl 73:573–597
12. Jain N, Khan N, Arya KV (2016) Local variance based anisotropic diffusion for efficient edge preserving smoothing. In: International conference on signal processing (ICSP 2016), IET, 7–9 Nov 2016, Samrat Ashok Technological Institute, Vidisha, India
13. Khan N, Arya KV, Pattanaik M (2014) Efficient image de-noising and edge enhancement by singular value decomposition on anisotropic diffused image data. In: Ninth IEEE international conference on industrial and information systems (ICIIS 2014), 15–17 Dec 2014, ABV-Indian Institute of Information Technology and Management, Gwalior, India
14. Kou F, Chen W, Wen C, Li Z (2015) Gradient domain guided image filtering. IEEE Trans Image Process 24(11):4528–4539
15. Sharma A, Chaturvedi R, Kumar S, Dwivedi UK (2020) Multi-level image thresholding based on Kapur and Tsallis entropy using firefly algorithm. J Interdisc Math 23(2):563–571
16. Perona P, Malik J (1990) Scale-space and edge detection using anisotropic diffusion. IEEE Trans Pattern Anal Mach Intell 12(7):629–639
17. Sharma A, Chaturvedi R, Dwivedi UK, Kumar S, Reddy S (2018) Firefly algorithm based effective gray scale image segmentation using multilevel thresholding and entropy function. Int J Pure Appl Math 118(5):437–443
18. Yu Y, Acton ST (2002) Speckle reducing anisotropic diffusion. IEEE Trans Image Process 11(11):1260–1270
19. Puvanathasan P, Bizheva K (2009) Interval type-II fuzzy anisotropic diffusion algorithm for speckle noise reduction in optical coherence tomography images. Opt Express 17(2):733–746

20. Vegas-Sanchez-Ferrero G, Aja-Fernandez S, Martín-Fernández M, Frangi AF, Palencia C (2010) Probabilistic-driven oriented speckle reducing anisotropic diffusion with application to cardiac ultrasonic images. In: International conference on medical image computing and computer-assisted intervention. Springer, Berlin, pp 518–525
21. Wu J, Tang C (2011) PDE-based random-valued impulse noise removal based on new class of controlling functions. IEEE Trans Image Process 20(9):2428–2438
22. Fabbrini L, Greco M, Messina M, Pinelli G (2014) Improved edge enhancing diffusion filter for speckle-corrupted images. IEEE Geosci Remote Sens Lett 11(1):99–103
23. Ramos-Llordén G, Vegas-Sánchez-Ferrero G, Martin-Fernandez M, Alberola-López C, Aja-Fernández S (2014) Anisotropic diffusion filter with memory based on speckle statistics for ultrasound images. IEEE Trans Image Process 24(1):345–358
24. Hu Z, Tang J (2016) Cluster driven anisotropic diffusion for speckle reduction in ultrasound images. In: 2016 IEEE international conference on image processing (ICIP). IEEE, pp 2325–2329
25. Mishra D, Chaudhury S, Sarkar M, Soin AS, Sharma V (2017) Edge probability and pixel relativity-based speckle reducing anisotropic diffusion. IEEE Trans Image Process 27(2):649–664
26. Zhou Z, Guo Z, Dong G, Sun J, Zhang D, Wu B (2015) A doubly degenerate diffusion model based on the gray level indicator for multiplicative noise removal. IEEE Trans Image Process 24(1):249–260
27. Gao M, Kang B, Feng X, Zhang W, Zhang W (2019) Anisotropic diffusion based multiplicative speckle noise removal. Sensors 19(14):3164
28. Xu HH, Gong YC, Xia XY, Li D, Yan ZZ, Shi J, Zhang Q (2019) Gabor-based anisotropic diffusion with lattice Boltzmann method for medical ultrasound despeckling. Math Biosci Eng MBE 16(6):7546–7561
29. Goyal S, Rani A, Yadav N, Singh V (2019) SGS-SRAD filter for denoising and edge preservation of ultrasound images. In: 2019 6th international conference on signal processing and integrated networks (SPIN). IEEE, pp 676–682
30. Krissian K, Westin CF, Kikinis R, Vosburgh KG (2007) Oriented speckle reducing anisotropic diffusion. IEEE Trans Image Process 16(5):1412–1424
31. Aja-Fernández S, Alberola-López C (2006) On the estimation of the coefficient of variation for anisotropic diffusion speckle filtering. IEEE Trans Image Process 15(9):2694–2701
32. Coupé P, Hellier P, Kervrann C, Barillot C (2009) Nonlocal means-based speckle filtering for ultrasound images. IEEE Trans Image Process 18(10):2221–2229