International Journal of Scientific Engineering and Applied Science (IJSEAS) - Volume-3, Issue-5, May 2017
ISSN: 2395-3470
www.ijseas.com

ENHANCEMENT OF NOISE CORRUPTED IMAGE USING WESNR AND SMQT

Manu Elizabath Raj[1], Sherin Thomas[2]
[1] Royal College Of Engineering & Technology, Thrissur, India
[2] Royal College Of Engineering & Technology, Thrissur, India

Abstract

Image denoising is a challenging task since the noise distribution usually does not have a parametric model. One kind of mixed noise is Additive White Gaussian Noise (AWGN) coupled with impulse noise (IN). Proposing a simple yet effective method, namely Weighted Encoding with Sparse Nonlocal Regularization (WESNR), for mixed noise removal. Output of WESNR is undergone a post processing step, Successive Mean Quantization Transform(SMQT) which reveals the organization or structure of the data and removes properties such as gain and bias of the image, which provides image enhancement. WESNR together with SMQT achieves leading mixed noise removal performance.

Keywords: weighted encoding, sparse, regularization, nonlocal, quantization.

1. Introduction

In many applications, while transmitting the images and acquiring an image from both digital cameras will be affected with few or more amount o the noise from a variety of sources. Further processing of these noisy images can be done only after removal of this random noise, because this type of noise elements will create some serious issues in practical applications such as satellite, biomedical, computer vision , artistic work or marketing and also in many fields. Denoising an image is a primary problem in the applications of image processing. Estimating an original image from the corrupted or sparse image by preserving its edge, texture and structural details is very important. In order to remove the noise from images, prior knowledge about the noise distribution plays a vital role. Mainly, there are two types of noises like impulse noise (IN), additive white Gaussian noise (AWGN). Due to thermal electrons thermal motion in camera sensors and circuits [22], AWGN will be introduced. In general, when there is a very small change in original pixel value that is known as Guassian noise.

IN is often introduced due to improper functioning of camera sensors, hardware impairment memory locations or bit errors in transmission [23].Median filters [1] have been used dominantly to remove IN. Many improvements have been done in median filters to enhance the performance and to preserve the local structures [2-10], which includes weighted median filter (WMF) [3], multistate median filter (MMF) [4] and center weighted median filter (CWMF) [3]. All of them do not recognize that the present pixel is noisy or not and they tend to over smooth the denoised image. Hence, based on this concept several filters have been proposed such as switching median filter

(SMF) [5], adaptive median filter (AMF) [6], tristate median filter (TMF) [7], adaptive CWMF [8], conditional signal AMF [9] and directional WMF [10] etc.

Bilateral filter (BF) [12] is a well-known nonlinear filter, which preserves the information about the edges. An extension for the BF is non local means (NLM) filtering algorithm [15]. BM3D approach has been proposed in [14] by combining the similar non local patches into a 3D cube and applying transform based shrinkage. Then after, LPG-PCA has been proposed in [16]. The work proposed in [13] initiates the dictionary learning from natural images to remove the AWGN and denoise the corrupted image using K-singular value decomposition (K-SVD). In [17], the author has proposed the use of both sparse representation and nonlocal self-similarity (NSS) regularization to remove the AWGN.

For enhancing image output of WESNR is undergoing a post processing step which is SMQT. Producing digital images that render contrast and detail well is a strong requirement in several areas, such as remote sensing, biomedical image analysis and fault detection. Performing these tasks automatically without human intervention is a particularly hard task in image processing.

SMQT uses an approach that performs an automatic structural breakdown of information. This operation can be seen as a progressive focus on the details in an image. However, the mixture of both AWGN and IN increases the difficulties and makes much more complex to denoise the images. Existing methods are detection based methods where noisy pixel detection and then removing it. But, when the AWGN and IN are very strong then this two phase has become less effective in mixed noise removal from the corrupted images. Therefore, here we proposed a simple and effective approach which includes both weighted encoding with sparse nonlocal regularization (WESNR). For enhancing this image Successive Mean Quantization Transform (SMQT) is used thus it will increases the performance.

2. Proposed Frame Work

2.1 Mixed noise model

Let x be an original image and its pixel locations be $x_{m,n}$ where ‘m’ denotes number of rows and n denotes number of columns. Consider noisy observation of x is y and is modeled as

$$y_{m,n} = x_{m,n} + v_{m,n} \qquad (1)$$

where $v_{m,n}$ denotes Additive White Guassian Noise (AWGN) with zero mean and standard deviation σ . Mixed noise considering is

- AWGN + SPIN

Signal observation model can be expressed as

$$\begin{aligned} y_{m,n} &= d_{min} \text{ with probability } s/2. \\ &= d_{max} \text{ with probability } s/2. \\ &= x_{m,n} + v_{m,n} \text{ with probability } 1\text{-}s. \end{aligned}$$

2.2 Denoising model

Considering original image $x \varepsilon R^u$. Let $x_m = R_m \ \varepsilon \ R^u$ be a stretched vector of an image. R_m is the extracting patch R_m is the extracting patch x_m matrix operator at location m. Considering the sparse representation for finding out the over-complete dictionary. Let the dictionary be Φ and can be represented as

$\Phi = [\Phi_1; \Phi_2; \ldots\ldots\ldots \Phi_u] \ \varepsilon \ R^{u,v}$ to sparsely code x_m where $\Phi_j \ \varepsilon \ R^u$ is the jth atom of Φ.

Representation of x_i over the dictionary Φ can be expressed as

$$x = \Phi\alpha \qquad (2)$$

where α = set of all coding vectors α_i.

When denoising an image the main aim is to estimate the desired image $\hat{x}$ from y over the Φ. Then the encoding model can be expressed as

$$\hat{x} = \arg\min_x \|y - x\|^2 + \lambda \,.\, R(x) \qquad (3)$$

By substituting Eq. (2) in Eq.(3) then encoding model becomes

$$\hat{x} = \arg\min_\alpha \|y - \Phi\alpha\|_2^2 + \lambda \,.\, R(\alpha) \qquad (4)$$

where R(α) denotes some regularization term that imposed on α and $\boldsymbol{\lambda}$ is a parameter of regularization.

The coding vector which has been resolved is a maximum a posteriori (MAP) solution at certain regularization term [17,39] for AWGN model. However, the noise distribution in an images those are corrupted by mixed noise is far from Gaussian. Hence, the data fidelity term $\|y - \Phi\alpha\|_2^2$ in eq. (4) will not lead to a MAP solution in removal of noise. The data fitting residual is much more irregular then to characterize the residual of coding, so that l_2 *norm* for handling mixed noise removal in a much easier way. This motivates to use robust estimation methods , which is weighting the residual, so that data fitting model can be more regular.

Let,

$$e = [e_1; e_2; \ldots\ldots\ldots; e_u] = y - \Phi\,\alpha \qquad (5)$$

where $e_i = (y - \Phi\,\alpha)(i)$. Instead of minimizing the residual $\|y - \Phi\,\alpha\|_2^2 = \sum_{i=1}^{u} e_i^2$, which actually assumes that e_i follows Guassian distribution. Minimizing the loss:

$$\min \sum_{i=1}^{u} f(e_i) \qquad (6)$$

'f' is the function which controls loss of residuals.

The function 'f' satisfy following conditions

i) $f(e) \geq 0$; symmetric condition.

ii) $f(e_i) \geq f(e_j)$ if $|e_i| \geq |e_j|$; non negative condition.

iii) $f(e) = f(-e)$; monotonic condition.

Assigning proper weights to residuals in order to reduce the mixed noise distribution. Rewrite residuals as follows

$$e^{W}{}_i = w_i^{1/2} e_i \qquad (7)$$

Residuals can be categorized in to 2 parts

i)Residuals found at AWGN corrupted pixels.

ii) Residuals found at IN corrupted pixels.

Residuals found at AWGN corrupted pixels follows Guassian distribution, so that weights assigned to that pixels will be close to 1. Residuals found at IN corrupted pixels having heavy tail distribution, to reduce heavy tails smaller weights are assigned to IN pixels. Function 'f' can be rewritten as

$f(e_i) = (w_i^{1/2} e_i)^2$

The new denoising model for mixed noise removal is

$$\hat{x} = \arg\min_\alpha \| w^{1/2} (y - \Phi\,\alpha)\|_2^2 + \lambda \,.R(\alpha)$$

(8)

where 'w' is the diagonal matrix which having diagonal elements. Some regularization terms based on natural image priors will be included in Eq.8, for making it more effective. Mainly there are two priors mainly used in denoising of image.

i) Local sparsity
ii) Non-local self-similarity(NSS)

These two priors integrated in to single prior named as sparse non local regularization. Eq.(8) can be rewritten as follows

$$\hat{x} = \arg\min_{\alpha} \| w^{1/2} (y - \Phi\, \alpha)\|_2^2 + \lambda. \sum_i \|\alpha_i - \mu_i\|_{lp} \qquad (9)$$

where $R(\alpha) = .\sum_i \|\alpha_i - \mu_i\|_{lp}$, p = 1 or 2 refers to l_p norm.

Eq.9 can be remodeled by using Laplacian distribution and leads to a MAP estimation and the equation becomes

$$\hat{x} = \arg\min_{\alpha}\{ \| w^{1/2} (y - \Phi\alpha)\|_2^2 + \lambda .\|\alpha - \mu\|_1 \} \quad (10)$$

'w' is a diagonal weight matrix, can be expressed as

$$w_{ii} = \exp (a e_i^2) \qquad (11)$$

where 'a' is a positive constant which controls the decreasing rate of w_{ii} with respect to e_i.

This denoising model can be solved by updating 'w' and 'α'. For the given patch dictionary will be adaptively indomitable. From Eq. 11 it is understood that weights is depending up on the coding residuals(e). For detecting salt and peper noise(SPIN) Adaptive median filter(AMF) is used. In WESNR noisy observation 'y' is applying to AMF in order to obtain image $x^{(0)}$, coding residual can be initialized as

$$e^{(0)} = y - x^{(0)} \qquad (12)$$

Final denoising model becomes

$$\alpha^{(k+1)} = (\Phi^T w\, \Phi + v^{(k+1)})^{-1} (\Phi^T w_y - \Phi^T w \Phi \mu) + \mu \qquad (13)$$

2.2 SMQT Technique

MQU is the main building block of SMQT and it consisting of mainly 3 steps calculating mean of the image, quantizing and splitting of the input set

i) Finding out the mean of image

$$\bar{v}(x) = 1/|D| \sum_{x\varepsilon D} v(x) \qquad (14)$$

ii) Quantizing the pixel values in to {0,1}.

$$\varepsilon(v(y), v(x)) = \begin{cases} 1, & \text{if } v(y) > \bar{v}(x) \\ 0, & \text{else} \end{cases} \qquad (15)$$

iii) Splitting the input image in to 2 subsets.

$$D_O(x) = \{x \mid v(x) \le \bar{v}(x), \text{ for every } x\ \varepsilon\ D$$
$$D_1(x) = \{x \mid v(x) > \bar{v}(x), \text{ for every } x\ \varepsilon\ D \qquad (16)$$

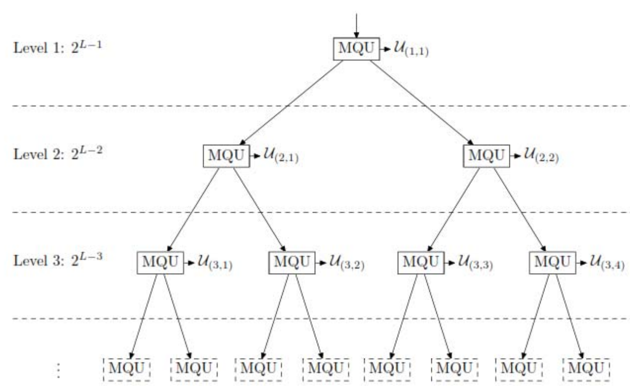

Fig. 1 SMQT Representation.

The main building block of SMQT is Mean Quantization Unit(MQU). Output of MQU denoted as 'u(x)'. u(x) mainly consisting of zeros and ones. MQU is independent of gain and bias adjustments of input. The first level transformation of SMQT is the output of MQU. SMQT can be described by using an binary tree which is shown in Fig. 1. Generally output of MQU is represented as $u_{(l,n)}$, where 'l' ranges from 1,2,…L, which is the current leveland 'n' ranges from 1,2,….,

$2^{(l-1)}$, which is the output number for the MQU at level 'l'. Values in the $u_{(l,n)}$ will be weighted and added to obtain the output. Weighting is performed by multiplying $2^{(l-1)}$ at each level. The final result obtained in $SMQT_L$ is

$M(x) = \{x|\ v(x) = \sum_{l=1}^{L} \sum_{n=1}^{2^{(l-1)}} v(u_{(n,l)}) \cdot 2^{L-1},$ $\forall x \in M, \forall u_{(n,l)} \in u_{(l,n)}\}$ (17)

Quantization levels $Q_L = 2^L$.

The level 'L' in the SMQT denotes the number of bits used to describe the transformed image. A SMQT of an image, which has a dynamic range represented by 8 bits, will yield an uncompressed image with enhanced details. The histogram equalization has some problems with over saturation and artifacts in several areas area in the images. Histogram equalized images have a tendency to get washed out or unnatural. These effects do not occur, or are very limited, in the SMQT enhanced images. The SMQT also has less computational complexity and fewer adjustments compared to more advanced enhancement techniques.

3. Algorithm of WESNR and SMQT

Removal of mixed noise by WESNR and enhancement of image by SMQT.

Input: Learning dictionary 'Φ', noisy observation 'y'.

Initialize e, by eq. (12) and then initialize w by eq.11

Output: Denoised image $\hat{x}$

Loop: Iterate on $k = 0,1, \ldots, K$'

1. Compute $\alpha^{(k)}$ using eq.13.
2. Compute $x^{(k)} = \Phi\alpha^{(k)}$.
3. Updating nonlocal coding vector μ.
4. Computing residual $e^{(k)} = y - x^{(k)}$.
5. Calculate the weights by using eq.11.

End

6. Output denoised image is fed to SMQT.
7. Finding mean of the image by eq.14.
8. Quantizing to $\{0,1\}$.
9. Splitting input set by eq.16

Output enhanced image $\hat{x}$.

4. Simulation Results

Experimental results have been done in MATLAB 2014a version with 4GB RAM and i3 processor. To verify the performance of the proposed image denoising model using the WESNR and enhancing image by SMQT with the existing denoising techniques such as AMF, Performed WESNR combined with SMQT for noise removal and enhancement. PSNR thus obtained is more. All the test images are intensity or gray scale images with the pixels ranging from 0 to 255.

Several parameters are used in the proposed algorithm and they all can be fixed. First, the parameter 'τ' which is controlling termination of iteration . To balance the denoising results, set it to 0.003. In Eq. (11), the parameter that is used to control the weights decreasing rate w.r.t. 'e', this can be set it to 0.0008. Fig.2 shows that the mixed noise removal from the Lena image, Fig.3 shows that the mixed noise removal from Boat image it displayed all the denoised images obtained by using conventional AMF, WESNR and WESNR + SMQT algorithms.

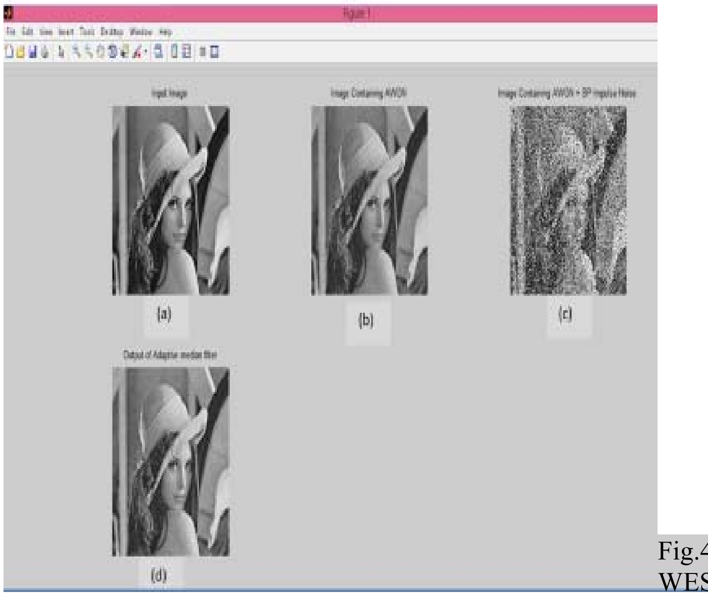

Fig. 2 Lena image (a) Input image, (b) Image containing AWGN, (c) Image containing AWGN and SPIN and (d) Output of AMF.

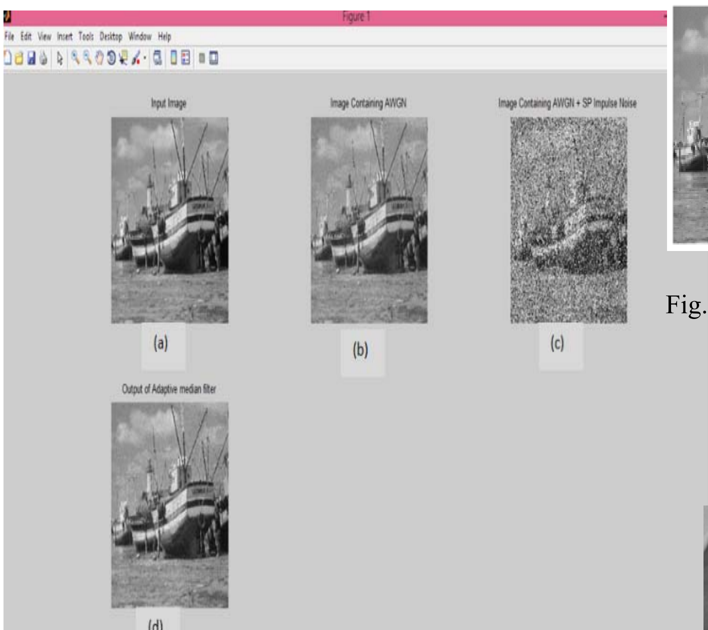

Fig. 3 Boat image (a) Input image, (b) Image containing AWGN, (c) Image containing AWGN and SPIN and (d) Output of AMF.

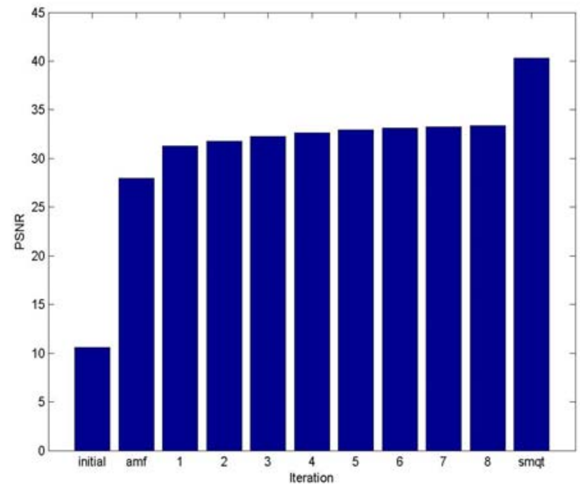

Fig.4 PSNR results of WESNR, AMF and combined WESNR and SMQT output for Lenaimage.

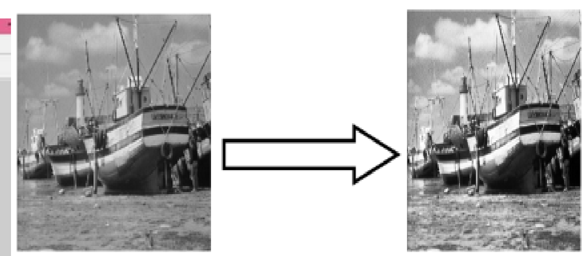

Fig. 5 WESNR Output, SMQT Output of Boat image.

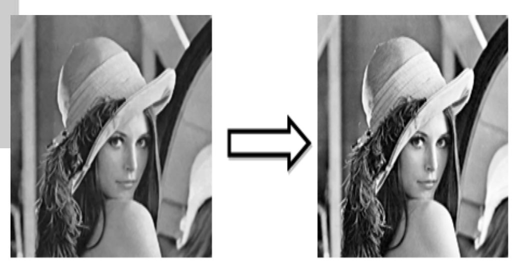

Fig. 6 WESNR Output, SMQT Output of Lena Image.

Table 1: PSNR Results of Boat Image

OBSERVATION	PSNR in dB
Noisy Image	10.64
AMF filtered Image	26.73
WESNR- Iteration1	29.38
WESNR- Iteration2	29.79
WESNR- Iteration3	30.13
WESNR- Iteration4	30.46
WESNR- Iteration5	30.60
WESNR- Iteration6	30.69
WESNR- Iteration7	30.72
WESNR- Iteration8	30.75
SMQT	38.45

Table 2: PSNR Results of Lena Image

OBSERVATION	PSNR in dB
Noisy Image	10.60
AMF filtered Image	27.99
WESNR- Iteration1	31.33
WESNR- Iteration2	31.84
WESNR- Iteration3	32.15
WESNR- Iteration4	32.71
WESNR- Iteration5	32.97
WESNR- Iteration6	33.18
WESNR- Iteration7	33.24
WESNR- Iteration8	33.43
SMQT	40.89

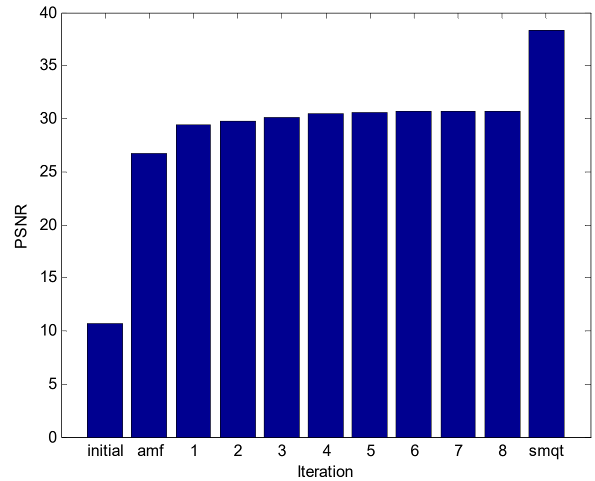

Fig.7 PSNR results of WESNR, AMF and combined WESNR and SMQT output for Boat image.

Able to observe that the visual quality is more in the proposed and PSNR ratio is more, thus performance is more.

5. Conclusion

Presented a novel model for mixed noise removal, namely weighted encoding with sparse nonlocal regularization (WESNR). The distribution of mixed noise, e.g., additive white Gaussian noise mixed with impulse noise, is much more irregular than Gaussian noise alone, and often has a heavy tail. To address this difficulty, adopted the weighted encoding technique to remove Gaussian noise and impulse noise jointly. First encoded the image patches over a set of PCA dictionaries learned offline, and weighted the coding residuals to suppress the heavy tail of the distribution. The weights were adaptively updated to decide whether a pixel is heavily corrupted by impulse noise or not. Meanwhile, image sparsity prior and nonlocal self similarity prior was integrated into a single nonlocal sparse regularization term to enhance the stability of weighted encoding. SMQT which is applied to WESNR output has properties that reveal the underlying organization or structure of data. The transform extracts the structure in a robust manner which makes it insensitive to changes in bias and gain of an image. Hence image is enhanced.

References

[1] I. Pitas and A. N. Venetsanopoulos, Nonlinear Digital Filters: Principles and Applications. Norwell, MA: Kluwer, 1990.

[2] D. Brownrigg, "The weighted median filter," Commun. ACM, vol. 27, no. 8, pp. 807-818, Aug. 1984.

[3] S. J. Ko and Y. H. Lee, "Center weighted median filters and their applications to image enhancement" IEEE Trans. Circuits syst., vol. 38, no. 9, pp. 984-993, Sep. 1991.

[4] A. Nieminen, P. Heinonen, and Y. Neuvo, "A new class of detail preserving filters for image processing," IEEE. Trans. Pattern Anal. Mach. Intell., vol. PAMI-9, no. 1, pp. 74-90, Jan. 1987.

[5] T. Sun and Y. Neuvo, "Detail-preserving median based filters in image processing," Pattern Recognit. Lett., vol. 15, no. 4, pp. 341347,Apr.1994.

[6] H. Hwang and R. A. Haddad, "Adaptive median filters: New algorithm and results," IEEE Trans. Image Process., vol. 4, no. 4, pp. 499-502, Apr. 1995.

[7] T. Chen, K. K. Ma, and L. H. Chen, "Tri-state median filter for image denosing," IEEE Trans. Image Process., vol. 8, no. 12, pp.1834-1838, Dec.1999.

[8] T. Chen and H. R. Wu, "Adaptive impulse detection using center weighted median filters," IEEE Signal Process. Lett., vol. 8, no.1, pp.13, Jan. 2001.

[9] G. Pok, J. C. Liu, and A. S. Nair, "Selective removal of impulse noise based on homogeneity level information," IEEE Trans. Image Process., vol. 12, no. 1, pp. 85-92, Jan. 2003.

[10] Y. Q. Dong and S. F. Xu, "A new directional weighted median filter for removal of random valuedimpulse noise," IEEE Signal Process. Lett., vol. 14, no. 3, pp. 193-196, Mar. 2007.

[11] N. I. Petrovic and V. Crnojevic, "Universal impulse noise filter based on genetic programming," IEEE Trans. Image Process., vol. 17, no. 7, pp. 1109-1120, Jul. 2008.

[12] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. IEEE Int. Conf. Computer Vision, 1998, pp. 839-846.

[13] M. Aharon, M. Elad, and A.M. Bruckstein, "KSVD: An algorithm for designing of overcomplete dictionaries for sparse representation," IEEE Trans. Signal Processing., vol. 54, no. 11, pp. 4311-4322, Nov. 2006.

[14] K. Dabov, A. Foi, V. Katkovnik, and K.Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative Filtering," IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080-2095, Aug. 2007.

[15] A. Buades, B. Coll, and J. M. Morel, "A review of image denoising methods, with a new one," Multiscale Model. Simul., vol. 4, no.2, pp. 490-530, 2005.

[16] L. Zhang, W. S. Dong, D. Zhang, and G. M. Shi, "Two-stage image denoising by principal component analysis with local pixel grouping," Pattern Recognit., vol. 43, no. 4, pp. 1531-1549, Apr. 2010.

[17] W. S. Dong, L. Zhang, G. M. Shi, and X. Li, "Nonlocally Centralized sparse representation for image restoration," IEEE Trans. Image Process., vol. 22, no. 4, pp. 1620-1630, Apr. 2013.

[18] H. Burger, C. Schuler, and S. Harmeling, "Image denoising: can plain neural networks compete with BM3D," in Proc. Int. Conf. Compu. Vis. Pattern Recognit., 2012, pp. 2392-2399.

[19] W. Dong, X. Li, L. Zhang and G. Shi, "Sparsity-based image denoising via dictionary learning and structural clustering," in Proc. Int. Conf. Compu. Vis. Pattern Recognit., 2011, pp. 457-464.

[20] A. Buades, B. Coll, and J. M. Morel, "A nonlocal algorithm for image denoising," in Proc. Conf. Comput. Vis. Pattern Recognit., 2005.

[21] L. Zhang, L. Zhang, X. Mou and D. Zhang, "FSIM: A Feature similarity index for image quality assessment," IEEE Trans. Image Process., vol. 20, no. 8, pp. 2378- 2386, Aug. 2011.

[22] R. Li and Y. J. Zhang, "A hybrid filter for the cancellation of mixed Gaussian noise and impulse noise," in IEEE. Int. Conf. Information. Communications. and Signal Processing, 2003, pp. 508-512.

[23] M. Yan, "Restoration of images corrupted by impulse noise and mixed Gaussian impulse noise using blind in painting," SIAM Journal on Imaging Science., vol. 6, no. 3, pp. 12271245, 2013.

[24] E. Abreu, M. Lightstone, S. K. Mitra, and K. Arakawa, "A new efficient approach for the removal of impulse noise from highly corrupted images," IEEE Trans. Image Process., vol. 5, no. 6, pp. 1012-1025, Jun. 1996.

[25] S. Peng and L. Lucke, "Multi-level adaptive fuzzy filter for mixed noise removal," in Proc. IEEE Int. Symp. Circuits Systems, Seattle,WA, Apr. 1995, vol. 2, pp. 1524-1527.

[26] E. Lopez-Rubio, "Restoration of images corrupted by Gaussian and uniform impulsive noise," Pattern Recognit., vol. 43, no. 5, pp. 1835-1846, May. 2010.

Author Details:

Manu Elizabath Raj pursued Bachelor of Technology in Electronics & Communication Engineering from Calicut University, in 2015. She is currently pursuing Master of Technology in Communication Engineering

under A. P. J Abdul Kalam Technological University, Kerala, India. Her main research work focuses on Image Processing.

Sherin Thomas pursued Bachelor of Technology in Electronics & Instrumentation Engineering from the University of CUSAT in 2011 and M.Tech, in VLSI & Embedded Systems from Mahatma Gandhi University in 2013. Currently working as Assistant Professor in the department of Electronics & Communication in Royal College of Engineering & Technology Thrissur. Her research interest include biomedical signal and image processing, Biomedical electronic system design and VLSI technologies and has guided 7 projects in these areas. She is a member of ISTE and IETE.