INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Check for updates

OPEN ACCESS

Received: 29-07-2022

Accepted: 10-10-2022

Published: 17-11-2022

Citation: Nitin , Gupta SB (2022) A Hybrid Image Denoising Method Based on Discrete Wavelet Transformation with Pre-Gaussian Filtering. Indian Journal of Science and Technology 15(43): 2317-2324. https://doi.org/10.17485/IJST/v15i43.1570

* **Corresponding author**.

nitin.cse.rs@igu.ac.in

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

A Hybrid Image Denoising Method Based on Discrete Wavelet Transformation with Pre-Gaussian Filtering

Nitin[1]*, Satinder Bal Gupta[2]

1 Research Scholar, Department of Computer Science and Engineering, Indira Gandhi University, Meerpur, Rewari, Haryana, India
2 Professor, Department of Computer Science and Engineering, Indira Gandhi University, Meerpur, Rewari, Haryana, India

Abstract

Background/Objectives: At the time of acquisition and transmission noise is embedded with the images. It introduces new but unwanted information (noise) in images. The elimination of noise to analyze such data is an essential step in preprocessing. The purpose of this study is to propose a novel image denoising approach to recover original images at high noise densities without introducing unwanted artifacts. **Methods:** A new hybrid method based on approximation subband thresholding with pre-Gaussian filtering is presented in this study. Google Colab as a platform and python as a programming language is used for the implementation of the proposed technique. To evaluate the performance Peak Signal to Noise Ratio (PSNR) is chosen. The standard jpeg images (Cameraman, Lena, Astronaut, Cat) have been taken as an input and random noise with different noise ratios (σ =0.05,0.20,0.30,0.50) is applied to get the noisy images for the experiment. In random noise scenarios, the proposed method experimented on different grayscale standard images, and performance is compared with different existing methods. **Findings:** The standard images with different noise ratios are denoised by the proposed method, and the quality of images is calculated in terms of PSNR. The results obtained from the proposed method on different standard images improve PSNR (PSNR= 25.80dB, σ =0.50) at high noise levels significantly. **Novelty:** Gaussian filter improve the quality of images. However, when wavelet decomposition is blended with filtered image and thresholding is applied on approximation band improved the quality of images. Hence, the proposed method has a wide area of application to improve image quality in the field of character recognition, agriculture, medical science, and remote sensing.

Keywords: Gaussian Filter; Discrete Wavelet Thresholding; Image denoising; Image Processing

1 Introduction

Image analysis for object detection and classification is one of the important areas having a wide range of applications in medical, military, agriculture, and industry. At the time of acquisition and transmission noise is embedded with the images. It introduces new but unwanted information(noise) in images. Therefore, the elimination of noise to analyze such data is an essential step in preprocessing[1]**.** Image denoising has always been an interesting area for researchers and yet there is lots of scope for improvement. Researchers proposed different types of image denoising methods such as Bilateral filtering[2], Gaussian filtering(GF), Discrete Wavelet Transformation (DWT)' and the Total variation(TV)[3] method in recent years.

Denoising techniques are generally divided into linear filters and non-linear filters. Linear filters such as Gaussian or match filters are used by the researcher for noise suppression[4,5]. But these filters have some limitations, such as it destroying lines, blurring the sharp edges, and becoming the reason for over-smoothing. To overcome the limitations of these filters[6] presented an improved Gaussian filter to enhance the quality and reduce noise in images. In this L2 norm of two corresponding pixels is calculated for similarity measurement. This method improved the denoising performance in the case of flat areas but fewer edges are prone due to over-smoothening. In this regard, non-linear filtering such as thresholding techniques becomes a favorable method. It transforms the noise-contaminated images into the transform domain and applies thresholding on the wavelet coefficient. Finally, the inverse of the wavelet transform is performed for image reconstruction. To improve the limitations of linear filters, an improved SVD filter in the transformation domain is proposed[7]. The proposed method gives effective results but the computational complexity is relatively large than other methods. However, to obtain the advantages of linear or non-linear filters to contain useful information Shreyamsha kumar[1] introduced a hybrid method named GBFMT based on noise thresholding and Gaussian filtering. The proposed method used the Bayes thresholding for noise estimation and shows better results at a lower noise ratio. But, at a higher noise ratio, it produces unwanted artifacts. Priya[8] proposed a hybrid technique based on a Weiner filter and NeighSure shrink noise thresholding to improve the quality of images. This method produces better results than GBFMT but suffered from the same problem.

To consider the shortcoming mentioned above, the authors proposed a hybrid method for image reconstruction in which Gaussian filtering and Wavelet thresholding on approximation sub-band is used that exploits the potential advantages of both linear and non-linear denoising algorithms at the same time. It gives better results than the existing methods in case of a high noise ratio.

In sections 2 & 3 introduction and mathematical intuition behind the Gaussian and Discrete wavelet thresholding are discussed. Section 4 includes a methodology that outlined the proposed work. Section 5 deals with the results and discussion. Section 6 includes the conclusion of this study.

2 Gaussian Filter

In image denoising, the elimination of noisy signals without loss of important features like spatial details and edges is the main target. In this, linear filters get the combination of neighborhood values with help of a constant matrix. Gaussian filter mainly gives smoothening effects of an image. In many cases, it acts like a mean filter. However, the smoothening ratio depends upon the standard deviation of the Gaussian function[9]. Further, in the case of narrow signal frequency, the spatial filter attenuates the frequency bands that help in increasing smoothing. Gaussian filters are linear filters and are easy to implement. In this, pixel values are emaciated by distance from the origin. Gaussian filter for the 2D is given in equation (1):

$$G_\sigma(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{(i^2+j^2)}{2\sigma^2}} \tag{1}$$

Here i and j represent the horizontal and vertical axis with distance from the center. σ(Sigma) represents the distribution of standard deviation.

Gaussian filter with this method produces concentric circular curves with regular distribution and smoothes the pixels by averaging the neighborhood.

3 Discrete Wavelet Transformation method

In a wavelet, a wave is a short fluctuation. It shows a non-redundant representation of the image that provides superior spectral and spatial localization of signal formation as compared to the other methods such as Laplacian and Gaussian[10]**.** It decomposes the signal into different independent spatial oriented channels. The data in the decomposition is related to the LL (low-low) sub-band also called the approximation area. The other sub-bands such as HL (high low) indicate the horizontal features, LH indicates vertical features and HH indicates diagonal features of images[11]. The wavelet analyzes the bands and gets accurate information from the high and low frequencies. Wavelet decomposition follows the hierarchy rule where frequency tire is used for the sub-component shown in Figure 1.

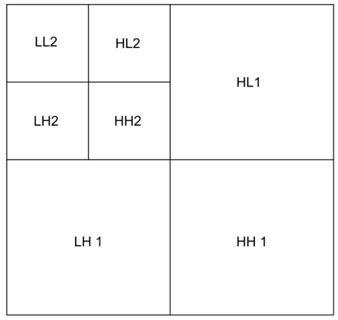

Fig 1. Two levels of signal decomposition

The label LH1, HH1, and HL1 show the first level hierarchy, whereas LL2, HL2, LH2, and HH2 shows the hierarchy at level 2. It follows two levels of decomposition to extract the minimal information from the images. It provides the facility of energy compactness where large coefficients of energy quantizing into a small portion of wavelet coefficients.

Definition of discrete wavelet transformation (DWT)**:** It discretizes the scaling factor and translation variable. Equation (2) shows the mathematical expression of DWT.

$$WT_t\,(i,j) \leq f\,(t)\,,\ \psi_{i,j}(t) \geq \int_R f\,(t)\widehat{\psi}_{i,j}(t)dt \tag{2}$$

Here f(t) is a square-integral function, ψ (t) is a wavelet basis function, and i is related to the scaling factor (a ε 2^i), j is the translation variable.

Minimizing noisy factors with the help of wavelet transformation is related to the function approximation. It is a method that helps to map the image into wavelet space for signal restoration. After the decomposition of the image, the energy is generally associated with the high frequency and the low frequency. The wavelet coefficients have a smaller value than the threshold value is considered to be 0. The larger value of the coefficient can be retained or changed according to the thresholding functions discussed in equations (3) and (4). Finally, the components of the signal can be reconstructed back into the input signal.

3.1 Thresholding

To minimize the level of noise in the original signal, an appropriate value of the threshold is required to be selected. The idea behind it is that in the wavelet representation, magnitude of the signal increasingly dominates the noise magnitudes and sets the value of the coefficients '0' if the magnitude is less than the threshold value. In this regard, soft and hard thresholding are two common thresholding schemes. Soft thresholding is set to be zero if the coefficient is smaller than T followed by subtracting T from the coefficient value larger than T shown in equation (3).

$$(Soft)w'_{i,j} = \begin{cases} sgn(w_{i,j})\,(\,(w_{i,j}| - T\,), & |w_{i,j}| \geq T \\ 0, & (w_{i,j}| < T \end{cases} \tag{3}$$

In hard thresholding, if the coefficient of the noisy signal is less than the predetermined threshold then it set it zero otherwise coefficient is unchanged shown in equation (4).

$$(Hard)w'_{i,j} = \begin{cases} w_{i,j}, & |w_{i,j}| \geq T \\ 0, & (w_{i,j}| < T \end{cases} \tag{4}$$

But to select the best-suited value of the threshold is a challenging task. Because, if the value of the threshold is much smaller it passes noisy components or if the value of the threshold is much higher it leads to loss of actual components in the signal. To select a suitable threshold value, there are some thresholding selection techniques used by the denoising models. These techniques have their own merits and demerits. In this regard, Donoho & Johnstone[11] initially proposed a method to select a universal threshold called VisuShrink. The selection of the threshold value depends on the signal size and noise power. It follows the idea of global thresholding where the scheme uses a universal value of threshold applied on each wavelet coefficient $T = \sigma\sqrt{2logm}$, where, σ is noise variance, and m is the total number of pixels. It uses a distinct value of thresholds at each level of the wavelet decomposition. It helps to select a threshold value that is efficient for data as well as minimizes risk[12].

4 Methodology

In this paper, the authors develop a hybrid image denoising technique based on 2 steps of the filtering mechanism. Here random noise with different noise ratios is added to the 4 standard images(Cameraman, Lena, Astronaut, cat) for performance evaluation. The images are collected from the internet. The first step of preprocessing, determines the Gaussian filter to denoise the noisy images. It gives smoothening effects. In the next step, DWT is used to obtain the decomposed image. In this, the approximation band coefficients that contained full information about the images are subjected to the second level of decomposition and used thresholding for further refinement. It helps to preserve edges in the image without introducing new artifacts.

The block diagram of the framework is shown in Figure 2 and the mathematical representation of the proposed framework is given by

$$\mathrm{I} = \mathrm{A} + \mathrm{N} \tag{5}$$

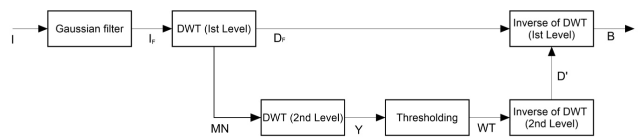

Fig 2. Proposed framework for image denoising (GFAT)

Where A is the real image, and N is the noisy factor that forms image I. I_F is the output generated by the Gaussian filter for input I. It is a convenient method that optimally deals with the flat part of images but textures and edges are blurred. It minimizes the noisy effect but it has also removed details of the image by pixel averaging. So, to estimate the details of the image, wavelet decomposition is performed. Hence, equation (6) is represented as

$$\mathrm{IF} = \mathrm{MN} + \mathrm{DF} \tag{6}$$

Now the I_F is decomposed into two parts D_F and MN. Here D_F holds HH, HL, LH bands and MN holds approximation band (LL). Now the problem is to denoise the approximation part of images with a minimal level of features. The decomposition of the approximation part in the wavelet domain can be represented by equation(7).

$$\mathrm{Y} = \mathrm{MN} + \mathrm{W} \tag{7}$$

Where W is the wavelet coefficient (approximation part), and MN is the noisy approximation(LL). Y is the subbands of the approximation part. Y used the VisuShrink thresholding scheme with hard thresholding to minimize loss so that it can retain a better approximation (LL) image; WT represented the approximation coefficient after thresholding.

After the thresholding, reconstruction of approximated images is performed. Now the concatenation of D' and DF is performed to get a final detailed image B, Hence, equation (8) is represented as

$$\mathrm{B} = \mathrm{D}' + \mathrm{DF} \tag{8}$$

Where B follows the Inverse of DWT with D' and D_F, Here D_F holds HL, HH, and LH subbands filtered by the Gaussian filter, and D' holds LL (approximation) band that follows wavelet denoising as well as pre-Gaussian filtering.

5 Results and Discussion

This experiment is carried out on different grayscale images (Lena, Cameramen, Cat, and Astronaut) of sizes 512 x 512 and 256 x 256 shown in Figure 3 using python. To evaluate the denoising algorithm some artificial methods are used by the authors that introduced heavy noise in images. The authors used skimage python library and randomnoise function for noise addition in original images. After that, the noisy image is denoised through the Gaussian filter and follows the level 1 decomposition. In the wavelet domain, the LL image is treated with thresholding to achieve good denoising results. The proposed algorithm is compared with Gaussian denoising, DWT with soft thresholding, and GBFMT[(1)] for different noise densities (σ =0.05, 0.20, 0.30, 0.50). A comparison in terms of PSNR[(13)] of the proposed algorithm with different existing methods is shown in Table 1. The proposed algorithm shows significantly better results as compared to the existing algorithms.

Fig 3. Original Image: (a) Cameraman, (b) Lena, (c) Astronaut, (d) cat

5.1 Accuracy measurement

To perform the quantitative analysis of proposed and included algorithms PSNR is used by the authors as an evaluation metric defined in equation (8).

$$PSNR = 10log_{10}\left(\frac{M^2}{mean\{(I(i,j) - B(i,j))^2\}}\right) \tag{8}$$

Where, I(i,j) indicates the image with noise, and B(i,j) indicates the denoised image, M is the maximum value of the pixel in the image. With a large value of PSNR (towards 1) considered the performance of a method is good and on the other hand value near 0 for MSE considered a method is good. For filtering, the wavelet method used 'haar' waves for decomposition. The value of PSNR is directly dependent on the noise variances.

PSNR of the recovered image using the proposed algorithm compared with Gaussian filter, DWT with soft Thresholding, and GBFMT. The performance of algorithms shows that the method approximation thresholding incorporated with pre-Gaussian filtering has better performance as compared to DWT (soft thresholding), GBFMT, and Gaussian filter.

Table 1. PSNR of Different Image Denoising Methods

Image Label	Noise Level	Noisy Image (dB)		Denoising Image							
				GF		DWT (soft thresholding)		GBFMT		Our method (GFAT)	
		512 x 512	256 x 256	512 x 512	256 x 256	512 x 512	256 x 256	512 x 512	256 x 256	512 x 512	256 x 256
Cameraman	0.05	14.47	14.47	22.41	20.41	21.47	20.17	22.56	20.91	22.38	20.31
	0.20	9.87	9.87	17.99	17.19	16.75	15.92	17.54	16.31	18.02	17.15
	0.30	8.82	8.81	16.55	15.99	15.41	14.81	16.08	15.16	16.61	15.96
	0.50	7.74	7.77	15.09	1459	14.07	13.61	14.66	1394	15.14	14.60
Lena	0.05	13.76	13.76	25.69	23.98	22.91	21.94	24.81	22.84	25.80	23.98
	0.20	9.59	9.55	20.95	20.18	19.23	18.24	20.15	18.75	21.17	20.28
	0.30	8.71	8.70	19.49	18.95	18.20	17.37	18.78	17.62	19.73	19.06
	0.50	7.86	7.84	17.95	17.47	17.07	16.39	17.30	16.38	18.16	17.61
Astronaut	0.05	14.20	14.20	22.32	20.67	19.95	19.06	22.00	20.42	22.10	20.34
	0.20	9.76	09.72	18.09	17.45	15.94	15.31	17.53	16.65	18.02	17.29
	0.30	8.73	08.73	16.77	16.24	14.81	14.26	16.25	15.50	16.73	16.12
	0.50	7.76	07.75	15.30	14.98	13.64	13.31	14.85	14.27	15.28	14.89

Continued on next page

Table 1 continued

Cat	0.05	13.40	13.42	25.56	24.02	23.67	21.99	25.97	23.92	25.51	23.75
	0.20	9.38	9.38	22.24	21.42	20.85	19.73	21.66	20.35	22.55	21.50
	0.30	8.65	8.65	21.28	20.79	20.22	19.18	20.66	19.42	21.62	20.95
	0.50	7.92	7.92	20.14	19.55	19.50	18.45	19.42	18.06	20.51	19.75

According to the observed results, the images denoised by proposed method gives the highest PSNR for image Cameraman (noise ratio= 0.20, 0.30, 0.50), Lena (noise ratio= 0.05,0.20,0.30, 0.50) and Cat(noise ratio= 0.20,0.30, 0.50). Similarly, Gaussian filtering gives the highest PSNR value for Astronaut (noise ratio= 0.05, 0.20, 0.30, 0.50), and Cat (noise ratio=0.05) image. Whereas, GBFMT has the highest PSNR value for the Cameraman at a noise ratio of 0.05.

Image with different noise variances and their zoomed portion is illustrated in Figures 4, 5, 6 and 7. In this, f), g), h), i), and j) are the zoomed portion of images a), b), c), d), and e) respectively. The results of image reconstruction in term of PSNR(dB) is listed in Table 1.

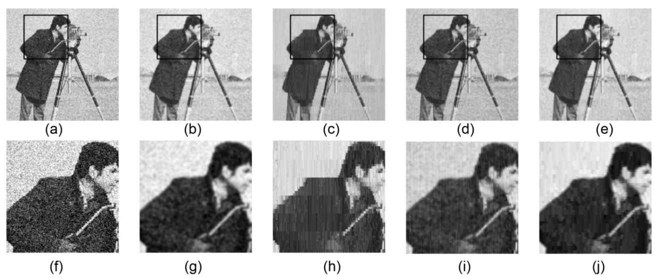

Fig 4. The Visual comparison on the 512x512 camera man image with a noise ratio of 0.05. a) Noisy image (14.47dB), b) Gaussian filtering (22.41dB), c) DWT with soft Thresholding (21.47dB), d) GBFMT (22.56dB) e) Our method (22.38dB);

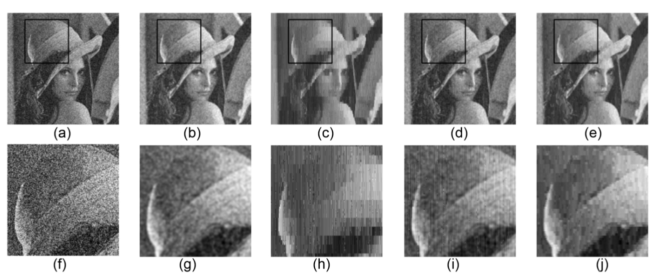

Fig 5. The Visual comparison of the 512x512 Lena image with a noise ratio of 0.05. a) Noisy image (13.76dB), b) Gaussian filtering (25.69dB), c) DWT with soft Thresholding (22.91dB), d) GF with noise thresholding (24.81), e) Our method (25.80dB);

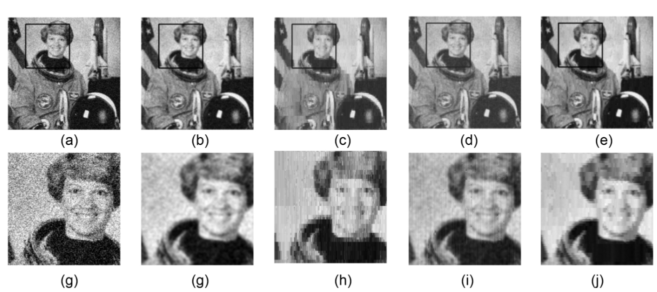

Fig 6. The Visual comparison of the 512x512 Astronaut image with a noise ratio of 0.05. a) Noisy image (14.20dB), b) Gaussian filtering (22.32dB), c) DWT with soft Thresholding (19.95dB), d) GF with noise thresholding (22.00dB), Our method (22.10dB);

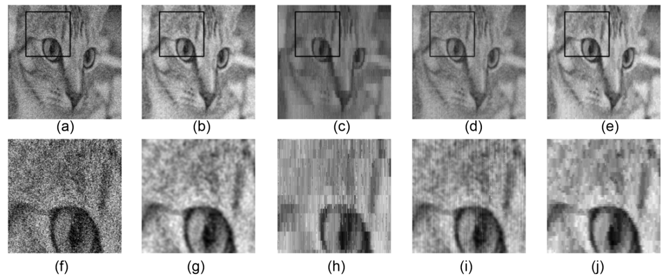

Fig 7. The Visual comparison of the Cat image with a noise ratio of 0.10. a) Noisy image (09.38), b) Gaussian filtering (22.24dB), c) DWT with soft Thresholding (20.85dB), d) GF with noise thresholding (21.66), e) Our method (22.55 dB);

As shown in Figures 4, 5, 6 and 7, proposed method gave satisfactory results as compared to other algorithms. The image provided by the Gaussian filter is highly blurred, especially from the edges. The result given by the DWT BayesShrink with soft thresholding generated new artifacts and affected textural region in case of the high occurrence of noise. The method proposed by the authors preserve the texture region and edges. The denoising method DWT with soft thresholding and GBFMT introduced some new artifacts. These artifacts are the extra information introduced by the denoiser during the reconstruction which can be illustrated by the zoomed portion of images (Figures 4, 5, 6 and 7). In comparison Table 1, for cat image with noise (σ =0.10) shows GF, DWT with soft thresholding, GBFMT methods achieve lesser PSNR values (22.24dB, 20.85dB, 21.66dB) as compared to the PSNR (22.55dB) of proposed work. For Lena image with noise (σ =0.05) shows GF, DWT with soft thresholding, GBFMT methods achieve lesser PSNR values (25.69dB, 22.91dB, 24.81dB) as compared to the PSNR (25.80dB) of proposed work. Table 1 shows that when the occurrence of noise is high (σ =0.50) the GF, DWT with soft thresholding, and GBFMT methods achieve less PSNR as compared to the proposed work. The proposed method helps to overcome this drawback. In this regard, the visual comparison also indicates that image details, texture, and other regions without introducing new artifacts in the image are well maintained by the proposed algorithm of this study.

After the experiment, the above results show that the proposed method reduces unwanted artifacts as well as improves the quality of the image. Table 1 shows that the average PSNR of the proposed method is better than the other denoising filters and gives a better visual perception. In addition, the proposed algorithm also reveals that it is more suitable in case of high noise variance.

6 Conclusion

This study proposed an effective and novel image denoising method to reconstruct the high noisy images. It is the hybridization of the Gaussian filter and DWT method to minimize the noise on digital images. Furthermore, the proposed method has good details as well as the edge-preserving capability and reflects a good similarity ratio between the denoised and the original image. The result shows that the proposed algorithm gave superior quantitative results as compared with the existing methods in case of high noise. But the PSNR value reduces at the low noise level (σ < 0.05). For the future scope, the proposed method will be used with genetic algorithms for parameter optimization.

References

1) Shreyamsha K. Image denoising based on gaussian/bilateral filter and its method noise thresholding. *Signal Image and Video Processing*. 2013;7:1159–1172. Available from: https://doi.org/10.1007/s11760-012-0372-7.
2) Robin G, Jérémie L, Nicolas M, Arthur M. Bilateral K-Means for Superpixel Computation (the SLIC Method). *Image Processing On Line*. 2022;12:72–91. Available from: https://doi.org/10.5201/ipol.2022.373.
3) Daneshmand PG, Mehridehnavi A, Rabbani H. Reconstruction of Optical Coherence Tomography Images Using Mixed Low Rank Approximation and Second Order Tensor Based Total Variation Method. *IEEE Transactions on Medical Imaging*. 2021;40(3):865–878. Available from: https://doi.org/10.1109/TMI.2020.3040270.
4) Ahamed B, Yuvaraj D, Priya S. Image Denoising With Linear and Non linear Filters. *International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*. 2019. Available from: https://doi.org/10.1109/iccike47802.2019.9004.
5) Mishro PK, Agrawal S, Panda R, Abraham A. A Survey on State-of-the-Art Denoising Techniques for Brain Magnetic Resonance Images. *IEEE Reviews in Biomedical Engineering*. 2022;15:184–199. Available from: https://doi.org/10.1109/RBME.2021.3055556.
6) Wei H, Zheng W. Image Denoising Based on Improved Gaussian Mixture Model. *Scientific Programming*. 2021;2021:1–8. Available from: https://doi.org/10.1155/2021/7982645.
7) Wang R, Cai W, Wang Z. A New Method of Denoising Crop Image Based on Improved SVD in Wavelet Domain. *Security and Communication Networks*. 2021;2021:1–11. Available from: https://doi.org/10.1155/2021/9995813.

8) Priya BS, Jagadale BN, Naragund MN, Hegde V, Panchaxri. An Efficient Image Denoising Based on Weiner Filter and Neigh Sure Shrink. *International Journal of Innovative Technology and Exploring Engineering*. 2019;9(2):76–80. Available from: https://doi.org/10.35940/ijitee.a4905.129219.
9) Peng YTT, Huang SWW. Image Impulse Noise Removal Using Cascaded Filtering Based on Overlapped Adaptive Gaussian Smoothing and Convolutional Refinement Networks. *IEEE Open Journal of the Computer Society*. 2021;2:382–392. Available from: https:/doi.org/10.1109/OJCS.2021.3117738.
10) Liu J, Huang J, Luo Y, Cao L, Yang S, Wei D, et al. An Optimized Image Watermarking Method Based on HD and SVD in DWT Domain. *IEEE Access*. 2019;7:80849–80860. Available from: https://doi.org/10.1109/ACCESS.2019.2915596.
11) Yijun Y, Yiguang L, Mingqiang Y, Huimin Z, Yanmei C, Jinchang R. Generic wavelet-based image decomposition and reconstruction framework for multi-modal data analysis in smart camera applications. *IET Computer Vision*. 2020;14(7):471–479. Available from: https://doi.org/10.1049/iet-cvi.2019.0780.
12) Badawy SM, Zidan HE, Mohamed AENA, Hefnawy AA, Gadallah MT, El-Banby GM. A Wavelet - Fuzzy Combination Based Approach for Efficient Cancer Characterization in Breast Ultrasound Images. In: 2021 International Conference on Electronic Engineering (ICEEM). IEEE. 2021;p. 2021–2024. Available from: https://doi.org/1109/ICEEM52022.2021.9480631.
13) Yepeng L, Xuemei L, Qiang G, Caiming Z. Adaptive iterative global image denoising method based on SVD. *IET Image Processing*. 2020;14(13):3028–3038. Available from: https://doi.org/10.1049/iet-ipr.2020.0082.