

A Comparative Study of Image Denoising Techniques

Vivek Gour¹, Neeraj Sharma²

Department of Electronics and Communication Engineering,
Vivekananda Global University, Jaipur

Abstract:

The formation of a picture is influenced by several elements, including the properties of the camera (sensor response, lenses), the illumination (spectra, source, and intensity), and the image itself. So, noise is the main culprit when it comes to picture quality loss. Important information in photos are obscured by noise. We need to eliminate noise from the photos while preserving all of the image data in order to improve the image quality. As part of the image processing pipeline, noise reduction is a pre-processing step. A variety of sounds may distort the pictures. Various sources of noise may manifest on photographs; they include inaudible sensors, malfunctioning scanners or digital cameras, transmission channel faults, and damaged storage media. Researchers have proposed a number of ways for improving photographs by eliminating noise while keeping crucial characteristics, such as structural elements and textural information. We provide a survey on noise categories, picture types, and techniques for noise reduction in this work. Pulse noise, speckle noise, and Gaussian noise were all taken into account from the two most valuable picture types: grayscale images, medical images, and sensor images. We examine every method that can remove noise from these photos. By the conclusion of the study, we have compared all of these algorithms and come up with some great ideas for where the field may go from here.

Keywords: Image processing, grayscale, sensor pictures, medical imaging, structural characteristics, textural information, impulse noise, speckle noise, and Gaussian noise.

1. Introduction

Researchers have been working on face identification in image processing for decades, and they have made a lot of progress in this area. In order to detect faces in photos—regardless of their orientation, position, occlusion, facial expression, or the presence or absence of structural components—face recognition is an essential step. First and foremost, noise is a major component that lowers the rate of face recognition. Various approaches have been developed to enhance the rate of recognition. The techniques were grouped into four types by Ming-Hsuan Yang et al. [1]: knowledge-based methods, appearance-based methods, template-matching methods, and feature-invariant approaches. When the test picture is devoid of noise, these approaches will work effectively. A crucial part of the image processing step is noise [2][3].

Enhancing photos by reducing noise while maintaining crucial details allows them to be used for face recognition. Images taken by sources such as sensors, digital cameras, CCTV, and storage media often include these sounds, which degrade the picture quality [3]. Two main picture formats exist: grayscale

and color. There are several types of noise, including striped noise, impulse noise, speckle noise, and Gaussian noise. The development of algorithms to eliminate or significantly lower noise levels is a major accomplishment of many academics. This document makes an effort to examine and evaluate all of the algorithms. Finding the optimal method for noise reduction from photos is the recommendation of this research.

The remainder of this work is structured with the goal of finding the optimum noise reduction technique for each picture category, as follows: In Section II, we cover every algorithm for noise reduction in depth. Study comparisons are provided in Section III. The last section contains the results.

2. Methods for Eliminating Background Noise

Here, we take a look at some of the current noise removal techniques available for use in improving picture quality. Based on their intended purpose, the technology used to collect and store them, and the frequency with which they are utilized, we have divided photos into three categories: sensor images, medical images, grayscale images, and the three most common forms of noise seen in these images: impulse, speckle, and Gaussian. Therefore, we divide noise removal techniques into three categories based on these three distinct forms of noise and pictures, as shown below:

- 1) Techniques for reducing impulsive noise in sensor pictures
- 2) Methods for filtering out speckle noise in medical photographs
- 3) Methods for Filtering Gaussian Noise in Ray Scale Images

2.1 Methods for Filtering Impulse Noise Sensor Images

In order to eliminate impulsive noise, L. Ganesh et al. [4] developed an image fusion technique. Various sensors, cameras, or other capturing devices often take pictures. In this case, several sensors are considered, and the resulting impulsive noisy pictures are distinct for each sensor. A number of non-linear filters, including the Vector Median Filter (VMF), Absolute Deviation VMF, Counter Weighted VMF, Rank Conditioned and Threshold VMF, and Rank Conditioned VMF, are applied one by one to the noisy picture. After the picture has been filtered, image fusion methods are used to combine it into a single image. The filtered fused picture is then created by applying absolute deviation VMF once again to the fused images; this time, the outcome is better than the original. There is a noise level of 10% to 60% when utilizing images. The mean square error, peak signal-to-noise ratio, and structural similarity index were used to measure the performance of each filter. The results showed that the filtered fused picture outperformed all of the separate non-linear filters.

In order to eliminate impulse noise, J. Harikiran et al. [5] have introduced an image fusing method. This study presents an improvement in performance over linear filters achieved by using order statistics filters to filter pictures impacted by impulse noises, such as salt and pepper noise and random valued impulse noise. The following static filters were tested with Fused Image: Median Filters (MF), Vector Median Filter (VMF), Basic Vector Directional Filter (BVDF), Spatial Median Filter (SMF), and Modified Spatial Median Filter (MSMF). The fused picture additionally makes use of the Canny filter to identify edges for further processing.

An effort was made to employ Fuzzy Filters for impulse noise reduction in [6], as an alternative to non-linear filters and the fusing approach in [5]. The fuzzy filters include the Fuzzy Median Filter (FM), Weighted Fuzzy Mean Filter (WFM), and Fuzzy Weighted Fuzzy Meanfilter (FWM). The Fuzzy Decision Directed filter (FDD), the Fuzzy Inference Ruled by Elseaction (FIRE) filter, the first Adaptive Weighted Fuzzy Mean filter (AWFM1), and the second Adaptive Weighted Fuzzy Mean filter (AWFM2). For any kind of impulse noise reduction, these filters are taken into account. We compare these techniques to some of the most well-known linear and non-linear filtering algorithms, including the Adaptive Weighted Mean, Standard Median, Adaptive Wiener, and Gaussian filters. There are impulsive sounds in the images, and their densities range from 3% to 30%. The two primary types of densitylevel classifications are: Varying densities. While DS-FIRE and PWL-FIRE are effective fuzzy filters for low-noise levels, AWFM2 is superior for high-noise levels. This is contrasted not just with numerical categorization but also with visual perception.

To eliminate pepper and salt noise from images, Rong Zhu et al. [7] enhanced the Median filter method. This updated Median Filter technique can identify noise in images and create a noise-marked matrix based on the noise's properties. In this case, the signal-marked pixel is not processed by it. Because of its great computational efficiency and capacity to remove noise, the Median filter is the best and most extensively used. However, the median filter's job is to substitute the median of each neighbor's grayscale value for each individual pixel. Image details are lost when the noise level is high. The author created an enhanced method of median filter based on local histogram to maintain picture fine details. In order to locate pixels that represent impulsive noise, the histogram is built. The histogram displays the number of noise detections in the picture for each pixel's grayscale value. An impulse noise is present when the histogram's peak value is high. Different noise densities, ranging from 10% to 50% with 10% increments, are used to assess the effectiveness of improved median filters. According to the performance indicators, the suggested strategy provides superior noise reduction. It is more suited for standard computer image de-noising and, according to the testing results; it keeps the picture details better.

Median filtering is the standard procedure for eliminating impulsive noise. However, the image's margins are not preserved. The tough job of preserving the image's boundaries has prompted the proposal of many approaches. We created a novel way to eliminate impulsive noise while keeping the original image's borders.

The Adaptive Switching Median Filter (ASMF) was suggested by J. Aalavandan et al. [8]. The Switching Median Filter (SMF) has been adjusted in this manner. This approach employs a two-stage process to eliminate noise. Identifying the noisy zone is the first step. Here, thresholding values are used to construct a binary picture, where pixels with a value of 0 indicate noise-free pixels and pixels with a value of 1 indicate noisy pixels. Adaptive switching median filter for noise reduction in the second stage. Metrics show that the suggested approach preserves important and edge features while providing the optimal performance. The suggested technique may eliminate Pepper and Salt sounds.

Remove salt and pepper noise using the Modified Median Filter technique suggested by K. Ratna Babu et al. [9]. To keep edges intact, this approach suggests inserting fake rows and columns at each boundary. We take a 3x3 neighborhood window into account, with the processing pixel located in the middle of the window. With the exception of the processing pixel, a vector is used to preserve the

intensity values of all nearby pixels. The processing pixel is substituted with the mean value of all the vector values if all the intensity values in the vector are 0 or 255 (Noisy). This is where the mean value is determined rather than the median. When the intensity value of this vector is not zero or two hundred and fifty, the processing pixel value is substituted with the product of all the values in the vector. The suggested approach achieves excellent results at densities of up to 80%.

The Min-Max and Mid-Point filters were suggested by M. Sreedevi et al. [10] as a means to eliminate impulsive noise. Find the darkest places in the picture and minimize salt noise by applying the min-max filter. Find the brightest points in the image and reduce pepper noise by using the same filter. If you want to know where the middle ground is between two sets of numbers, the midpoint algorithm is what you need. This procedure applies to all pixel corruptions in the picture. As the noise density level rises to 70%, the suggested approach begins to outperform its predecessor.

Another area of study is the adoption of a decision-based approach to impulse noise removal, as opposed to a classical or enhanced technique. In a comparative analysis of state-of-the-art denoising algorithms, Mahantesh R Choudhari et al. [11] suggested a decision-based approach to eliminating pepper and salt noise. They took into account the Median Filtering Algorithm, the Tolerance based Selective Arithmetic Mean Filtering Technique (TSAMFT), the Improved Tolerance based Selective Arithmetic Mean Filtering Technique (ITSAMFT) Technique (Levels I and II), and so on. The median filtering approach, with its unique algorithms, is the most preferred way to eliminate pepper and salt noise. The original picture is blurred and certain fine features are affected when the noise density level is high using this procedure. According to performance measurements, ITSAMFT is effective even when dealing with images with high density noise, and this approach manages to save all of the image's characteristics, including its edges. The TSAMFT approach uses either all of the $m \times n$ pixels in the mask or only the pixels that aren't noisy to get the arithmetic mean value. Intensity replacement of the interesting pixel (the center pixel of the mean mask) is defined by tolerance. In the updated procedure, an enlarged 5×5 mask with pixels either inside or outside of the defined range is used to compute the arithmetic mean. With a depth of 95%, Level-II ITSAMFT outperforms Level-I, TSAMFT, and the Median Filter, and this refined approach reliably reduces noise while preserving details across a wide range of pictures.

Recent work by R. Pushpavalli et al. [12] introduced an innovative approach to picture improvement. For better impulsivity removal, use the suggested Switching Median Filter method. Processing pixels are considered uncorrupted according to this suggested approach if their intensity falls within the range of the images lowest and maximum pixel values in the chosen mask and stays the same. This corrupted processing pixel's intensity is altered by adjusting the median pixel value or processing the immediately next processed pixel if does not lie. While maintaining edges and fine features, this switching Median Filter effectively eliminates impulsive noise up to 70% of noise density.

2.2 Methods for Filtering Speckle Noise in Medical Images

Within the framework of wavelet analysis, Y. Murali Mohan Babu et al. [13] presented a technique based on naval Bayesian theory. The author of this research has used a variety of wavelet methods, including the Haar, Db4, Sym, and bior wavelets, as well as thresholding approaches like soft,

hard, and Bayes soft. Wavelet with Bayes soft thresholding outperforms other methods and keeps picture details intact, according to this research.

A comparative analysis of speckle noise reduction strategies and their effects on picture edge localization was reported by Rakesh Singh et al. [14]. Multiplicative in nature is speckle noise. Because it only impacts the light parts of a picture and not the dark ones, it lowers the image quality. Due of its multiplicative nature, speckle noise is more difficult to eliminate than additive noise. The two types of speckle noise reduction are contrasted in this study. There are two main types of non-linear partial differential equations (PDEs): those based on the anisotropic diffusion approach and those based on wavelets, namely decimated and un-decimated wavelets. The input picture is decomposed into fine-detailed coefficients using decimated or un-decimated wavelets and the appropriate orthogonal or bi-orthogonal wavelet families, as presented in this study. The noise is muted by using a soft threshold. An improved picture may be obtained by using the inverse wavelet transform. The results reveal that the wavelet-based approach is the most effective. It turns out that un-decimated orthogonal wavelet is the most effective approach out of all the wavelet-based ones.

The approach described above presents soft thresholding utilizing wavelet. To lessen the impact of speckle noise, ManishGoyal et al. [15] suggested a hybrid threshold approach that makes use of wavelets. In this case, Discrete Wavelet Transform 2-level image decomposition is used to get sub bands from a damaged picture. Before using the wiener filter method, the soft threshold approach is used to acquire the threshold values for each sub-band coefficient. This proposed technique performs well over a range of noise levels and standard deviations, as seen by the results. There is a combination of qualitative and quantitative analysis of the experimental outcomes.

For data that has not been logarithmically converted, T. Sreekanth Rao et al. [16] suggested using wavelet-based image de-noising. There is a compounding effect on speckle noise. As a result, the procedure described above transforms it into additive noise by calculating the logarithm. Here, however, the author uses single-level decomposition in an effort to de-noise the picture without first applying a logarithmic modification. In order to get sub bands, the speckle-corrupted picture is deconstructed. If the variation factor of the corresponding block in the high-high sub band is smaller than the standard deviation of all sub bands, then the mean value of each pixel in that block is used as a replacement. Under no circumstances was the block altered. Disjointed wavelet

Wavelet decomposition makes use of the Density-Discrete Wavelet Transform (DWT) and the Double Density-Discrete Wavelet Transform (DD-DWT). Lastly, the de-noised picture was obtained by applying the Inverse Wavelet Transform to the sub-bands. Various de-noising approaches, such as Lee filter, Hard Thresholding, and Soft Thresholding, are examined and contrasted with the suggested method. The suggested approach attains the lowest possible Mean Square Error.

An effort at a comparative research of speckle noise reduction in ultrasonic B-scan pictures was done by R. Sivakumar et. al. [17]. Wiener filtering in the wavelet domain using soft thresholding was compared to the traditional speckle noise reduction approach and found to be the best method. Separate subbands are created from the input image's noisy data. The picture is rebuilt from the denoised sub bands by utilizing the inverse Discrete Wavelet transform and a Wiener filter with soft thresholding to eliminate noise in each sub band. The suggested approach outperformed the alternatives in terms of both visual quality and performance parameters.

2.3 Approaches to Filtering Gaussian Noise in Grayscale Pictures

To effectively eliminate Gaussian noise from both grayscale and color pictures, V.R. Vijay Kumar et al. [18] developed an adaptive window based technique. This approach defines the threshold value by calculating the noise variance in the flat area of the damaged picture. A 3x3 adaptable window has now been created. If the window's variance is below the threshold, the processing pixel of the window is replaced with the mean value of the window. If it doesn't happen, the window will grow in size. This approach works well for photos with varying densities of noise.

Research by M.S. Safari et al. [19] introduced a genetic mixed noise model based on a FIR filter. Consideration is given to a 5-by-5 window. Assuming the window is situated in a flat region with no sudden changes in gray levels, the center pixel is estimated as the average of the pixels around it. If the region is not flat, there are sudden fluctuations in the pixel's intensity, and the core pixel's assessment is based on the average of just the surrounding identical pixels. Instead of bit strings, real valued chromosomes are employed so that there is no conversion between the two. According to the experimental results, the suggested filter outperformed the wiener and median filters in the salt and pepper noise density scenario (from 0 to 0.4), but not in the case of Gaussian noise variance.

Spatially adaptive denoising technique for a single picture distorted by Gaussian noise was reported by Tuan-Anh Nguyen et. al. [20]. Methods for identifying noise in this study include local weighted means, local weighted activities, and local maxima. Utilizing a spatially additive Gaussian filter, the additive noise is mitigated. Since it is expressed as a function of local statistics, this filter is an acceptable technique to manage the degree of local smoothness. To successfully eliminate the noise components, this suggested technique considers characteristics such as computing cost, over-smoothness, detection error, and the smoothing degree of the reconstructed picture.

For images with a combination of Gaussian noise, Yiwen Qiu et al. [21] introduced an adaptive de-noising technique. A better approach for noise estimation is built by looking at Immerkaer's work in [22]. With little processing burden, it produces noise standard deviation (stable estimate deviation) by combining block-based and filter-based methods. For noise reduction, the adaptive de-noising approach is used using the standard deviation retrieved during the noise estimate step. Based on performance measures, it seems that the proposed strategy is effective.

Filtering out Gaussian noise was suggested by Rashi Agarwal et. al. [23] using bit plane average. The adjusted average filter is used. Moving average filtering is done on each bit plane after slicing the noise-corrupted picture at several bit planes. Then, to restore the original picture, sort all bit-planes according to their significance. Comparisons of Bit-Plane Moving Average Filtering (BPMAF) with Moving Averaging Filter (MAF) and other methods' performance measures reveal that BPMAF outperforms them all.

Denoising images using a curvelet transform and a Log Gabor filter was shown by Vishal Gard et. al. [24]. The curvelet transform is contrasted with the Gabor filter rather than low-pass filtering. In addition to the standard curvelet transformation, the input picture is split into resolution layers, with information of varying frequencies stored in each. By using the Log Gabor filter, these frequencies are reduced and approximated. Quantitative measurements are made possible by the performance metrics. The suggested approach is contrasted with the conventional curvelet. The experimental results show that

compared to the curvelet transform without the Gabor filter, the one with the filter is much better at reducing Gaussian noise and performing well overall.

A method to remove Gaussian noise was suggested by Kun He et.al. [25] and it relies on the image's local features. First, the image's edge and texture are extracted using binary morphology. Then, the noise locations are located. To remove noise from pixels that aren't on the edge or texture, we use the mean value of the non-noise points in the adaptive neighborhood. Assume that the noisy pixels are located on the texture or edge region, and that you want to smooth out that area by utilizing the pixel points of the nearby texture and edge. Using adaptive neighborhood, we can reduce noise if noisy pixels or points are placed on the smooth area. This method is effective for picture regions with smooth surfaces and uses local smoothing for regions with rough surfaces. Thus, there is still some noise in the picture, and it's mostly around the edges and textures.

A spatially adaptive filtering approach for quickly and efficiently restoring images with Gaussian noise was introduced by Tuan-Anh Nguyen et al. [26]. Comparable work is given in [21]. With the use of local statistics and a modified Gaussian filter algorithm, this technique successfully eliminates noise throughout the detection and removal phases.

3. Performance Evaluation

An analysis is conducted on the stated performance of the three primary types of noise reduction algorithms mentioned earlier. It mostly impacts the sensor pictures, and Table I highlights the effectiveness of several impulse noise filtering approaches. The primary goal of noise reduction is to improve the identification rate and enhance images. To assess the image's quality after noise reduction, metrics such the Peak Signal Noise Ratio (PSNR) and Mean Square Error (MSE) are used.

TABLE I Impulse Noise Filtering Methods' Effectiveness

S.No	FilteringMethod	Noise Density	MSE	PSNR
1	Fused Filter Image[4]	60%	125	27.19
2	Fusing Technique[5]	40%	10.63	37.87
3	Fuzzy Filters[6]	30%	89.46	28.61
4	Improved Median Filter based on locallist[7]	50%	28.4	33.59
5	Enhanced Switching Median Filter [8]	65%	4.74	41.37
6	Modified Median Filter[9]	80%	228.4549	24.54
7	Min-Maxand Mid Point Filter [10]	70%	162.53	26.02
8	Second Level of ITSAMFT[11]	95%	1028.13	18.01
9	Switching Median Filter[12]	90%	870.86	18.72

Table I shows the results of the several filters that were investigated for the first category, namely the filtering techniques for impulse noise. The approaches in table I have all been tried and

compared. Images taken by various sensors are compiled here for testing purposes. The approach that yields good results for this density is shown in Table I. After noise reduction, the noise-free picture looks almost identical to the original, as shown by Schneier et al. [27], with a PSNR ranging from 30 to 45. As a result, high-quality images are generated by lying the range. However, even with a very high noise level, Level 2 ITSAMFT has shown outstanding results. For high density noise, the switchingmedian filtering approach also performs rather well. The correlation between a drop in MSE and an increase in PSNR has also been noted. The ESMF (at Sr. No. 5) and PSNR (between 30 and 45) are the regions where the minimum MSE is achieved. However, up to 65% of noise density, it works well. The conclusion is that all filtering techniques are effective up to a noise level of 60%. When it goes up, quality goes down.

Table II Effectiveness of Filtering Techniques for Speckle Noise

Sr No	Filtering Method	Noise Density	MSE	PSNR
1	Bayesian-based algorithm in wavelet Transform[13]	0.1	0.094	58.39
2	Wavelet Transform with soft thresholding: Undecimated Orthogonal Wavelet [14]	0.6	14.32	36.57
3	Hybrid Techniques based on Wavelet Thresholding [15]	0.09	98.22	28.26
4	Orthogonal Wavelet Transform[16]	0.8	17.36	35.78
5	Wiener filtering with Bayes Shrink Thresholding[17]	0.06	65.93	29.93

Filtering techniques for the second kind of categorization As you can see from Table II, speckle noise has been included into the analysis and results of several approaches. When compared to other wavelet approaches, the Bayesian based algorithm in wavelet transform produces the best results. Even though it's lower than the Bayesian model, the noise density level in the un-decimated orthogonal wavelet is still above 50%. It improves picture quality and maintains the image's edges. The amount of noise managed for speckle noise reduction between 0.01% and 0.09%. The Bayesian model is very near to this degree of dense noise. A hybrid technique based on wavelet thresholding is used to suppress instead of removing. In terms of edge preservation, this strategy outperforms more conventional approaches as well. As a result of severe corruption caused by orthogonal wavelet thresholding,

this strategy outperformed every other method in Table II when noise is taken into account. As the number of pictures utilized increases, the performance analysis of the images becomes more crucial. Here, 200 photos were subjected to wiener filtering using the Bayshrink thresholding approach. Among the approaches shown in Table II, the wavelet-based methodology stands out for its much better results and high level of performance.

Table III shows the results of the third categorization of this study, which is based on the performance of filtering techniques for removing Gaussian noise. As a rule, the occurrence of Gaussian noise is associated with picture taking and storage by photon counting. Every pixel in the picture is somewhat altered by the standard deviation of the noise, according to [28]. In order to eliminate the Gaussian noise, one may use the adaptive window approach. You may use this approach to get rid of random noise in both color and grayscale images. Differentiating between noise and edge information becomes very challenging in every picture that has been degraded by noise. Therefore, fuzzyconcept is used to maintain edges.

Table III Filtering Methods for Gaussian Noise and Their Performance

Sr No	Filtering Method	Noise Density	MSE	PSNR
1	Adaptive window based efficient Algorithm[18]	30	9.02	27.12
2	FIR-Filter based Fuzzy GeneticMixed Noise removal [19]	5.01	2542.9	14.07
3	Spatially adaptive de-noisingalgorithm [20]	30	31.9	33.09
4	An Adaptive Image De-noising Method [21]	10.843	14.178	36.61
5	Bit Plane Average Filtering [23]	20	96.63	28.28
6	Curvelet Transform with Gaborfilter [24]	3	.02442	64.25
7	Local Feature Method[25]	40	632.89	20.12

It is difficult to determine the kind of noise, the region of the picture that is impacted, and then to eliminate the mixed sounds that may have contaminated the image. It is taken into account that the image is contaminated by Gaussian noise and the Salt & Pepper nose, and FIR To eliminate these intermingled sounds, a fuzzy filter is used. According to the results of the trial, this method's effectiveness degrades as the noise level increases. Therefore, removing Gaussian noise will not work here. We must prioritize the reduction of processing cost, blurring, and over-smoothness in order to preserve edges. With these considerations in mind, the Spatial Adaptive approach provides the most accurate noise detection. Various sounds will contaminate various parts of the photos. These pictures are subjected to an Adaptiveimagede-noising technique and evaluated. Low density noise is affecting one part of the picture, while high density noise is affecting another part of the image. The adaptive image de-noising approach is inferior to our spatially adaptive de-noising method. A lot of similarities exist between this result and the Bit Plane average filtering approach. This approach highlights the critical relevance of high contrast images in noise reduction.

4. Conclusion

An exhaustive review of noise estimation techniques is the goal of this work. The most common types of noise that we have concentrated on are impulse noise, speckle noise, and gaussian noise, which may vary from very faint to quite loud. We have examined techniques that can eliminate certain types of noise. Feature and edge preservation, cheap cost, reduced time, high density noise, over-smoothness, high contrast picture, and combination of noises were the criteria used in this investigation. Declaring which techniques really have lowest error rate with maximum noise ratio would be a bold move due to the lack of consistency in method evaluation. As a result, we have relative method performance from our study. While our research does apply to impulse, speckle, and Gaussian noise, it does not provide a universally applicable strategy for noise reduction.

In order to get a higher identification rate, noise reduction remains a tough issue. Therefore, it is important to remember that a reliable system should meet all the aforementioned criteria while removing numerous sounds from both individual and multiple photos.

References

1. Adil H Kuan, Jawad F Al-Asad & Ghazanfar Latif 2018, 'Speckle Suppression in medical ultrasound images through Schur decomposition', IET Image processing, vol. 12, no. 3, pp. 307-313.
2. Amandeep Kaur & Karamjeet Singh 2010, 'Speckle Noise Reduction by Using Wavelets', Proceedings of National Conference on Computational Instrumentation, pp. 198-203.
3. Amarjit Roy, Joyeeta Singha, Lalit Manam & Rabul Hussain Laskar 2017, 'Combination of adaptive vector median filter and weighted mean filter for removal of high density impulse noise from colour images', IET Image Processing, vol. 11, no. 6, pp. 352-361.
4. Amarjit Roy, Lalit Manam & Rabul Hussain Laskar 2018, 'Region Adaptive Fuzzy Filter: An Approach for Removal of Random-Valued Impulse Noise', IEEE Transactions on Industrial Electronics, vol. 65, no. 9, pp. 7268-7278.
5. Awad, AS & Man, H 2008, 'High performance detection Filter for impulse noise removal in images', Electronics Letters, vol. 44, no. 3, pp. 192-194.
6. Ayman, M Abdalla, Mohammed S Osman, Hanadi AlShawabkah, Osaid Rumman & Mutaz Mherat 2018, 'A Review of Nonlinear ImageDenoising Techniques', Proceedings of Second World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), pp. 96-100.
7. Birgir Bjorn Saevarsson, Johannes R.Sveinsson & Jon Atli Benediktsson 2004, 'Combined Wavelet and Curvelet Denoising of SAR Images' Proceedings of IEEE International Geoscience and Remote Sensing Symposium, pp. 4235-4238.
8. Chih-Yuan Lien, Chien-Chuan Huang, Pei-Yin Chen & Yi-Fan Lin 2013, 'An Efficient Denoising Architecture for Removal of Impulse Noise in Images', IEEE Transactions on Computers, vol. 62, no. 4, pp. 631-643.
9. Christos, P Loizou, Constantinos, S Pattichis, Christodoulos, I Christodoulou, Robert, Istepanian, SH MariosPantziaris & Andrew Nicolaides 2005, 'Comparative Evaluation of Despeckle Filtering In Ultrasound Imaging of the Carotid Artery', IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 52, no. 10, pp. 1653-1669.
10. Darwin T Kuan, Alexander A Sawchuk, Timothy C Strand & Pierre Chavel 1985, 'Adaptive noise

- smoothing filter for images with signal dependent noise. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 7, no. 2, pp. 165–177.
11. Deepika Koundal, Savitha Gupta & Sukhwinder singh 2016, ‘Speckle reduction method for thyroid ultrasound images in neutrosophic domain’, IET Image Processing, vol. 10, no. 2, pp. 167-175.
 12. Diego Gragnaniello, Giovanni Poggi, Giuseppe Scarpa & Luisa Verdoliva 2016, ‘SAR Image Despeckling by Soft Classification’, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 9, no. 6, pp. 2118-2130.
 13. Dinesh Kumar Gupta, Satish Pawar & Yogendra Kumar Jain 2015, ‘Wavelet based Multilevel Sub-Band Adaptive Thresholding for Image Denoising using Modified PSO Algorithm’, International Advanced Research Journal in Science, Engineering and Technology vol. 2, no. 12, pp. 24-30.
 14. Donoho, DL & Johnstone, IM 1995, ‘Adapting to unknown smoothness via wavelet shrinkage’ Journal American Statistical. Association, vol. 90, no. 432, pp. 1200-1224.
 15. Fabrizio Russo 2010, ‘New Method for Performance Evaluation of Grayscale Image Denoising Filters’, IEEE Signal Processing Letters, vol. 17, no. 5, pp. 417-420.
 16. Faten Ben Arfia, Mohamed Ben Messaoud & Mohamed ABID 2009, ‘Nonlinear adaptive filters based on Particle Swarm Optimization’, Leonardo Journal of Sciences, no. 14, pp. 244-251
 17. M.S.Safari,A.Aghagolzadeh,” FIRfilterbasedFuzzy-GeneticMixednoiseremoval”,IEEE2007
 18. Tuan-Anh Nguyen, Won-Seon Song, Min-Cheol Hong,” Spatially Adaptive Denoising algorithm for a single image corrupted byGaussian noise”, IEEE Transaction on Consumer Electronics, Vol. 56, No. 3, Aug 2010, pp 1610-1615
 19. Yiwen Qin, Zongliang Gan, Yaqiong Fan, Xiuchang Zhu, “An Adaptive Image Denoising method for Mixure Gaussian Noise”,2011,IEEE
 20. J. Immerkaer, “Fast Noise Variance Estimation”, Computer Vision and Image Understanding-Academic Press, Vol 64, No 2, Sep1996, pp 300-302
 21. Rashmi Agarwal,”BitPlaneAverage Filtering to remove Gaussian noise from High Contrast Image”, InternationalConference on Computer Communication and Informatics (ICCCI-2012), Jan 10-12,2012, IEEE
 22. Vishal Garg, Nisha Raheja,” Image Denoising using Curvelet Transform Using Log Gabor Filter”, IJAR CET, Vol. 1, Issue 4, June2012, pp 671-679
 23. KunHe,Xin-ChengLuan,Chun-HuaLi,RanLiu,”GaussianNoiseRemovalofImageontheLocalFeature”,IEEEComputerSociety, 2nd International Symposium on Intelligent Information Technology Application, 2008, IEEE, pp 867-871
 24. Tuan-Anh Nguyen,Myoung-JinKimandMin-Cheol Hong,” Fast and Efficient GaussianImageRestoration Algorithm bySpatiallyAdaptive Filtering”, 28th Picture Coding Symposium(PCS 2010), Dec 8-10, 2010, IEEE, pp 122-125
 25. Schneier. M and Abdel-Mottaleb. M ,”Exploiting the JPEG Compression Scheme for Image Retrieval”, IEEE Transaction PatternAnalysis and Machine Intelligence”, Vol 18, No. 8, 1996, pp 849-853
 26. Rafael C. Gonzalez, Richard E. Woods, “Digital Image Processing – 3rd Edition”, Pearson Education, Inc, publishing as PrenticeHall , 2008.