De-noising Infrared Image Using OWA Based Filter

Ruchika, Munish Vashisht, S. Qamar

***Abstract*—**Detection of small ship is crucial task in many automatic surveillance systems which are employed for security of maritime boundaries of a country. To address this problem, image de-noising is technique to identify the target ship in between many other ships in the sea. Image de-noising technique needs to extract the ship's image from sea background for the analysis as the ship's image may submerge in the background and flooding waves. In this paper, a noise filter is presented that is based on fuzzy linguistic 'most' quantifier. Ordered weighted averaging (OWA) function is used to remove salt-pepper noise of ship's image. Results obtained are in line with the results available by other well-known median filters and OWA based approach shows better performance.

***Keywords*—**Linguistic quantifier, impulse noise, OWA filter, median filter.

I. Introduction

INFRARED imaging plays a crucial role in detection of strategically important motion of military troops and arms, due to its strong heat signatures. But, handling security is more complex in case of sea water. In this case, targeted ships might get submerged in the background and flooding waves. Moreover, impulse noise may be introduced into thermal metaphors through getting hold of transmission, and flooding waves. And breaching of huge sea border is easier task for intruders. Attack on hotel Taj in Mumbai, the commercial capital of India on 26, November, 2008 is the result of such type of breaching of maritime boundary. In addition, image de-noising has been an active area in image processing and thermal vision in recent past [1], [2]. Hence, in this paper, OWA based linear objective function is used to remove impulse noise to get de-noised image of ship in a sea environment.

The OWA operator was introduced by Yager [3]. Determination of OWA weights are more extensively presented in the literature. Proper determination of operator weights is governed principally by two criteria, namely, degree of 'OR-ness' and the number of input arguments. The mathematical programs with nonlinear objective functions like maximum entropy [5], [6], the minimal variability (MV) [7], the maximal Renyi entropy [8], the least square method (LSM) [9], and the chi-square method [10] are also reported in literature. The linear objective functions, although relatively few in number, include the minimax (or improved) disparity [11]-[14] and parametric approach [15].

In the task of removing impulse noise, various successful techniques have been reported in recent years. Among them 'Block Matching Three Dimensional filtering technique' shows exceptional performance [16]. Moreover the sparsity-based regularization has achieved great success in various image processing applications such as image de-noising [4], [17]-[19], de-blurring [20], and super resolution [21].

Although local and global intensity are applied to remove noise, very less number of effort have been made by considering manifold structure of images. In [22], removal of noise from image is done by filter diffusing technique; moreover, the author has used neighborhood similarity based information of patches to construct a manifold structure to construct a global diffusion energy function and de-noising the image. However in [23], an efficient noise removal technique is reported, which is based on non-local similarity of pixels.

The sparse coding model deals with Gaussian Noise very well [24]-[26]. However, the impulse noise makes the de-noising problem more complicated. Many existing de-noising techniques [27] usually first detect impulse noise and then remove noise. This two-step procedure of de-noising technique is very sensitive if the level of impulse noise nurtures the computational proficiency and de-noising effect decay. Detection of impulse noise has been done by using sparse coding based methods in [28], [29]. Nonetheless, the weight introduced in [30] depends upon residual of data fidelity on the uncorrupted pixels. These methods have limitations as noise level increases. The 'median filter' yields excellent results for images corrupted by impulse noise or salt pepper noise [31]. Thus, it is necessary to recover the pixel intensity that is robust against impulse noise, as well as preserve the image feature, rather than detecting impulse noise.

To remove impulse noise, 'spatial filtering' is one of the effective tools. Median filters, Ordered Statistics Filters and Adaptive Filters are the leading filters for this problem. Median filter is based on Ordered Statistics. The median filter yields excellent results for images corrupted by impulse noise or salt pepper noise. In this paper, linear objective function is used to remove impulse noise. The results are compared with median filter and better performance is shown by presented method. For the moment, heat sensors enhanced the images of the objects of interest and diminished the background and noise. Hence, in this work infrared image of ship is used as input. Please refer to Fig. 2 (f).

The remainder of this paper is organized as follows. The computations of median filter are introduced in Section II. Section III elaborates the method called OWA based filter. Experimental work and results on removal are reported in Section IV. In Section V, we summarize the paper.

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Fig. 1 Sample Images (a) Leena (b) Zelda (c) Barbara (d) Goldhill (e) Boat (f) Cameraman

Fig. 2 Sample Images (a) Aeroplane (b) Arctic hare (c) Baboon (d) Boy (e) Cat (f) Ship

II. Computation of Median Filter

Median filters are quite popular; they provide certain excellent noise-reduction capabilities. Median filters are particularly effective in presence of impulse noise, also called salt-and-pepper noise. The median of a set of intensity values is such that, half of the values in the set are less than or equal to median and half are greater than or equal to median. The median filtering of an image is a two-step process.

1) Select a point (pixel) in an image and then sort the pixel in question and its neighbors.
2) Determine median and assign this value to that selected point.

In this work, 3X3 neighborhood is taken and arranged in descending order. The median is the 5th element of the stored array. For example, sorted values are 174, 171, 170, 166, 166, 163, 163, 162, 162. Referring Table I, the median of above 3X3 neighbors is 5th element, i.e. 166.

TABLE I
3X3 MASK

166	166	163
174	171	170
163	162	162

Other variations of ordered statistic filters are max and min filter. Max filter finds out the brightest point whereas Min filter is used for finding darkest point in image. Moreover, the proper aggregation of different pixel of image may generate appropriate intensity by selecting robust point. This is shown in next section.

III. Computation of OWA Based Filter

Aggregation operator is the central concept of information aggregation and was originally introduced by Yager [3]. Subsequent part discloses a brief account of OWA operators, detailed discussion about the behavior of operators in OWA is in [11]. The OWA operation involves following three steps shown in Fig. 3.

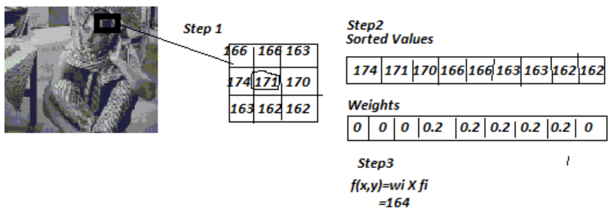

Fig. 3 Summary of OWA Method

a) Reordering of Inputs

The input factors are x_1, x_2, x_3,…x_n, the intensity is denoted by y_1, y_2,y_3……y_m, where y_j is the j^{th} major number and $y_1 \geq y_2 \geq y_3 \geq \ldots \geq y_m$. However, the weights w_j are the ordinal position of y_k.

b) Weight Determination Related with OWA Operators

The degree of "OR-ness" (β) is defined by (1):

$$\beta = \frac{1}{\mathrm{m}-1} \sum_{j=1}^{m} w_j (m-1) \tag{1}$$

Here, β (OR-ness) ranges between [0, 1]. On every occasion the value of $\beta = 1$ generates the weight vector as (1, 0, 0,...0). Hence, the extreme value of x_j attains the whole weight, resulting in an extreme OWA operator as extreme operator when $\beta = 0$, produces the weight vector as (0, 0, 0, .., 1) which enables the lowest value of x_j to attain the entire weight, resulting in lowest OWA operator. When $\beta = 0.5$, weight vector produced is as (1/n, 1/n, 1/n,… 1/n), which means that arithmetic mean of weights is steadily scattered among the inputs.

The membership function of a relative quantifier can be represented by (2):

$$Q(r = \begin{cases} 0 & if \quad r<a \\ (r-a|b-a) & if\ a \le r \le b \\ 1 & if \quad r>b \end{cases} \qquad (2)$$

where a, b, r ∈ [0,1].

In [3], Yager calculates the weights w_j of the OWA aggregation from the function Q describing the quantifier, with m number of criteria.

$$W_j = Q(j|m) - Q(j-1|m) \qquad (3)$$

where j=1,2,...,m and Q(0) = 0.

There are three relative quantifiers “most”, “at least half” and “as many as possible” taking the parameter ‘a’ and ‘b’ as (0.3, 0.8), (0, 0.5) and (0.5, 1) respectively. In this work ‘most’ quantifier is used.

c) Aggregation Process

OWA determines the f-validity in f-objects by aggregating multiplication of ordered input parameter and weight as shown in (4):

$$OWA(x_1, x_2, x_3, \dots\dots. x_m) = \sum w_j y_j \qquad (4)$$
$$for\ j = 1\ to\ m$$

where (x_1, x_2, $x_{3,\dots}x_m$) are input parameters with the criteria of size multiple of m and y_j is the j^{th} largest input parameter.

IV. Experimental Work and Results

In this section, the OWA model is compared with median noise removal method. The visual performance of OWA method is higher or equal to median filter as shown in results, Figs. 6, 7. The noise parameter is set 0.01 for the impulse noise.

To remove noise we have considered each and every pixel’s intensities and have taken 8 neighborhoods for consideration. In Section III, it is shown that OWA based filter has three steps. First step is arranging the inputs image. So we have considered the entire pixel in question and 8 pixels of neighborhoods, and arranged them in descending order.

TABLE II
Values of Intensities in Neighborhoods

162	162	163
174	171	170
163	166	166

Sorted values are (174, 171, 170, 166, 166, 163, 163, 162, 162).

A. Weight Calculation

The fuzzy quantifier used for weight estimation is ‘most’. Since, the number of input parameters is nine, the value of ‘m’ is 9 for the OWA. The estimation of weights is done by (2) and (3) for m = 9. The values of variable ‘a’ and ‘b’ are taken 0.3 and 0.8 respectively. As per our interest, we have considered an array of different size; the values are varying from 0-255. To get improved intensity aggregation process step 3 is applied.

$$g'(x,y) = \sum w_j * g(x,y)_j \qquad (5)$$

B. Estimation of Intensity Values

To counter impulse noise, the determined weight vector is convoluted as a 3X3 mask on all pixel of image. Meanwhile, intensity of all other elements and current pixel $g'(x,y)$ is enhanced and $g(x,y)_j$ is j^{th} biggest value of intensity among other 8 elements of current pixel.

$$g'(x,y) = (0 * 174 + 0 * 171 + 0.066667 * 170 + 0.222 * 166 + 0.222 * 166 + 0.222 * 163 + 0.222 * 163 + 0.04444 * 162 + 0 * 162)$$

$$g'(x,y) = 157.5996$$

After rounding off, the value of intensity is 158.

The same procedure is carried out for each and every pixel. The neighborhoods of boundary pixels are padded with zeros.

C. Results and Discussion

The samples images taken as input are shown in Figs. 1 and 2. First, we have applied impulse or salt and pepper noise. Then, the images are obtained after de-noising with OWA method. The results are also compared with median filter. It is observed that, the results are satisfactory.

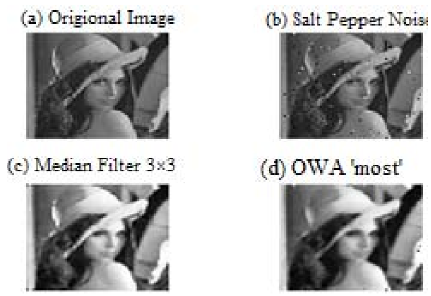

Fig. 4 Comparative Images of Leena

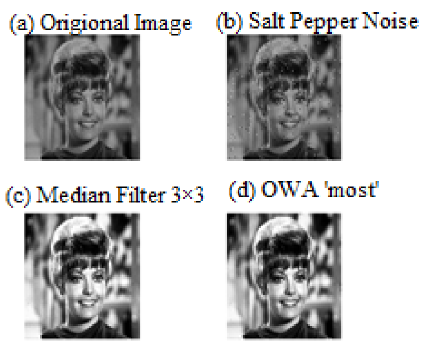

Fig. 5 Comparative Images of Zelda

TABLE III
ESTIMATION OF WEIGHTS

i/m	0/9	1/9	2/9	3/9	4/9	5/9	6/9	7/9	8/9	9/9
Q(i/m)	0	0.1111	0.2222	0.333333	0.4444	0.556	0.67	0.7778	0.8889	1
Q(r)	NA	0	0	0.066667	0.2889	0.511	0.73	0.9556	1	1
weights	NA	0	0	0.066667	0.2222	0.222	0.2222	0.2222	0.04444	0

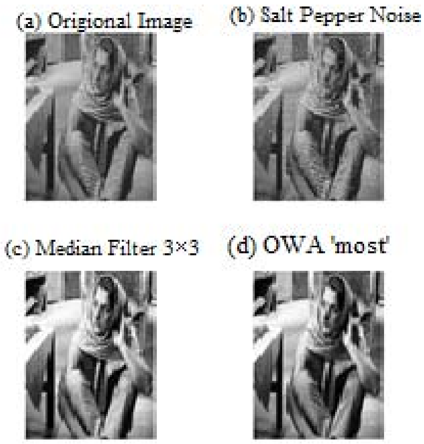

Fig. 6 Comparative Images of Barbara

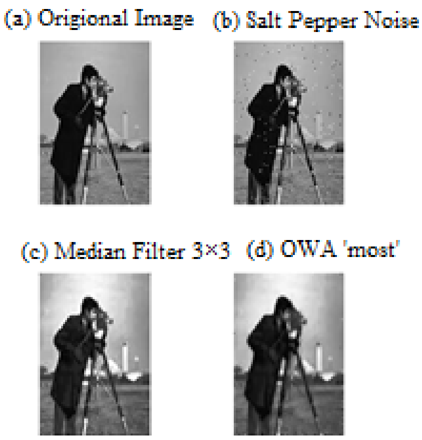

Fig. 7 Comparative Images of Camera Man

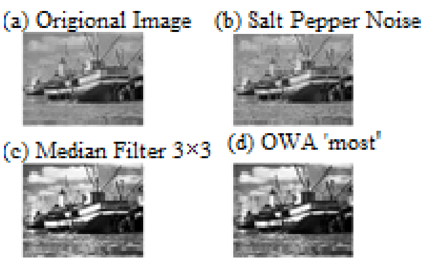

Fig. 8 Comparative Images of Boat

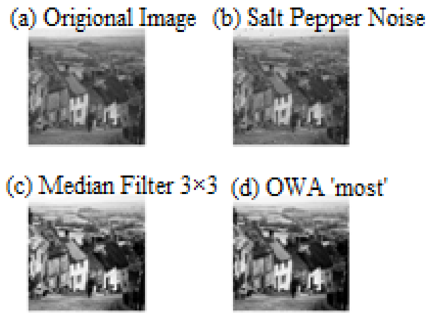

Fig. 9 Comparative Images of Gold hill

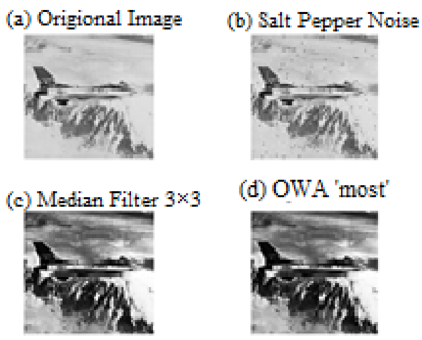

Fig. 10 Comparative Images of Aeroplane

Fig. 11 Comparative Images of Architect

Figs. 4-15 have four parts; (a) is showing original image (b) has salt pepper noise, whereas (c) and (d) show de-noised image after applying median filter and OWA based filter, respectively. After taking a close observation of the images of Fig. 16, it is clear that OWA produces more clear images as compared to traditional median filter.

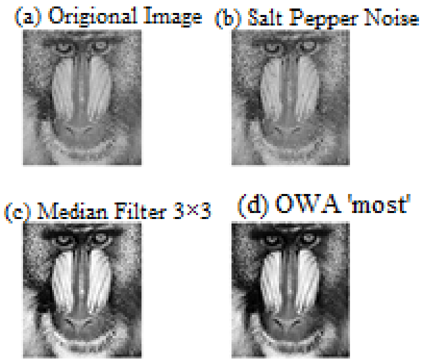

Fig. 12 Comparative Images of Baboon

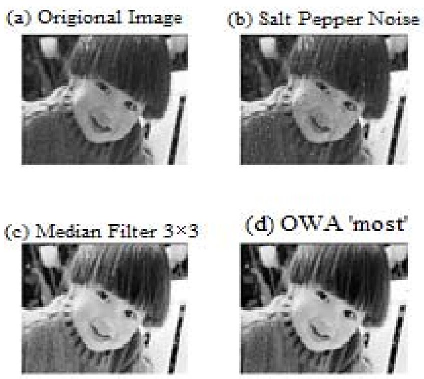

Fig. 13 Comparative Images of Boy

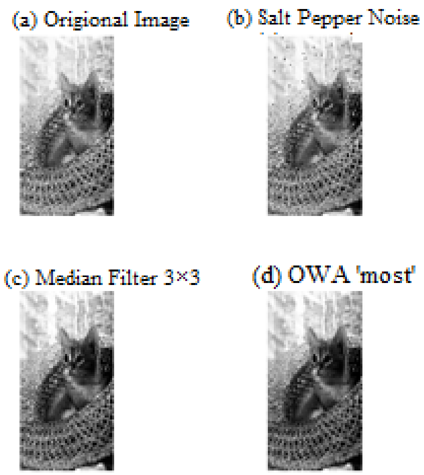

Fig. 14 Comparative Image of cat

V. CONCLUSION AND FUTURE DIRECTIONS

In this work, infrared image of ship in sea is de-noised from Impulse noise. Impulse noise may be introduced into thermal images either due to flood waves in sea water or during acquisition and transmission. A noise filter is introduced, that is based on fuzzy linguistic most quantifier. This naïve filter is compared with well-established median filter. A mask of 3X3 is generated by OWA operator and convoluted with every pixel of OWA images with 8 neighbors. Results generated by method show quite satisfactory performance.

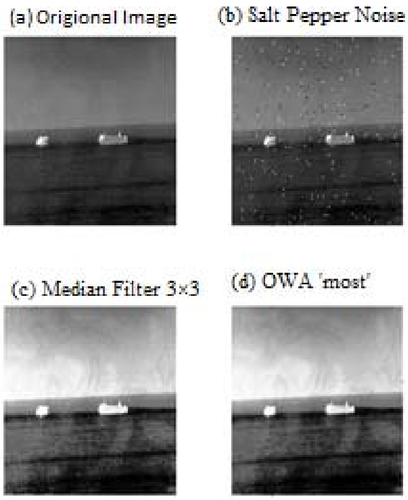

Fig. 15 Comparative Images of Ship

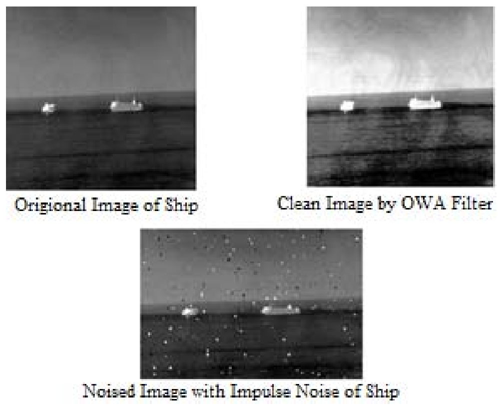

Fig. 16 Clear Images of Ship in Sea Water

In future, more fuzzy quantifiers like ‘as many as possible’, ‘at least half’ can also be used for de-noising the image. The filtered image can be used for tracking of ship or movement of military troops in the water territory by using different segmentation techniques.

REFERENCES

[1] L. Zhang, W. Dong, D. Zhang, and G. Shi, “Two-stage image denoising by principal component analysis with local pixel grouping,” Pattern Recognition., vol. 43, no. 4, pp. 1531-5549, Apr. 2010.

[2] A. Buades, B. Coll, and J.-M. Morel, “A non-local algorithm for image de-noising,” in Proc. Conf. Computer Vision Pattern Recognition., vol. 2. pp. 60-65, 2005.

[3] R. R. Yager, “On ordered weighted averaging aggregation operators in multi criteria decision making,” IEEE Trans. Syst., Man, Cybern., vol. 18,no. 1, pp. 183–190, Jan./Feb. 1988.

[4] M. Elad and M. Aharon, “Image de-noising via sparse and redundant representations over learned dictionaries,” IEEE Transaction Image Processing, vol. 15, no. 12, pp. 3736-3745, Dec. 2006.

[5] D. Filev and R. R. Yager, “Analytic properties of maximum entropy OWA operators,” Information Science, vol. 85, pp. 11–27, 1995.

[6] M. O’Hagan, “Using maximum entropy-ordered weighted averaging to construct a fuzzy neuron,” in Proc. 24th Annu. IEEE Asilomar Conf. Signals Syst. Computer, Pacific Grove, CA, 1990, pp. 618–623.

[7] R. Fuller and P. Majlender, “On obtaining minimal variability OWA operator weights,” Fuzzy Sets Syst., vol. 136, pp. 203–215, 2003.
[8] P. Majlender, “OWA operators with maximal Renyi entropy,” Fuzzy Sets Syst., vol. 155, pp. 340–360, 2005.
[9] Y. M. Wang, Y. Luo, and X. Liu, “Two new models for determining OWA operator weights,” Computer Ind. Eng., vol. 52, pp. 203–209, 2007.
[10] G. R. Amin, “Note on A preemptive goal programming method for aggregating OWA operator weights in group decision making,” Information Science, vol. 177, pp. 3636–3638, 2007.
[11] A. Emrouznejad and G. R. Amin, “Improving minimax disparity model to determine the OWA operator weights,” Information Science, vol. 180, pp. 1477– 1485, 2010.
[12] D. H. Hong, “On proving the extended minimax disparity OWA problem,” Fuzzy Sets Syst., vol. 168, pp. 35–46, 2011.
[13] Y. M. Wang and C. Parkan, “A minimax disparity approach for obtaining OWA operator weights,” Information Science, vol. 175, pp. 20–29, 2005.
[14] G. R. Amin and A. Emrouznejad, “Parametric aggregation in ordered weighted averaging,” Int. J. Approx. Reason., vol. 52, pp. 819–827, 2011.
[15] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, “Image De-noising by Sparse 3D Transform-Domain Collaborative Filtering,” IEEE Transaction Image Processing, vol. 16, no. 8, pp. 2080-2095, Aug. 2007.
[16] J. Mairal, F. Bach, J. Ponce, G. Sapiro, and A. Zisserman, “Non-local sparse models for image restoration,” in Proc. Int. Conf. Computer Vision, pp. 2272-2279, Sept. 29, 2009-Oct. 2, 2009.
[17] W. Dong, L. Zhang, and G. Shi, “Centralized sparse representation for image restoration,” in Proc. Int. Conf. Computer. Vision, pp. 1259-1266, 6-13 Nov. 2011.
[18] W. Dong, L. Zhang, G. Shi, and X. Li, “Nonlocally centralized sparse representation for image restoration,” IEEE Transaction Image Processing, vol. 22, no. 4, pp. 1620-1630, Apr. 2013.
[19] W. Dong, L. Zhang, G. Shi, and X. Wu, “Image deblurring and super resolution by adaptive sparse domain selection and adaptive regularization,” IEEE Transaction Image Processing, vol. 20, no. 7, pp. 1838-1857, Jul. 2011.
[20] J. Yang, J. Wright, T. Huang, and Y. Ma, “Image super-resolution via sparse representation,” IEEE Transaction Image Processing, vol. 19, no. 11, pp. 2861-2873, Nov. 2010.
[21] Z. He, S. Yi, Y. Cheung, X. You, and Y. Tang, “Robust Object Tracking via Key Patch Sparse Representation”, IEEE Transactions on Cybernetics, no.99, pp.1-11, 2016.
[22] Francois G. Meyer and Xilin Shen, “Perturbation of the Eigenvectors of the Graph Laplacian: Application to Image Denoising”, Applied and Computational Harmonic Analysis, vol. 36, no. 2, pp. 326-334, 2014.
[23] H. Talebi and P. Milanfar, “Global Image De-noising”, IEEE Transaction Image Processing, vol. 23, no. 2, pp.755-768, Feb. 2014.
[24] M. Yuan and Y. Lin, “Model selection and estimation in regression with grouped variables,” J. Royal Stat. Soc., Ser. B, Stat. Methodology., vol. 68, no. 1, pp. 49-67, 2006.
[25] W. Zuo, L. Zhang, C. Song, D. Zhang, and H. Gao, “Gradient Histogram Estimation and Preservation for Texture Enhanced Image Denoising,” IEEE Transaction Image Processing, vol. 23, no. 6, pp. 2459-2472, Jun. 2014.
[26] R. Garnett, T. Huegerich, C. Chui, and W. He, “A universal noise removal algorithm with an impulse detector,” IEEE Transaction Image Processing, vol. 14, no. 11, pp. 1747-1754, Nov. 2005.
[27] S. Schulte, M. Nachtegael, V. De Witte, D. Van der Weken, and E. E. Kerre, “A fuzzy impulse noise detection and reduction method,” IEEE Transaction Image Processing, vol. 15, no. 5, pp. 1153-1162, May. 2006.
[28] J. F. Cai, R. Chan, and M. Nikolova, “Two-phase methods for deblurring images corrupted by impulse plus gaussian noise,” Inverse Problem Imaging., vol. 2, no. 2, pp. 187-204, 2008.
[29] J. Jiang, L. Zhang, and J. Yang, “Mixed Noise Removal by Weighted Encoding with Sparse Nonlocal Regularization,” IEEE Transaction Image Processing, vol. 23, no. 6, pp.2651-2662, Jun. 2014.
[30] J. Liu, X. C. Tai, H. Y. Huang, and Z. D. Huan, “A Weighted dictionary learning models for de-noising images corrupted by mixed noise,” IEEE Transaction Image Processing, vol. 22, no. 3, pp. 1108-1120, Mar. 2013.
[31] Rafeal C. Gonzalez, Richard E. Wood, “Digital Image Processing Second Edition”, Prentice Hall Publication.