

Implementation Of Spatial-Scale Domain Based De-Noising Techniques using Different Thresholding



Dawar Husain, Upendra kumar, Monauwer Alam

Abstract: This paper aims in presenting a thorough comparison of performance and usefulness of multi-resolution based de-noising technique. Multi-resolution based image de-noising techniques overcome the limitation of Fourier, spatial, as well as, purely frequency based techniques, as it provides the information of 2-Dimensional (2-D) signal at different levels and scales, which is desirable for image de-noising. The multi-resolution based de-noising techniques, namely, Contourlet Transform (CT), Non Sub-sampled Contourlet Transform (NSCT), Stationary Wavelet Transform (SWT) and Discrete Wavelet Transform (DWT), have been selected for the de-noising of camera images. Further, the performance of different de-noising techniques have been compared in terms of different noise variances, thresholding techniques and by using well defined metrics, such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE). Analysis of result shows that shift-invariant NSCT technique outperforms the CT, SWT and DWT based de-noising techniques in terms of qualitative and quantitative objective evaluation.

Keywords: Image De-noising, multi-resolution Domain Filtering, Non Sub-sampled Contourlet Transform

I. INTRODUCTION

Development in the field of computer and technology have given many exposure to the human which supports easy searching and develop any digital content on the internet. Over the years, the importance of digital images have been recognised and are used in many applications, such as, GIS, astronomy, computer tomography, etc. Images captured by image sensors are usually contaminated by noise. There are various factors accountable for degrading the quality of images such as, imperfect instruments, problems associated with the process of data acquisition, and interfering natural phenomena. Thus, de-noising is to be carried out first, before the digital images can be further utilized and analyzed. The process of de-noising can be accomplished by using efficient de-noising techniques to compensate for such data corruption [1-2].

Analysis of non-stationary image contaminated with time-varying noise, is a difficult task, as their characteristics change with time.

Further, non-stationary image cannot be studied efficiently by only spatial and frequency domain representations.

Therefore, in order to overcome this weakness, the spatial-scale domain combined with multi-resolution concept has been demonstrated to be a prevailing means for detection and analyzing of spatial-scale properties of non-stationary images in a more descriptive manner. Multi-resolution based image de-noising techniques, such as DWT, SWT, CT and NSCT, overcome the shortcomings of the spatial, Fourier and frequency domain based techniques. However, it is found that DWT and SWT suffers from poor directionality, while, CT, from lack of shift invariance. Thus, to resolve the limitation of DWT, SWT and CT, NSCT has been introduced [10-13]. NSCT is the multi-direction and shift-invariant technique which is advantageous in image processing applications, such as, image de-nosing, edge detection, etc. In the literature, wide range of literature published on image de-noising methods for the de-nosing of images, however, there is no such literature published, which provides a comparative study of different multi-resolution techniques in terms of different noise models, noise variances, subjective and objective performances.

Thus, the comparison of performance of multi-resolution techniques in terms of different noise models, variances, subjective and objective performances, is the central theme of this study.

II. IMAGE DE-NOISING TECHNIQUES

Before discussing the image de-noising techniques, first of all, it would be appropriate to discuss in general different types of noises, such as, Salt & Pepper, Poisson, Speckle and Gaussian noise. Salt & pepper Noise also known as intensity spikes. It is generated due to errors in transmission of data and mutilation of pixel elements in the camera sensors, error occurs during digitization process, as well as, due to error in memory locations, while Gaussian noise arises due to detectors or amplifiers and is uniformly distributed over the image. Here, in this study, Salt and Pepper, Gaussian and Speckle noises have been selected for testing, analysis and implementation purpose. Multi-resolution based image de-nosing techniques, such as, NSCT, CT, SWT and DWT, have been selected and implemented.

Revised Manuscript Received on January 30, 2020.

* Correspondence Author

Dawar Husain*, Department of Electronics, A.I.M.T Lucknow, India.

Upendra kumar, Department of Electronics A.I.M.T Lucknow, India.

Monauwer Alam, Department of Electrical Engg. Integral University, Lucknow, India.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>

The brief description of DWT, SWT, CT and NSCT based de-noising techniques are discussed below:

2.1 Image De-nosing by Discrete Wavelet Transform (DWT)

In the DWT algorithm, the decomposition of image has been carried out using analysis filter bank, followed by decimation operation.

The former consist of Low Pass (LP) and High Pass (HP) filter at each stage of decomposition. when a non stationary image process through these filters, it divides the image into two bands i.e., LP and HP bands [5-9].

The LP filter performs an averaging operation to extract the average information of the image, whereas, the HP filter performs an differencing operation to extract the lines, points and edges information of the non stationary image. Thereafter, the output of filtering operation is decimated by 2. A 2-D transformation is achieved by performing two individual 1-D transforms.

First, the image is filtered along the row and decimated by 2. It is then followed by filtering the sub-image along the column and decimated by 2 [8-9].

This operation splits the image into four bands namely *LL, LH, HL and HH* respectively. The de-noising procedure followed by DWT technique has been explained in the section 2.4.

2.2 Image De-noising by Stationary Wavelet Transform (SWT)

In order to resolve the problem of shift-variance associated with DWT, SWT based de-noising technique has been introduced [7-11]. It is also known as 'à trous' algorithm. In the SWT algorithm, the filter is up-sampled by inserting zeros between the filter coefficients and eliminating the down-sampling step.

Further, it uses a 2-D filter bank obtained from the scaling function, which in turn produces two images, of which one is an approximation image, whereas, the other is a detailed image called the wavelet plane.

A wavelet plane contains the horizontal, vertical and diagonal detail between 2^j and 2^{j-1} resolution and is calculated as the difference between two successive approximations I_{j-1} and I_j levels.

All the approximation images obtained through this decomposition, have equal number of rows and columns as the original image.

This is due to the fact that the filters at each stage are up-sampled by inserting zeros between the coefficients, which in turn make the size of the image equal [8-10]. The procedure for the de-noising of images by SWT has been explained in the section 2.4.

2.3 Image De-nosing by Contourlet Transform (CT)

To overcome the shortcomings of wavelets and curvelets [10], proposed a newly method of image representations named contourlets, which is a "true" two dimensional transform that can capture the intrinsic geometrical structures information of images, as well as, provides flexible number of directions [12]. The Contourlet Transform (CT) is a real 2-D transform, which is based on the concept of non-

separable filter banks and provides an efficient directional multi-resolution image representation. The foremost two steps by means of which enactment of the CT is carried out: first, the Laplacian Pyramid (LP) is used to seize the point incoherence and then followed by a Directional Filter Bank (DFB) to join point discontinuities into linear structures.

The procedure for the de-noising of images by CT has been explained in the section 2.4.

2.4 Image De-nosing by Non Sub-sampled Contourlet Transform (NSCT)

In order to reduce the frequency aliasing of contourlets, to achieve the property of shift-invariance, as well as, enhance directional selectivity, [11] proposed a method known as, Non Sub-sampled Contourlet Transform (NSCT). This is based on the Non Sub-sampled Pyramid Filter Banks (NSPFB) and the Non Sub-sampled Directional Filter Banks (NSDFB) structure.

The former provides multi-scale decomposition using two channel non sub-sampled 2-D filter banks, while the later provides directional decomposition, which is used to split Band Pass (BP) sub-bands in each scale into different directions.

Since, NSCT is shift-invariant technique, which in turn results in better frequency selectivity and regularity than CT.

The NSCT structure classify 2-D frequency domain into wedge-shaped directional sub-band as shown in Fig. 1.

The general methodology adopted for the de-noising of images using DWT, SWT, CT and NSCT based de-noising techniques can be summarized as follows (Fig: 2):

- i) Decompose the noisy image into a contourlet and wavelet domain.
- ii) Apply a specific thresholding rule to the coefficients in contourlet and wavelet domain
- iii) Reconstruct the de-noised data using inverse Wavelet and Contourlet Transform from the threshold coefficients.

III. EVALUATIONS CRITERIAS

In order to evaluate the quality of the de-noised image other than simple qualitative assessment of the images.

Metrics such as, RMSE and PSNR have been used for the assessment of generated de-noised images [13-14]. The mathematical representation of these measures have been discussed below:

i) RMSE

RMSE is one of the most usable and effective metric for the estimation of quality of image when reference image is present. RMSE is a good measure of accuracy [14].

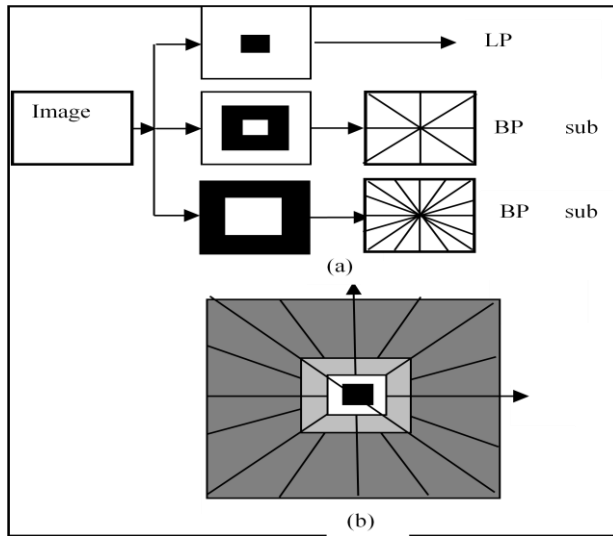


Fig. 1. Two level NSCT decomposition (a) NSFB structure that implements the NSCT (b) the corresponding frequency partition

ii) PSNR

PSNR is one of the most popular metric used to measure the distortion of the de-noised image compared with the reference image. Large value of PSNR indicates lesser amount of image distortion, the value of PSNR should be large for better output [14].

$$PSNR = 10 \log \left(\frac{255}{RMSE} \right)^2 \quad \dots (2)$$

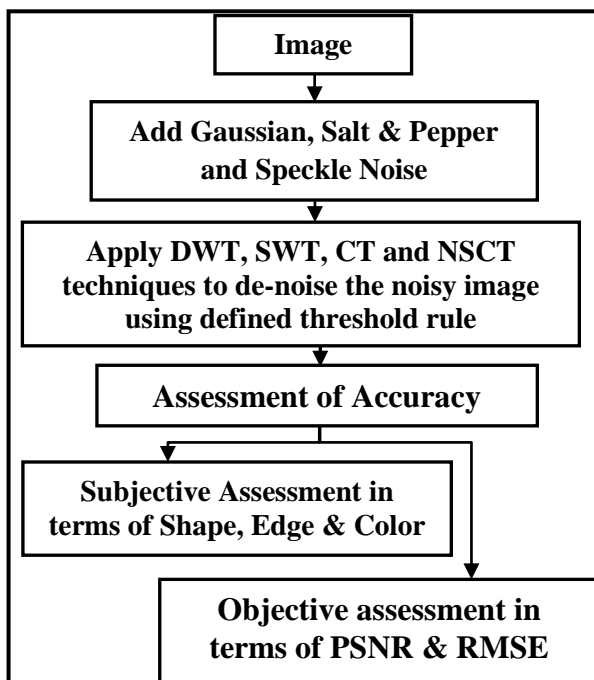


Fig 2: Methodology adopted for image de-noising by DWT, SWT, CT and NSCT techniques

$$RMSE = \sqrt{\sum_{i=1}^M \sum_{j=1}^N \frac{(F(i,j) - R_o(i,j))^2}{m \times n}} \quad \dots (1)$$

where, m, n indicate the size of the image is $m \times n$. $F(i, j)$ and $R_o(i, j)$ indicate the de-noised and reference image. Smaller the value of RMSE, lesser is the difference between the images.

IV. EVALUATIONS OFS RESULTSS ANDS DISCUSSIONS

The analysis of results of various image de-noising techniques belonging to multi-resolution techniques, has been carried out using camera images. In order to analyze the performance and capability of the de-noising techniques used in this study, it is necessary to perform the assessment of accuracy and review the results. Further, a thorough analysis of the performance of the image de-noising techniques have been carried out for dataset, both visually and quantitatively.

4.1 Visual (Qualitative) Analysis

The visual comparison of the de-noised images is carried out for the subjective assessment, since, it is a simple, yet one of the effective method for assessing advantages and disadvantages of any de-noising technique. Here, in this study for the simulation purpose, image of size 512×512 has been taken. The de-noised images are visually evaluated in terms of different parameters as listed below

- i) Colour Radiometry (CR),
- ii) Shape of the object (SO)
- iii) Edge Sharpening (ES)

Further, these parameters have been used for the purpose of visual assessment. For visualization purposes, de-noising techniques have been categorized from "Excellent" to "Poor", as shown in Table 1.

Table 1 Assessment of quality of image by qualitative method

Grade	Absolute Measure	Relative Measure
1	Excellent (E)	The best in group
2	Good (G)	Lower than the excellent level
3	Above Average (AA)	Better than the average in group
4	Average (A)	Average level in group
5	Below Average (BA)	Lower than the average level
6	Poor (P)	The lowest in the group

a) Analysis of Image Contaminated with Gaussian Noise for different thresholding techniques

It is observed that the spatial information of all the de-noised images has improved when compared to the noisy image indicating that the small features that were not noticeable in the noisy image are now be distinguishable and identifiable. Fig. 4 shows the de-noised images generated by different de-nosing techniques for dataset DS contaminated with Gaussian, noise, for different noise variances.

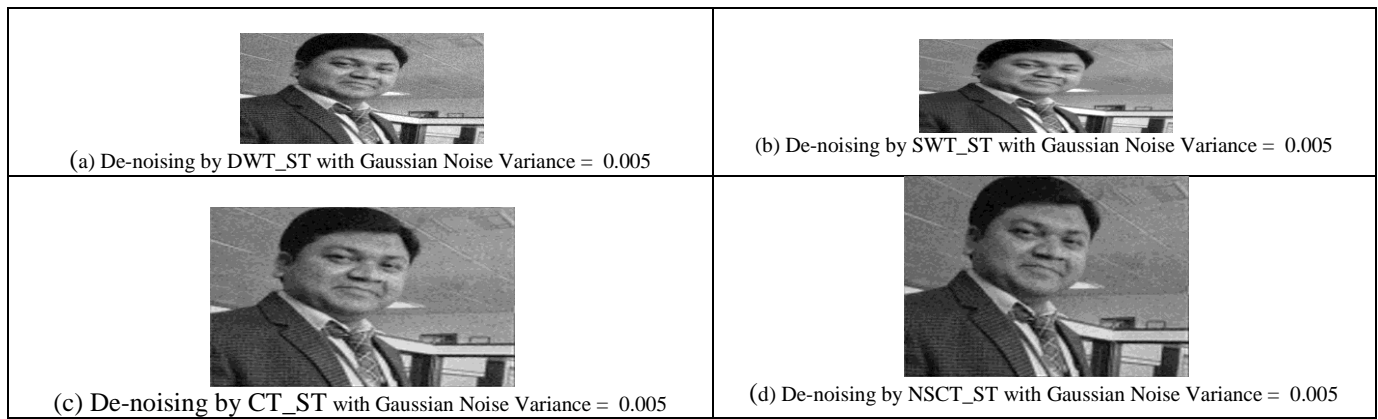


Fig. 3 De-noised images generated by different de-nosing techniques using soft thresholding technique for DS dataset contaminated with Gaussian noise.

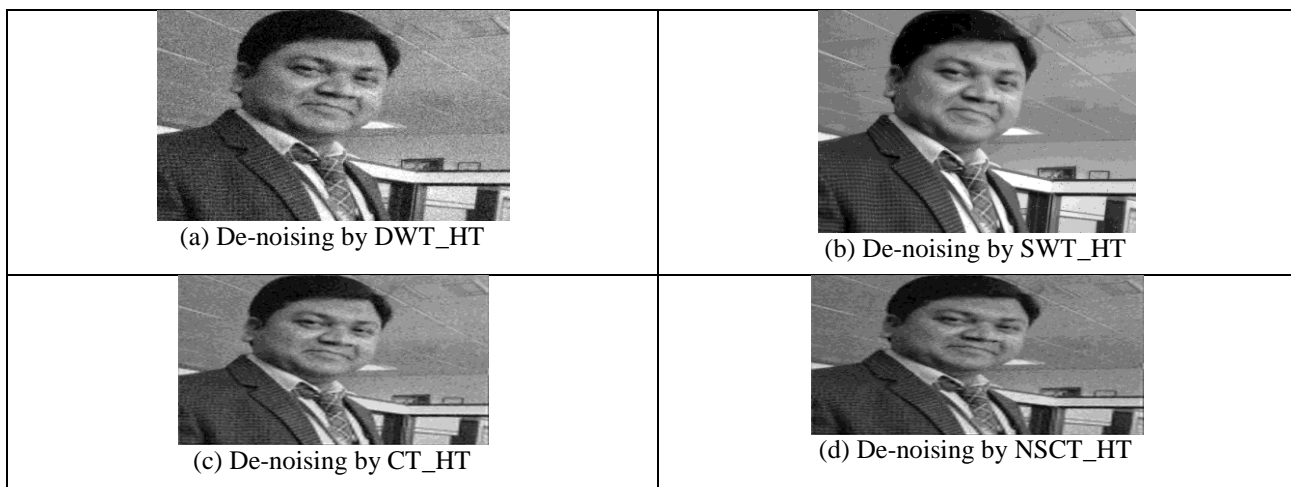


Fig. 4 De-noised images generated by different de-nosing techniques using hard thresholding technique for DS dataset contaminated with Gaussian noise.

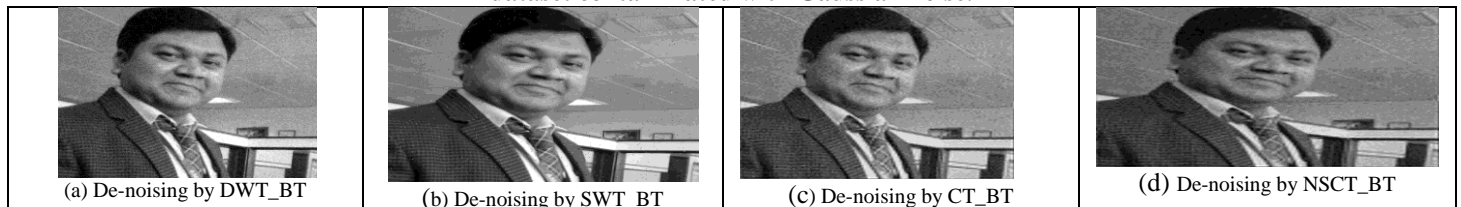


Fig. 5 De-noised images generated by different de-nosing techniques using baye's thresholding technique for DS dataset contaminated with Gaussian noise.

Note: Soft Thresholding: ST, Hard Thresholding: HT, Baye's Thresholding: BT

Table 2 Comparison of de-noising techniques on the basis of visual object detection

D a t a s e t	Type of Noise	Thresholding Technique	Noise Variance	De-noising Technique											
				DWT			SWT			CT			NSCT		
				CR	SO	ES	CR	SO	ES	CR	SO	ES	CR	SO	ES
D S	GAUSSIAN NOISE	Soft (ST)	0.005	A	A	A	A	A	A	A	AA	A	G	AA	AA
			0.050	A	A	A	A	A	AA	AA	A	AA	AA	AA	AA
			0.500	BA	BA	BA	A	A	BA	A	A	A	AA	AA	A
		Hard (HT)	0.005	A	A	A	AA	A	A	AA	A	AA	G	G	AA
			0.050	A	A	A	A	A	AA	AA	A	A	AA	AA	AA
			0.500	BA	BA	BA	A	A	BA	A	A	A	AA	AA	A
		Baye's (BT)	0.005	A	A	A	AA	A	A	AA	A	AA	G	G	AA
			0.050	A	A	A	A	A	AA	AA	A	A	AA	AA	AA
			0.500	A	A	BA	A	A	A	BA	A	A	A	AA	AA

Table 2 shows that NSCT based de-noising technique yields the highest performance for the image corrupted with gaussian noise for different variances, when compared to CT, SWT and DWT based de-noising techniques. In other words, the background of the de-noised images with NSCT appears smoother and removes the noise pretty well in the smooth regions, as well as, along the edges. Thus, visually, it can be inferred that NSCT de-noising technique for different noise variances works well and yields the better performance in terms of preservation of spectral, spatial and structural similarity information. This is followed by CT, SWT and DWT based de-noising techniques using different thresholding. However, the de-noised image generated by DWT_BT, DWT_ST and DWT_HT based de-noising techniques (Fig. 3, 4 & 5 (a,b & c)) yields lower spatial quality. This is due to the sub-sampling process involved in DWT technique, leading to the introduction of artifacts such as, existence of square blocks, making the linear features zigzag in the image, when images are zoomed in to see very small objects. Another factor affecting the performance of DWT based de-noising technique in terms of spatial quality is due to the

limited directional selectivity *i.e.* horizontal, vertical and diagonal directions possess by the technique, which in turn deteriorate the geometry of the features in the fused images. Further, the intensity of colour in the de-noised images generated by NSCT is slightly lighter, when compared to the original image, followed by CT, SWT and DWT based de-noising techniques.

Furthermore, the de-noised image generated by baye's thresholding (BT) technique yields better spatial, spectral and structural similarity quality, when compared to Soft and Hard thresholding techniques. This may be due to the efficient thresholding process involved in the estimation of gaussian noise affected coefficients effectively from the original image.

(b) Analysis of Image contaminated with Salt & Pepper Noise for different noise variances using different thresholding techniques

Fig. 4 shows the de-noised images generated by different de-noising techniques for dataset (DS) contaminated with Salt & Pepper noise, for different noise variances.

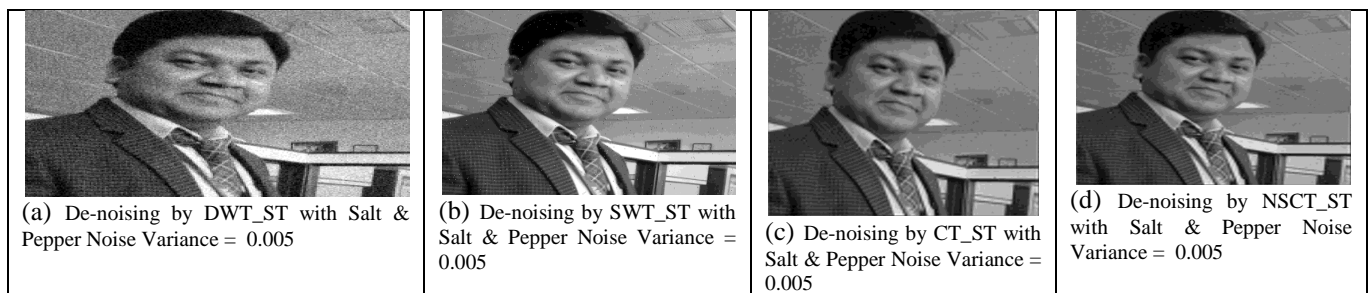


Fig. 3 De-noised images generated by different de-noising techniques using soft thresholding technique for DS dataset contaminated with Salt & Pepper noise.



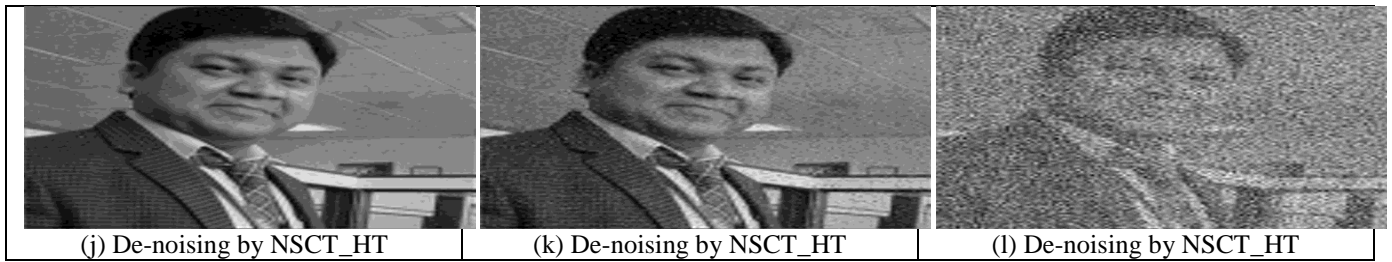


Fig. 3 De-noised images generated by different de-nosing techniques using hard thresholding technique for DS dataset contaminated with Salt & Pepper noise.



Fig. 3 De-noised images generated by different de-nosing techniques using baye's thresholding technique for DS dataset contaminated with Salt & Pepper noise.

With reference to Fig. 4, it is observed that the de-noised images generated by NSCT (Fig. 4(j), (k) & (l)), and CT (Fig. 4(g), (h) & (i)), techniques exhibit good geometric details, when compared to the original image. However, the intensity of colour in the de-noised images generated by NSCT technique are slightly lighter, when compared to the reference image, followed by CT, SWT (Fig. 4(d), (e) & (f)), and DWT (Fig. 4(a), (b) & (c)), based de-noising techniques. However, the de-noised image generated by CT, SWT and DWT technique yields lower spatial quality. Amongst the de-noising techniques, DWT yields lowest performance in terms of subjective measure. This may be due to the limited directional selectivity *i.e.* horizontal, vertical

and diagonal directions possess by the technique, which in turn deteriorate the geometry of the features in the de-noised images.

With reference to Fig. 5, it is observed that the de-noised images generated by NSCT (Fig. 5(j), (k) & (l)), and CT (Fig. 5(g), (h) & (i)), techniques exhibit good geometric details, when compared to the original image. However, the intensity of colour in the de-noised images generated by NSCT technique are slightly lighter, when compared to the original image, followed by CT,

SWT (Fig. 5(d), (e) & (f)) and DWT (Fig. 5(a), (b) & (c)) based de-noising technique. However, the de-noised image generated by DWT technique yields lower spatial quality. This may be due to the limited directional selectivity *i.e.* horizontal, vertical

and diagonal directions possess by the technique, which in turn deteriorate the geometry of the features in the de-noised images. The comparison results of different de-nosing techniques on the basis of visual object detection are listed in Table 2.

Table 2 Comparison of de-noising techniques on the basis of visual object detection

Dat aset	Type of Noise	Threshol ding Tech nique	Noise Variance	De-noising Technique											
				DWT			SWT			CT			NSCT		
				CR	SO	ES	CR	SO	ES	CR	SO	ES	CR	SO	ES
DS	SALT & PEPPER NOISE	Soft	0.005	A	A	A	A	A	A	A	AA	A	G	AA	AA
			0.050	A	A	A	A	A	AA	AA	A	AA	AA	AA	AA
			0.500	BA	BA	BA	A	A	BA	A	A	A	AA	AA	A
		Hard	0.005	A	A	A	AA	A	A	AA	A	AA	G	G	AA
			0.050	A	A	A	A	A	AA	AA	A	A	AA	AA	AA
			0.500	BA	BA	BA	A	A	BA	A	A	A	AA	AA	A
		Baye's	0.005	A	A	A	AA	A	A	AA	A	AA	G	G	AA
			0.050	A	A	A	A	A	AA	AA	A	A	AA	AA	AA
			0.500	A	A	A	A	A	A	A	A	A	AA	AA	AA

Table 2 shows that NSCT based de-nosing technique yields the highest performance for different types of noises for different variances, when compared to CT, SWT and DWT based de-nosing techniques. In other words, the background of the de-noised images with NSCT appears smoother and removes the noise pretty well in the smooth regions, as well as, along the edges. Thus, visually, it can be inferred that NSCT de-nosing technique for different noise variances works well and yields the better performance in terms of preservation of spectral, spatial and structural similarity information. This is followed by CT, SWT and DWT based de-nosing techniques.

4.2 Quantitative Analysis

The investigation and analysis of results obtained from different de-noising techniques have been carried out using quantitative indicators, as mentioned in the Table 3. It is observed that all types of noises causes degradation in the image quality which in turn results in loss of information. The de-noising of degraded image is performed using NSCT, CT, SWT and DWT techniques. The de-noised image which will best preserve the spectral, spatial and structural similarity information of the original image is the one that has satisfied the following conditions (Table 3).

Table 3 The ideal and error value of different quantitative indicators

S.	Metric	Ideal	Error
1	Root Mean Square Error	0	> 0
2	Peak Signal-to-Noise	NA	> 1

Based on these parameters, the performance and accuracy of the de-noising techniques will be carried out.

Table 4 Comparison of RMSE for DS dataset corrupted with Gaussian, Salt & Pepper and Speckle noise for different noise variances

Dataset	Type of Noise	Different Thresholding	Noise Variance	RMSE Metric			
				De-noising Technique			
				DWT	SWT	CT	NSCT
DS	GAUSSIAN NOISE	Soft	0.005	6.46	6.15	5.11	4.21
			0.050	6.51	6.35	5.65	4.48
			0.500	8.02	7.35	6.67	5.34
		Hard	0.005	6.49	6.17	5.49	5.17
			0.050	7.67	7.42	6.57	6.05
			0.500	9.07	8.37	7.21	6.37
		Baye's	0.005	5.92	5.39	5.86	5.02
			0.050	5.82	5.77	5.24	5.12
			0.500	6.37	6.32	5.48	5.76
	SALT & PEPPER NOISE	Soft	0.005	5.45	5.15	4.11	3.21
			0.050	5.51	5.35	4.65	3.48
			0.500	7.02	6.35	5.67	4.34

		Hard	0.005	5.49	5.17	4.49	4.17
			0.050	6.67	6.42	5.57	5.05
			0.500	8.07	7.37	6.21	5.37
		Baye's	0.005	4.92	4.39	4.86	4.02
			0.050	4.82	4.77	4.24	4.12
			0.500	5.77	5.32	4.48	4.76

4.2.1 Analysis based on RMSE

Generally, smaller RMSE value represents a greater accuracy measure in terms of image fidelity. The results of RMSE generated by different image de-noising techniques for different datasets are tabulated in Table 4. Table 4 shows the comparison of RMSE for dataset (DS) for various noise variances.

a) Analysis of DS dataset

Analysis of result shows that the Gaussian and Salt & Pepper noise affected images are effectively de-

noised with NSCT based de-nosing technique, as indicated by low RMSE value, when compared to CT, SWT and DWT based de-nosing techniques. Amongst de-nosing techniques, DWT based de-nosing technique exhibits low performance in terms of RMSE metric. This is due to the sub-sampling process involved in DWT technique, leading to the introduction of artifacts such as, existence of square blocks, making the linear features zigzag in the image.

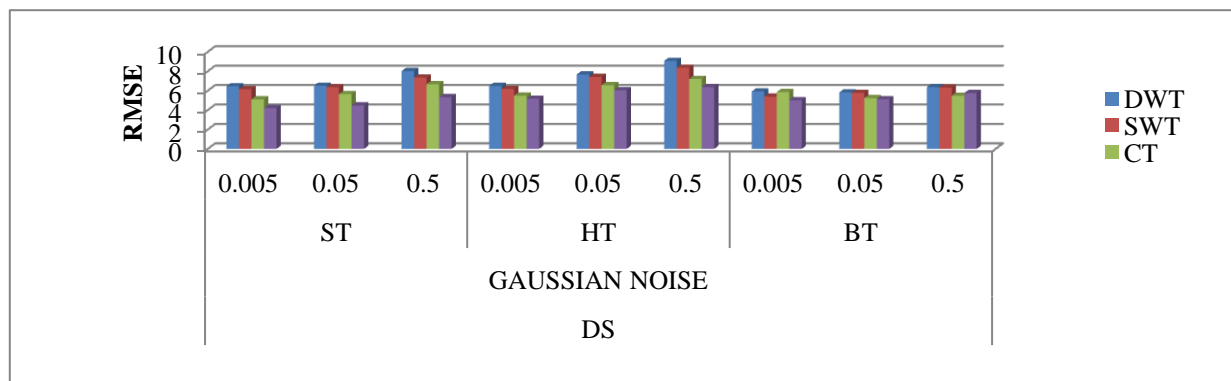
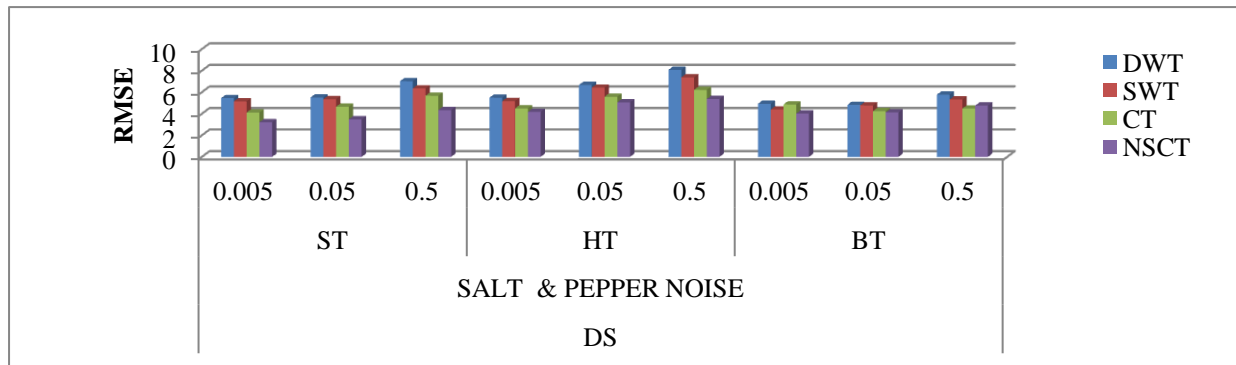


Fig. 6 RMSE values corresponding to different de-noising techniques for Gaussian Noise, Salt & Pepper and Speckle Noise for different noise variances using DS.



Thus, it can be concluded that NSCT based de-noising technique yields the highest performance in terms of preservation of edge information, when compared to CT, SWT and DWT de-nosing techniques. In other words, NSCT technique is suitable for de-nosing of images contaminated with Gaussian and Salt & Pepper noise, when compared to other based de-nosing techniques. The RMSE

values corresponding to different de-noising techniques has been plotted for DS, as shown in Fig. 6.

4.2.2 Analysis based on PSNR

Generally, higher values of PSNR reflect less amount of image distortion. The analysis of PSNR values for different de-nosing techniques are tabulated in Table 5.

Table 5 Comparison of PSNR for DS dataset contaminated with Gaussian, Salt & Pepper Noise for different noise variances

Dataset	Type of Noise	Different Thresholding	Noise Variance	PSNR Metric			
				De-noising Technique			
				DWT	SWT	CT	NSCT
DS	GAUSSIAN NOISE	Soft	0.005	29.5431	30.5581	31.5620	32.2317
			0.050	27.1879	28.1428	28.9857	29.1648
			0.500	24.8780	25.8017	26.2782	26.5471
		Hard	0.005	28.5421	29.5872	30.3186	30.9640
			0.050	24.1859	25.1218	25.9857	27.1573
			0.500	23.8690	24.8277	25.2789	26.5422
		Baye's	0.005	31.5453	31.9966	33.6286	34.2670
			0.050	29.1879	30.1058	30.9257	31.1543
			0.500	25.0750	26.8123	27.1289	28.1570
	SALT & PEPPER NOISE	Soft	0.005	30.5453	31.5586	32.5282	33.2677
			0.050	28.1879	29.1558	29.9857	30.1728
			0.500	25.8690	27.8279	28.2789	28.5365
		Hard	0.005	29.5453	30.5961	31.5286	31.9757
			0.050	25.1879	26.1572	27.9857	29.1589
			0.500	24.8690	25.8252	26.2789	27.5421
		Baye's	0.005	32.5453	33.5863	34.5286	35.2672
			0.050	30.1879	31.1558	32.1257	33.1558
			0.500	25.8690	27.8258	28.2789	29.9570

a) Analysis of DS dataset

With reference to Table 5, a high value for PSNR is observed for NSCT based de-noising technique. In other words, NSCT technique produces good quality de-noised image with high PSNR values in comparison to CT, SWT and DWT based de-noising techniques. Amongst the de-nosing techniques,

the de-noised image generated by DWT technique yields low values of PSNR. This may be due to the sub-sampling process associated with the DWT technique, leading to the introduction of artifacts in the resulting de-noised image. The different de-nosing techniques outputs corresponding to PSNR values are shown for image in Fig 7.

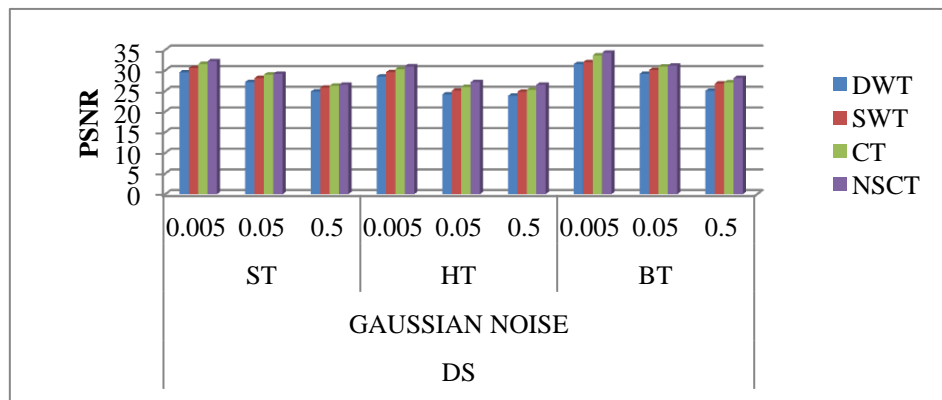


Fig. 7 PSNR values corresponding to different de-noising techniques for, Gaussian, Salt & Pepper and Speckle Noise for different noise variances using DS.

A visual interpretation of PSNR values (Fig. 7) suggests that NSCT based de-nosing technique using yields the highest performance in terms of preservation of spectral, spatial and structural similarity information, when compared to CT, SWT and DWT based de-nosing techniques. Thus, it can be ascertained that NSCT technique is best in

preserving the structural similarity, spatial and spectral information, when compared to other based de-nosing techniques. In other words, NSCT based de-nosing technique emerged as one of the most effective de-nosing technique, followed by CT, SWT and DWT based de-nosing techniques.

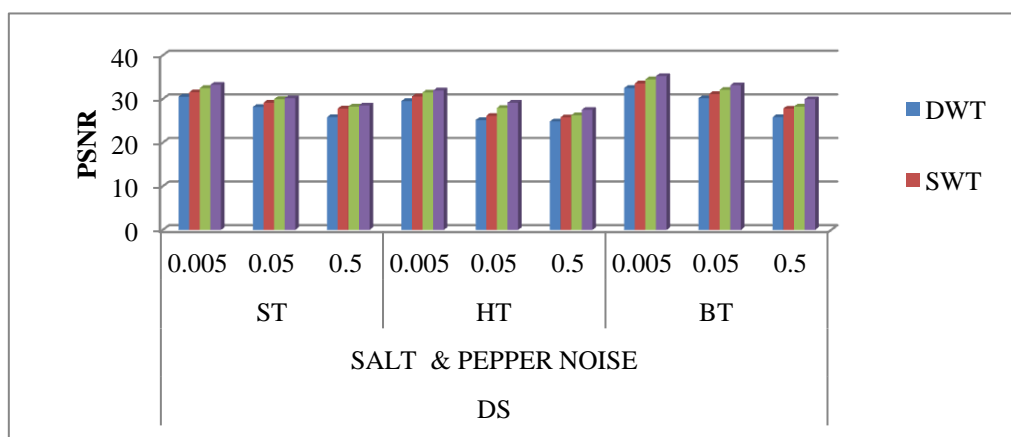


Fig. 7 PSNR values corresponding to different de-noising techniques for, Gaussian, Salt & Pepper and Speckle Noise for different noise variances using DS

V. CONCLUSION

In this study, a comparison of performance of multi-resolution based de-noising techniques, has been carried out in terms of different noise models, noise variances, quantitative and qualitative measures. The image is contaminated with Gaussian, Salt & pepper and speckle noises for varying noise variances. Analysis of result shows that de-noising of image by NSCT technique, yields the best result in terms of objective and subjective measures. Further, NSCT technique exhibits good performance in terms of PSNR and RMSE. This may be due to the reason that NSCT technique possess the property of shift-invariant and multi-directionality, which in turn avoids the introduction of artifacts in the resulting image. Thus, it can be concluded from this study that analysis and de-nosing of 2D signals can be analyzed effectively by using shift-invariant NSCT technique, when compared to CT, SWT and DWT techniques. The outcome of this study could therefore be utilized for further image processing tasks.

ACKNOWLEDGMENTS:

The authors are grateful to Dean, R&D, Section, Integral University, Lucknow, for quick and crisp revision of manuscript and for allotting manuscript number (IU/R&D/2019-MCN-000596)

REFERENCES

1. S. G. Mallat and W. L. Hwang, 1992. Singularity detection and processing with wavelets," IEEE Trans. Inform. Theory, 38, 617–643.
2. D. L. Donoho, 2000. "De-noising by soft-thresholding", IEEE Trans. Information Theory, 41(3), 613– 627.
3. R. Coifman and D. Donoho, 1995. Translation invariant de-noising," in Lecture Notes in Statistics: Wavelets and Statistics, vol. New York: Springer-Verlag, 125- 150.
4. R. Yang, L. Yin, M. Gabbouj, J. Astola, and Y. Neuvo, 1995. Optimal weighted median filters under structural constraints," IEEE Trans. Signal Processing, 43, 591–604.
5. A.K. Jain, Fundamentals of digital image processing. Prentice-Hall, 1989
6. T. D. Bui and G. Y. Chen, 1998. Translation-invariant De-noising using multi-wavelets", IEEE Transactions on Signal Processing, 46 (12), 3414-3420.
7. J. Lu, J. B. Weaver, D.M. Healy, and Y. Xu, 1992. Noise reduction with multiscale edge representation and perceptual criteria," in Proc.

IEEE-SP Int. Symp. Time- Frequency and Time-Scale Analysis, Victoria, BC, 555–558.

8. P. Moulin and J. Liu, 1999. Analysis of multi-resolution image De-noising schemes using generalized Gaussian and complexity priors", IEEE Information Theory, 45(3), 909-919.
9. Bamberger, R. H., & Smith, M. J. T., 1992. A filter bank for the directional decomposition of images: Theory and design. IEEE Transaction Signal Processing, 40(4), 882–893.
10. Do, M.N. and Vetterli, M., 2005. The contourlet transform: an efficient directional a multi-resolution image representation. IEEE Transactions on Image Processing, 14(12), 2091-2106.
11. Cunha, A.L., Zhou, J. and Do, M.N., 2005. Non sub sampled Contourlet Transform: Filter Design and Applications in De-noising. In IEEE International Conference on Image Processing, 1, pp. 749-752.
12. Cunha, A.L., Zhou, J. and Do, M.N., 2006. The Non Sub- sampled Contourlet Transform: Theory, Design and Applications. IEEE Transactions on Image Processing, 15(10), 3089-3101.
13. Li, S., Li, Z. and Gong, J., 2010. Multi-variate statistical analysis of measures for assessing the quality of image fusion. International Journal of Image and Data Fusion, 1(1), 47–66.
14. Li, S., Yang, B. and Hu, J., 2011. Performance comparison of different multi-resolution transforms for image fusion. Information Fusion, 12(2), 74–84.

AUTHORS PROFILE



Dawar Husain did B-Tech from Uttar Pradesh technical University, India. M Tech (Electronics Circuit) from Integral University, Lucknow. He is pursuing PhD in Image processing Presently he is working as Assistant Professor, in Ambalika Institute of Management and Technology, Lucknow, India. He has 11 years of teaching experience. His area of expertise is signal processing, communication systems, and image processing. He has many valuable publications to his credit.



Monauwer Alam received his B.Sc(Engg) degree in Electronics and Communication from Magadh University Bodh Gaya, India in 2000 and and MTEch (Digital Communication) from UPTU, Lucknow India. His PhD was on Signal processing in 2014 from Integral University Lucknow. Presently he is working as Associate Professor, Integral University, and Lucknow. He has 18 years of experience. He has authored and co-authored over many papers in refereed academic journals and international conference proceedings. His research interest include image compression and image enhancement.