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Evaluation of Noise Exclusion of Medical Images using Hybridization of Partical Swarm Optimization and Bivariate Shrinkage Methods

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ABSTRACT

Denoising of images got corrupted by addition of noise signals (generated by no single reason) has always a subject of interest for researchers. This paper proposes and classifies the efficiency of an algorithm based on bivariate shrinkage further optimized by Particle Swarm Optimization (PSO).The estimator for undecimatedfilterbank which incorporate the adaptive subbands thresholding further represented with singal threshold based on denosing performs. The paper evaluates performance of medical image denoising by calculation of PSNR, MSE, WPSNR and SSIM. The simulation results based on testing the model at MATLAB 2010A platform shows significant enhancement in mitigation of Gaussian noise, speckle noise, poisson noise and salt & pepper noises from experimental data.

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1. INTRODUCTION

Medical information, composed of images, physiological signals and other clinical data, has become an essential part of a patient's care, during screening, in the diagnostic stage and in the treatment phase. Over the past few decades, there has been a rapid development in information technology (IT) & Medical Instrumentation which has lead & facilitated the growth of digital medical imaging. This growth has mainly focused on Computed Tomography (CT), the different digital radiological processes for vascular, nuclear medical imaging with Single Photon Emission Computed Tomography (SPECT), cardiovascular and contrast imaging, mammography, Magnetic Resonance Imaging (MRI), diagnostic ultrasound imaging, and Positron Emission Tomography (PET). All these processes are producing increasing quantities of images. These images are typically different from other photographic images because they reveal internal framework as opposed to an image of external surfaces.

In view of this, survey of literature has been done in the area of tomography, wavelets, multi wavelets and various denoising techniques.. A number of researchers have published image denoising literature [9-25] there is tremendous research that is going on, for better image quality throughout the globe. The thresholding is undertaken on the pixel by pixel basis [26–28] or by considering theinfluence of neighborhood wavelet coefficients on the wavelet coefficients to be thresholded. Cai and Silverman [29] proposed a thresholding method which takes the immediate neighboring coefficients into account to form the threshold. The idea of neighboring wavelet thresholding was extended by Chen and Bui [30] in to the multi waveletscheme. It was proved that neighbor multi wavelet denoising outperforms the neighbor single wavelet denoising [31] for some test images and real time signals. Chen et al. [32] proposed a noise suppression method which considers asquare neighborhood window to customize the wavelet filter threshold for image denoising. These methods removethe noises from the images effectively. Crouse et al [33] developed a framework for statistical signal processing basedon wavelet domain hidden markkov models (HMM). Kingsbury [34] proposed the 2D dual tree complex wavelet which satisfies these requirements effectively. But this method is less efficient for motion estimation since the motion information is related to the coefficientphase, which is nonlinear function of estimation.Aim of the paper is to emphasize the problems and solutions in relation to tomographic images which arise in medical field in view of its increasing importance in the present day requirements.

2. RESEARCH METHOD

The proposed methodology is basically contains two functional steps

1. generation of initial element
2. determination of fitness function

A. Generation of Initial Element

In the first process, n_{at} initial atom, each part of element n_E are generated. The set representation of initial elements are given as

$\{R\}_{il} = \{r0, r1, r2 \ldots r_{nE-1}\}_{il}; 0 \le l \le n_{at}-1$

Where $\{R\}_{il}$ is the l^{th} element generated to obtain windows that are closer to the i^{th}window of the original noisy image. Each atom of the generated element r_{il} $k \in \{R\}_{il}$; $0 \le k \le n_E-1$, is an arbitrary integer generated within the interval $[0, n_w-1]$ provided that all the atoms of each element has to satisfy the condition $r0 \ne r1 \ne \ldots \ne r_{nE}-1$.

B. Determination of Fitness Function

A fitness function decides whether the generated element are fit to survive or not, that can be given as

$$f_i(l) = \frac{1}{n_c} \sum_{k=0}^{n_c-1} L2_{ilk}$$

Wher, $f_i(l)$ is the fitness of thel^{th}element generated for the i^{th} window &$L2_{ilk}$ *is the L2* norm distance determined between the w_i& the window indexed by the k^{th} atom of the l^{th} element. The $L2_{ilk}$ is determined as follows

$$L2_{ilk} = \sqrt{\sum_{a=0}^{m-1} \sum_{b=0}^{n-1} \left(\left| W_i(a,b) - W'_{r_{ilk}}(a,b) \right| \right)^2}$$

Where, $W'r_{ilk}$ is the window indexed by r_{ilk} that is converted to multi-wavelet transformation domain as done in (4) and (5).

The procedure for wavelet multi resolution transform in is described below

Step 1: At level *j* 2-D real image is convolved with scale and wavelet filters along the rows of 2-D image.

Step 2: The results obtained after step 1 are convolve again with scale & wavelet filters along the columns of the 2-D image.

Step 3: Then filter is sub-sampled by a factor of two.

Step 4: At level *j* the approximation is considered as the input to the next level *j+1*. This procedure is followed for all the levels.

C. Bivariate Shrinkage Function Model (BFM):

Bivariate shrinkage function model (BFM) is a new modest non-Gaussian bivariate probability distribution function to perfect the statistics of wavelet coefficients of natural images. The model arrests the dependence amongst a wavelet coefficient & its parent. Using Bayesian estimation theory we develop from this model a modest non-linear shrinkage function for wavelet denoising, which take a broad view of soft

thresholding approach. The new shrinkage function, which hangs on both the coefficient & its parent, produces improved results for wavelet-based image denoising.
Let us consider that w2 symbolize the parent of w1 (w2 is the wavelet coefficient at the identical spatial position as w1, but then again at the next coarser scale). Then

$$y = w + n \tag{4}$$

Where w = (w1, w2), y = (y1, y2) & n = (n1, n2). The noise standards n1, n2 are iid zero-mean Gaussian with variance\sigma n^2.
The standard MAP estimator for w given the noisy observation y is:

$$\hat{w}(y) = \arg\max_w \left| P_{w|y}(w \mid y) = \arg\max_w \left[P_n(y-w) P_w(w) \right] \right.$$

The equation for wavelet coefficient w_1 is given as

$$\hat{w}_1 = \frac{\left(\sqrt{y_1^2 + y_2^2} - \frac{\sqrt{3}\sigma_n^2}{\sigma} \right)_+}{\sqrt{y_1^2 + y_2^2}} y_1$$

Let consider that

$$T = \frac{\sqrt{3}\sigma_n^2}{\sigma} \tag{5}$$

Then we denote the bivariate shrinkage function model (BFM) BFM=(Y_c, Y_p, σ_n, σ, T), where $Y_c$is the coefficient of each sub-band Y_p is its parent of the coefficient, $\sigma_n$is the variance of noisy signal, $\sigma$is the marginal variance &T is the threshold value.

D. Methodology for Window Selection in Image Denoising:
Let, first discuss the already present window selection methodology used in the technique, here, is a brief description.
Let us assume that, I (x, y) be the unique CT image and I_{AWGN} (x, y) be the image corrupted by Additive White Gausian Noise, where $0 \leq x \leq M-1$, $0 \leq y \leq N-1$. The I_{AWGN} is applied to the first stage of the proposed technique, window-based thresholding. The window selection procedure described here is one of the key mechanisms of the first stage of processing of the CT image denoising technique.
In the procedure, a carbon copy of the I_{AWGN}, labeled as I'_{AWGN}, is generated. I_{AWGN} and I'_{AWGN}, a window of pixels are considered &set to a multi-wavelet transformation. The process of extracting the windows from the image I_{AWGN} is given in the Figure 1.

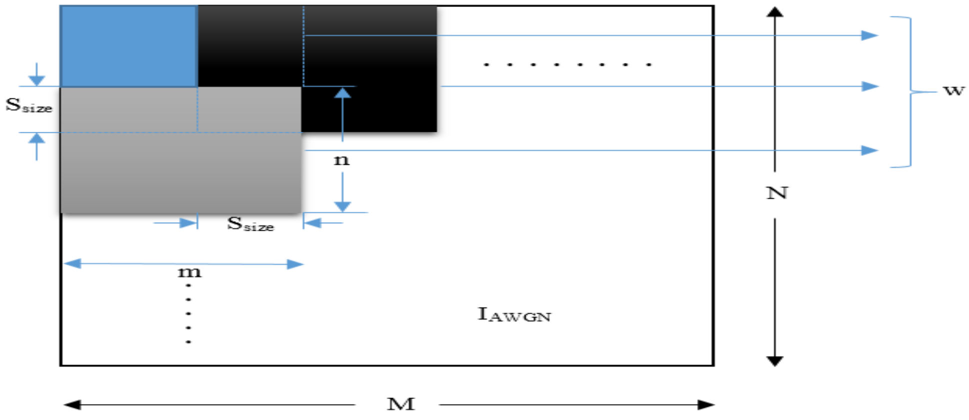


Figure 1. Process of extracting the windows from the given image I_{AWGN}

In the Figure 1, w indicates the window of pixels pulled out from the image I_{AWGN} & S size is the step size of the window. This is carried out all over the image and so $w_j$windows are achieved, where, $0 \le i \le n_w - 1$. By the same way, it is also executed in the image I_{AWGN} and receives w_j, $0 \le j \le n_w - 1$, where, $n_w$signifies number of windows. Then, the obtained window of pixels are transformed to multi wavelet transformation domain as follows

$W_i\,(a,b) = F_{GHM}(a,b).w_i(a,b).F^T_{GHM}(a,b)$ [30](6)
$W_j\,(a,b) = F_{GHM}(a,b).w_j(a,b).F^T_{GHM}(a,b)$[50](7)

Where, $0 \le a \le m-1$, $0 \le b \le n-1$ and mXn indicates the window size. In (6) and (7) F_{GHM} is the concatenated filter coefficient of GHM multi-wavelet transformation, $W_i$and W_j are $w_i$and $w_j$in multi-wavelet domain, respectively.
For each W_i, $W_j$that are nearer to W_i are selected founded on L2 norm distance ($L2_{ij}$), which can be calculated using (9),

$$L2_{ij} = \sqrt{\sum_{a=0}^{m-1}\sum_{b=0}^{n-1}(|W_i(a,b) - W'_j(a,b)|)^2} \tag{8}$$

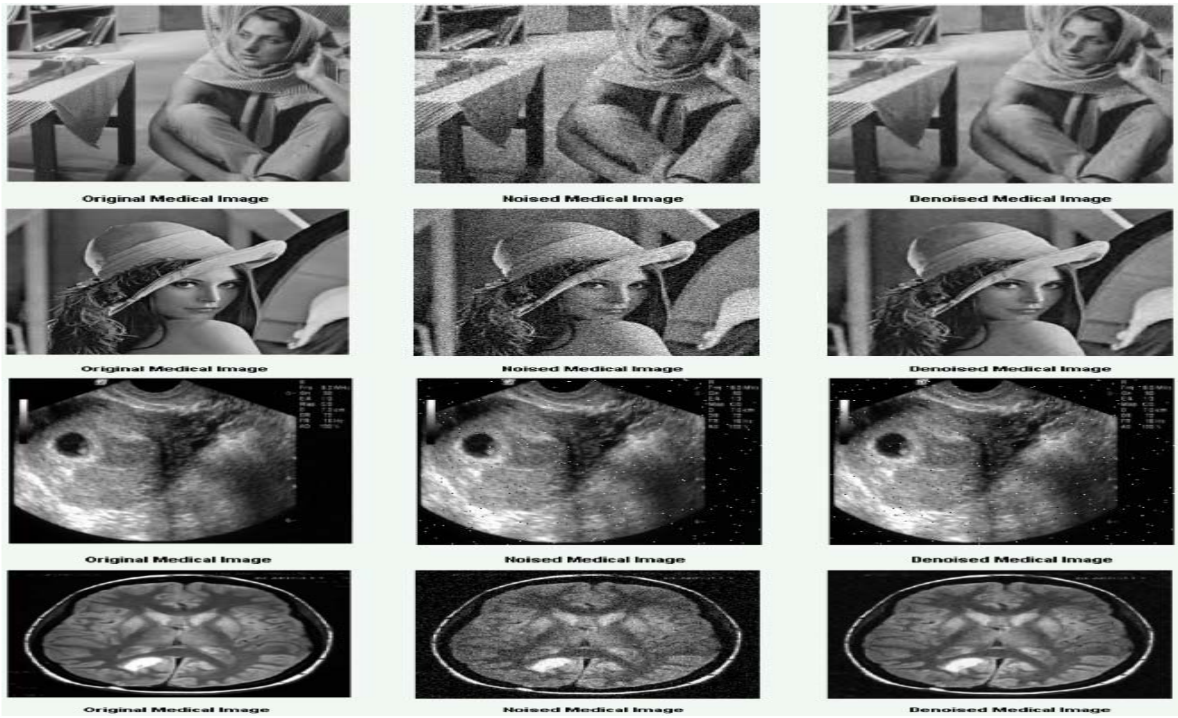
Using the $L2_{ij}$, the $W_j$windows that are nearer to the W_i, W'_{L2ij}can be demarcated as $W'_{L2ij} = W_{L2ij} - \phi$, where, $W_{L2ij}$is given as

$$W_{L2_{ij}} = \begin{cases} W'_j & ; \quad if \quad L2_{ij} \le L2_T \\ \phi & ; \quad else \end{cases} \tag{9}$$

Every i^{th}window sets in W'_{L2ij} are organized in ascending order based on their corresponding $L2_{ij}$. From the sorted window set, n_c number of windows are chosen (for every W_i) and the remaining are omitted out, which leads to receive $W'L2ik$, where, $0 \le k \le n_c - 1$.

3. RESULTS AND ANALYSIS

With this algorithm subjected to various type of image corrupted by well known type of noises it is being found from the table 2 that all the images has shown a quite improvement in when corrupted by either type of above mentioned noises.Table 1 shows the comparison of our obtained data with the results from WT-TNN approach with db8 and bior6.8 [44] it can be seen that our proposed method has performed well in removing the different type of noises.



(a) (b) (c)

Figure 2. Image (a) original image, (b) Image with Gaussian noise (c) denoised image

Image denoising using bivariate shrinkage function and which are in turn subjected to Particle Swarm Optimization (PSO) has shown a much significant improvement in salt and pepper noise. Nearly 50% improvement is seen in PSNR, whereas MSE has decreased to nearly 97% after adaptive filters. These improvements has helped to achieve better WPSNR between 29% to 40% improvement in various image type.Apart from salt and pepper noise, gaussion noise, speckle noise & poisson noise has shown improvement to some extent but salt and pepper has stood apart from all the noises.

Table 1. Comparative performance of proposed approach with db8 and bior 6.8 wavelet filter

Set of results from WT-TNN approach with db8 wavelet filter[44]			Set of results from WT-TNN approach with bior6.8[44]		Proposed with PSO	
Image	Noise Std. dev.	PSNR	Noise Std. dev.	PSNR	Noise Std. dev.	PSNR
Leena	10	34.29	10	34.34	10	35.32
Barbara	10	31.76	10	31.81	10	34.3
Ultra Sound	10	33.86	10	34.64	10	33.85

Table 2. Performance comparision of proposed methodology and its effect on various noise and image type

Image-Barbara	**PSNR**	**MSE**	**WPSNR**	**SSIM**	**TIME**
POISSON NOISE	36.9248	13.2008	42.1271	0.947244	0.225509
GAUSSIAN NOISE	34.3078	24.1155	37.7427	0.88342	0.232728
SALT & PEPPER NOISE	46.2095	17.2363	48.8016	0.860089	0.218133
SPECKLE NOISE	34.164	24.9279	39.123	0.918154	0.248614

Image-Leena	**PSNR**	**MSE**	**WPSNR**	**SSIM**	**TIME**
POISSON NOISE	37.8394	10.694	43.088	0.953933	0.206691
GAUSSIAN NOISE	35.3205	19.1	38.5271	0.890729	0.212508
SALT & PEPPER NOISE	47.0804	16.27364	48.9249	0.834926	0.213186
SPECKLE NOISE	34.7653	21.7047	39.6693	0.923108	0.184577

Image-CT Scan	PSNR	MSE	WPSNR	SSIM	TIME
POISSON NOISE	35.0613	20.2743	40.7958	0.954622	0.228942
GAUSSIAN NOISE	34.5149	22.9926	38.1528	0.789865	0.208839
SALT & PEPPER NOISE	48.8002	18.8571	43.8698	0.828432	0.222314
SPECKLE NOISE	33.7675	27.3103	38.7148	0.949395	0.220501

Image-Ultrasound	PSNR	MSE	WPSNR	SSIM	TIME
POISSON NOISE	34.8795	21.1415	40.5439	0.961004	0.231137
GAUSSIAN NOISE	33.8518	26.7853	37.4314	0.767568	0.211641
SALT & PEPPER NOISE	48.5434	20.9093	42.8133	0.840776	0.196596
SPECKLE NOISE	33.3418	30.1235	37.8567	0.950667	0.225587

3. CONCLUSION

In this paper, new technique has been presented. The proposed Bivariate and PSO based technique approach not only computationally efficient but also gives better performance indicated by performance indices PSNR, MSE, WPSNR, SSIM and time. Finally, it is concluded that the proposed approach in terms of PSNR, WPSNR improvement is outperformed.The proposed technique optimize the possibility of low pass coefficient from each subbandbased on amount of shrinkage is related to signal dependent noise variance.In this paper a new technique is proposed to mitigate the noise in images. According to results the novel Bivariate technique optimized by Particle Swarm Optimization is computationally efficient and performs significantly superior in performance indices indicated by PSNR, MSE, WPSNR, SSIM and time. Finally, we can conclude that in terms of WPSNR and PSNR the proposed approach is outperformed.

REFERENCES

[1] Arivazhagan S., Deivalakshmi S., and kannan. K.B.N. Gajbhiye, C. Muralidhar, Sijo N. Lukose, M.P. Subramanian, "Performance analysis of wavelet filters for image denoising", *Advances in Computational sciences and Technology*, vol. 1, no. 1, pp. 1-10, ISSN 0973-6107, 2007.

[2] A.C. Kak and M. Slaney, "Principles of computerized tomographic imaging," IEEE, Inc., New York: *IEEE* Press. 2006.

[3] Alexander Wong, Akshaya Mishra, Paul Fieguth and David Clausi, 2008, "An adaptive Monte Carlo approach to nonlinear image denoising", Proceedings of the *19th IEEE International Conference on Pattern Recognition*, Tampa, pp. 1-4. 1988.

[4] Anja Borsdorf, Rainer Raupach, Thomas Flohr and Joachim Hornegger, "Wavelet based noise reduction in CT images using correlation analysis," *IEEE Transactions on Medical Imaging*, vol. 27, no. 12, pp. 1685-1703. 2008.

[5] Aleksandra Piˇzurica, "A Versatile Wavelet Domain Noise Filtration Technique for Medical Imaging", *IEEE Transactions on Medical Imaging*, VOL. 22, NO. 3. 2003

[6] Arivazhagan S., Deivalakshmi S., and kannan. K.B.N. Gajbhiye, C. Muralidhar, Sijo N. Lukose, M.P. Subramanian, "Performance analysis of wavelet filters for image denoising", *Advances in Computational sciences and Technology,* vol. 1, no. 1, pp. 1-10, ISSN 0973-6107, 2007.

[7] Bart Goossens, Aleksandra Pizurica and Wilfried Philips, "Removal of correlated noise by modeling the signal of interest in the wavelet domain", IEEE Transaction on Image Processing, vol. 18, no. 6, pp. 1153-1165. 2009.

[8] Bhatia M. Karl W. and Willsky, A.S.J.P.Morgan & Co., "Tomographic reconstruction and estimation based on multi-scale natural-pixel bases", *IEEE Transactions on Image Processing* Vol. 6, Issue 3, pp. 463-478. 1997.

[9] Bing-gang Ye and Xiao-ming Wu, "Wavelet denoising arithmetic research based on small hepatocellular carcinoma CT image", in proceedings of *3rd International Conference on Bio-informatics and Biomedical Engineering*, ISBN No: 978-1-4244-2901-1, pp. 1-3. 2009.

[10] D. Gnanadurai and V. Sadasivam, "An efficient adaptive thresholding technique for wavelet based image denoising", *International Journal of Signal Processing*, volume 2, number 2, pp. 114-119. 2005.

[11] Detlev Marpe Hans L. Cycon, Gunther Zander and Kai-Uwe Barthel, "Context-based denoising of images using iterative wavelet thresholding", *Proc. SPIE Proceedings* vol.4671, *Visual Communications and Image Processing*, C.C.Jay Kuo. Editors, pp. 907-914. 2002.

[12] Dimitrios Charalampidis, "Steerable weighted median filters", *IEEE Transactions on Image Processing*, vol. 19, no. 4, pp. 882-894. 2010.

[13] D. Donoho, M. Raimondo, "A fast wavelet algorithm for image deblurring", *IEEE Transactions on image processing* 16 (2). 2006

[14] D.R.K. Brownrigg, The weighted median filter, *Communications of the ACM* 27 (8) 807–818. 1984

[15] Erdem Bala, Aysin Ertuzun, "A multivariate thresholding technique for image denoising using multiwavelets," EURASIP Journal on Applied Signal Processing, *Hindawi Publishing Corporation*, vol. no. 2005, issue 8, pp. 1205-1211. 2005.

[16] F. Natterer, The mathematics of computerized tomography: *Classics-in applied mathematics*, SIAM 32, ISBN 0898714931. 2001.
[17] G. Chen, T. Bui, Multiwavelet denoising using neighbouring coefficients, *IEEE signal processing letters* 10 ,211–214. 2003.
[18] G. Chen, T. Bui, A.Krzyzak, Image denoising using neighbouring wavelet coefficients, *Integrated Computer-Aided Engineering* 99–107. 2005.
[19] Hossein Rabbani, "Image denoising in steerable pyramid domain based on a local Laplace prior", *Pattern Recognition*, vol. 42, no. 9, pp. 2181-2193. 2009.
[20] Hossein Rabbani, "Wavelet-domain medical image denoising using bivariate Laplacian mixure model", *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 12, pp. 2826-2837. 2009.
[21] Joao M. Sanches, Jacinto C. Nascimento, and Jorge S. Marques, "Medical image noise reduction using the Sylvester-Lyapunov equation", *IEEE Transactions on Image Processing*, vol. 17, no. 9, Sept. pp. 1522-1539, 2008.
[22] Landi G. and Loli Piccolomini. E., "An algorithm for image denoising with automatic noise estimation", *Journal of Mathematical Imaging and Vision*, vol. 34, no. 1, pp. 98-106. 2009.
[23] M. Crouse, R. Nowak, R. Baraniuk, Wavelet based signal processing using hidden markov models, IEEE Transactions on signal processing, 46, 886–902. 1998.
[24] N.P. Anil and S. Natarajan, "A new technique for image denoising using fourth order PDE and Wiener filter", International Journal of Applied Engineering Research, vol. 5, no. 3, pp. 509-516. 2010.
[25] N.T. Binh, A. Khare, Adaptive complex wavelet technique for medical image denoising, ICDBME in Vietnam, IFMBE Proceedings, www.springerlink.com, 27, 196–199. 2010,
[26] Priyam Chatterjee, and Peyman Milanfar, "Is denoising dead?," *IEEE Transactions on Image Processing*, vol. 19, no. 4, pp. 895-911. 2010.
[27] Prof. S.A. Ali, Dr. S. Vathsal and Dr. K. Lal Kishore, "GA-based Window Selection Methodology toEnhance Window-based Multi-wavelet transformation and thresholding aided CT imagedenoising technique", *IJCSIS*, Vol. 7, No. 2. 2010.
[28] R. Vijaykumar, P.T. Vanathi, P. Kanagasabapathy and D. Ebenezer, "Robust statistics based algorithm to remove salt and pepper noise in images," *International Journal of Signal Processing*, vol. no. 5, issue no. 3, pp. 164-173. 2009.
[29] R. Neelamani, H. Choi, R. Baraniuk, Forward: Fourier-wavelet regularized deconvolution for ill-conditioned systems, *IEEE Transactions onsignal processing*, 52, 418–433. 2004.
[30] R. Silva, R. Minetto, W. Schwartz, H. Pedrini, Adaptive edge-preserving image denoising using wavelet transforms, Pattern Analysis and Applications 1–14doi:10.1007/s10044-012-0266-x.URL http://dx.doi.org/10.1007/s10044-012-0266-x, 2012.
[31] S. Arivazhagan, S. Deivalakshmi, K. Kannan, B.N. Gajbhiye, C. Muralidhar, Sijo N. Lukose, M.P. Subramanian, "Performance analysis of image denoising system for different levels of wavelet decomposition", *International Journal of Imaging Science and Engineering* , GA, USA, vol. 1, no. 3, July, pp. 104-107. 2007.
[32] T. Downie, B.W. Silverman, The discrete multiple wavelet transform and thresholding methods, *IEEE transactions on signal processing*, 46, 2558–2561. 1998.
[33] T. Cai, B.W. Silverman, Incorporating information on neighbouring coefficients into wavelet estimation, Sankhya: *The indian journal of statistics*, 63(b), (2), 127–148. 2001.
[34] T.D. Bui, G.Y. Chen, Translation invariant denoising using multivavelets, *IEEE transactions on signal processing* 46, 3414–3420, 1998.
[35] V. Strela, P. Heller, G. Strang, P. Topiwala, C. Heil, The application of multiwavelet filter banks to image processing, *IEEE transactions onimage processing* 8, 548–563. 1999.
[36] W. N, W. GT, Wavelet shrinkage and generalized cross validation for image denoising, *IEEE Transactions on image processing*, 7(1), 82–90. 1998.
[37] Yaniv Gal, "Denoising of Dynamic Contrast-Enhanced MR Images Using Dynamic Nonlocal Means", *IEEE Transactions on Medical Imaging*, Vol. 29, No. 2. 2010.
[38] Akshaya. K. Mishra, Alexander Wong, David. A. Clausi and Paul. W. Fieguth, "Adaptive nonlinear image denoising and restoration using a co-operative Bayesian estimation approach", *Sixth Indian Conference on Computer Vision*. 2011.
[39] Francisco Estrada, David Fleet and Allan Jepson, "Stochastic image denoising", British Machine Vision Conference, London 2009.
[40] G. Eason, B. Noble, and I. N. Sneddon. On certain integrals of Lipschitz-Hankel type involving products of Bessel functions [J]. Phil. Trans. Roy. Soc. London. 1995, A247: 529-551.
[41] G.G. Bhutada, R.S. Anand, S.C. Saxena, "PSO based learning of sub-band adaptive thresholding function for image denoising", SIViP (2012) 6: 1-7.
[42] H. Chipman, E. Kolaczyk, R. Mc Culloch, Adaptive bayesian wavelet shrinkage, J Am Stat Assoc, 440(92), 1413–1421, 1997.
[43] J. K. Mandal, S. Mukhopadhyay, A novel technique for removal of random valued impulse noise using all neighbor directional weightedpixels, Proceedings of the International Conference on Commmunications in Computer and Information Science(CCIS), Springer, 203, 102–111. 2011.
[44] J. K. Mandal, S. Mukhopadhyay, Edge preserving restoration of random valued impulse noises (eprrvin), Proceedings of International Conferenceon Recent Trends in Information Systems-RETIS 2011, IEEE 309–314. 2011.

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