ISSN: 0975-8585

Research Journal of Pharmaceutical, Biological and Chemical Sciences

A Framework of Image Denoising Algorithms.

A. Lenin Fred[1], L.R Jonisha Miriam[2]*, S.N Kumar[3], and Ajay Kumar H[4].

[1]School of Computer Science and Engineering, Mar Ephraem College of Engineering and Technology, Marthandam, Tamil Nadu, India.
[2, 4] School of Electronics and Communication and Engineering, Mar Ephraem College of Engineering and Technology, Marthandam, Tamil Nadu, India.
[3]Research Scholar, Department of Electronics and Communication Engineering, Sathyabama University, Chennai, Tamil Nadu, India.

ABSTRACT

A very large portion of digital image processing is devoted to image restoration. Image denoising plays a vital role in computer vision and pattern recognition. It reveals the removal of noise from image. The images acquire from the acquisition sources are prone to noise and the selection of restoration algorithm for a particular application is crucial. This paper analyzes various sources of noise in medical images and the algorithms for the restoration. The characteristics of various spatial and transform domain filters are analyzed and the outcome of this paper will be an aid for the researchers for the development of new restoration mode.
Keywords: Image Processing, Denoising, Spatial filtering, Transform domain filtering, wavelets.

***Corresponding author**

INTRODUCTION

Image processing is a subfield of signals and systems which focuses on developing a computer system that can perform processing on an image. A very large portion of digital image processing is devoted to image restoration. The purpose of image restoration is to compensate for or undo defects which degrade an image. Degradation comes in many forms such as motion blur, noise and camera misfocus. In case of motion blur, it is possible to come up with a very good estimate of actual blurring function and undo the blur to restore the original image.

Image denoising is an important image processing task that reveals the removal of noise from image. It is the method of estimating unknown signal from available noise data. It aims to remove whatever noise is present regardless of signal frequency content. The main property of good image denoising model is that it will remove noise while preserving edges. Traditionally, linear models have been used. One common approach is to use a Gaussian filter. In some cases, this kind of denoising is adequate. Though linear noise removal model is fast they cannot preserve edges in a good manner. Nonlinear models on the other hand can handle edges in a much better way than linear models. One popular model for non-linear image denoising is the Total Variation (TV) filter, introduced by Rudin, Osher and Fatemi. This filter is very good for preserving edges, but smoothly varying regions in the input image are transformed into piecewise constant regions in the output image. A. Aboshosha et.al [1], provides the comparative analysis of different spatial domain denoising methods. In order to determine the efficiency of various spatial filters for different noises, subjective and objective evaluation methods are employed. Ch. Kranthi Rekha et.al [2], compares the higher order diffusion filters which is essential for speckle noise reduction. The methods used are higher order partial differential equations followed by many adaptive filters such as SRAD filter, Kaun filter, Lee filter and Frost filter. In [3], the combined median and mean filtering is compared with smoothing, median and mid-point filter. The combined filters provide better results but structural details are still retained.

JanMark G et.al, introduces eminent computing perspective techniques like anisotropic convolution and Gaussian filtering. Gaussian filtering uses one dimensional filter to find the edge and ridge maps whereas convolution scheme is used for the detection of dashed lines in engineering drawings [4]. Buades et.al, defines a general mathematical and experimental methodology to compare and classify classical image denoising algorithms. Also, nonlocal means algorithm is addressed for the preservation of various structures in a digital image [5].

Sivakumar [6] presents both wavelet and curvelet transform image denoising modus. Denoising using curvelet transform is simple, fast, invertible, less redundant and it recovers original image from the noisy one using lesser coefficients in comparison with wavelet transform. Z.C. Bao et.al [7], presents a new non-tensor product bivariate orthogonal wavelet filter banks for image denoising. The major characteristics are by making non-tensor products iterative, it is very much easier for interpretation and implementation and it provides more directional features than tensor products.

The rest of the paper is organized as follows. Section II deals with the modus involved in eradicating various medical image noises. Section III introduces the evolution and frame work of image denoising algorithms. Section IV is drawn with conclusion.

CATEGORIES OF MEDICAL IMAGE NOISES

Noise depicts the redundant information which corrupts the image. Distinctive noises play a crucial aspect in image denoising. Feasible noises present in images are either additive or multiplicative component. Additive white Gaussian noise is an additive model noise which is depicted as

$$w(x,y) = h(x,y) + \eta(x,y)$$

and speckle noise is a multiplicative noise which is denoted as

$$w(x,y) = h(x,y) \,.\, \eta(x,y)$$

where *w(x, y)* is the corrupted image, *h(x, y)* is the original image and *η(x, y)* is the noise component present in an image. Various types of noises present in medical images are Gaussian noise, Salt and Pepper noise, Speckle noise, Poisson noise and Rician noise.

$$F(x) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{\frac{(x-\mu)^2}{2\sigma^2}}$$

where $F(x)$ is the Gaussian distribution noise, μ is the mean and σ is the standard deviation.

Gaussian noise in magnetic resonance images is removed by using adaptive anisotropic filter [8]. Wavelet based approach is the best denoising method in case of Gaussian noise [9]. In [10], self-learning based image decomposition technique is used for the elimination of Gaussian noise. Han Liu et.al [11], uses wavelet image denoising method based on least square support vector machine. Moreover, for different values of signal-to-noise ratio, this method is compared with Waveshrink and median filter methods. Results reveal that least square SVM is efficacious to clear away the Gaussian noise. Sivakumar [6] investigates that curvelet transform gives high peak signal-to-noise ratio values and it is capable of evacuating Gaussian noise from medical images when compared to wavelet transform method.

Salt and pepper noise is a randomly occurring spike noise comprising of dark pixels at bright regions and bright pixels at dark regions. It has two values 0 for pepper and 255 for salt. In [9], Asoke N reveals that median filter is optimal when compared to mean filter and LMS adaptive filter for salt and pepper noises. In [12], for removing impulse noise, decision based signal adaptive median filtering method is used. To enumerate signal adaptive and flexible thresholds the idea of homogeneity level is taken into account. Xiaoyin X. et.al, presents an adaptive two-pass rank order filter to remove impulse noise in highly corrupted images. The adaptive process detects irregularities in the spatial distribution of estimated impulse noise. The adaptive filter performs better than using the underlying filter alone in removing impulse noise and reducing false alarms [13].

Speckle noise is a multiplicative granular noise which is mainly occurs in ultrasound images and it degrades the quality of active radar and Synthetic Aperture Radar (SAR) image. Also, it is a grainy image which is inherent in nature. The probability density function of speckle noise is

$$F(x) = \frac{x^{a-1} e^{\frac{x}{a}}}{(a-1)!\, a^{\alpha}}$$

where $F(x)$ is the speckle noise distribution, x is the gray level value and a^{α} is the variance.

Y Yu et.al, developed a speckle reducing anisotropic diffusion that is meant for mean preservation, variance reduction and edge localization. This technique is applicable for ultrasound and radar sections [14]. For the removal of speckle noise in ultrasound and MRI, wavelet based denoising technique is used in [15]. P Raj et.al, investigates that the presence of speckle noise leads to low contrast images due to the incorrect detection of low contrast lesions and tumours during diagnostic phase [16].

Poisson noise is a dark current shot noise caused by statistical nature of electromagnetic waves and quantum fluctuations. The probability density function of Poisson noise is

$$P(k) = \frac{e^{-\lambda}\lambda^{k}}{k\,!}$$

where e is Euler's constant which is approximately equal to 2.718, λ is the mean value and k is the number of successes. In [17], with the help of variance stabilization transformation poisson noise is deducted to additive white Gaussian noise.

Rician noise brings out the bias for MRI evaluations and it becomes a powerful concussion on shapes and orientation of tensors in diffusion tensor magnetic resonance images [18]. Due to the presence of Rician noise, images endure from contrast values and signal dependent bias. The probability density function of Rician noise is

$$P(x) = \frac{x}{\sigma^2} e^{\frac{-(x^2+v^2)}{2\sigma^2}} I_0\left(\frac{xv}{\sigma^2}\right)$$

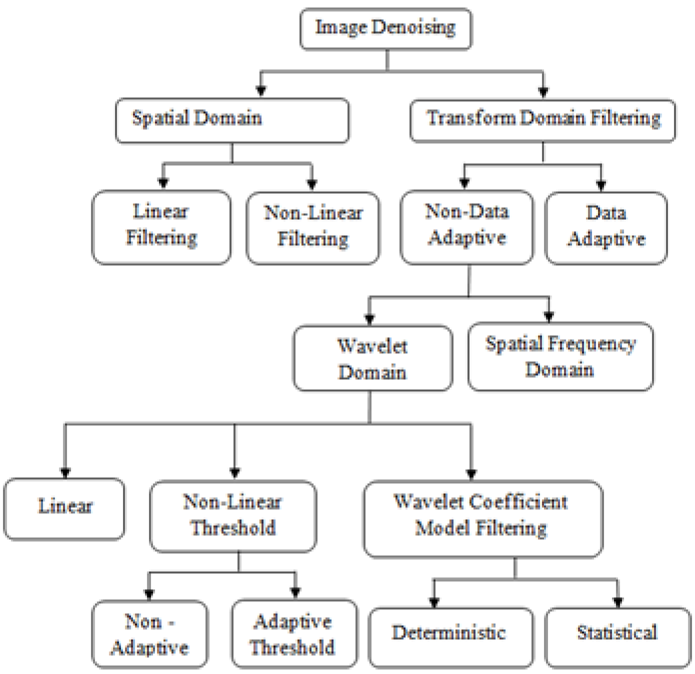
where I_0 is the modified Bessel function of the first kind with order 0, σ is the standard deviation of Gaussian noise in real and imaginary images and x is the pixel intensity in the absence of noise.

In [8], J. Sijbers introduces adaptive anisotropic diffusion which is adapted for magnetic resonance images by adding Rician noise. By using variance stabilization and patch based algorithms Rician noise from magnetic resonance images can be discarded. Most probably, bilateral filters are used for the deportation of Rician noise. J Aelterman et.al, proposes a new method for Magnetic Resonance Imaging (MRI) restoration. Because MR magnitude images are corrupted by Rician distributed noise, these images suffer from a contrast-reducing signal-dependent bias. For low SNR, bias suppression is used for discarding Rician noise and it is not used for high SNR [18].

EVOLUTION OF IMAGE DENOISING RESEARCH

Noise suppression in corrupted image remains a fundamental problem in the field of medical image processing. There are mainly two basic approaches involved in image denoising namely spatial domain filtering approach and transform domain filtering approach. Initially spatial domain filtering approach was used. Spatial filters operate on a set of pixels related to a given pixel, usually by a sliding window. Normally the shape of the window (kernel) is square but can be of any shape. Though this approach was fast and it was unable to preserve the edges (discontinuities in image) in an efficient manner. On the contrary we can preserve the edges by using transform domain filtering approach. In general, transform domain filters change the basis of signal space to aid some processing on the image data. Some of the transform domain filtering approach is Fourier transform and wavelet transform. Fourier transform is applicable to stationary signals but it is not applicable to non-stationary signals. Therefore the focus is shifted from Fourier domain to wavelet domain. Wavelets provide a remarkable performance in image denoising due to sparsity and multiresolution structure. Also, by the application of thresholding methods to non-orthogonal wavelet coefficients artifacts are reduced.

Fig.1: Framework of Image Denoising Algorithms



Ridgelets and curvelets plays a vital role in image denoising. In medical images, edges are curved rather than straight lines hence ridgelet transform yields better results than wavelet transform. However for more efficient results, localization of ridgelets like mono scale and multi scale ridgelets are done. The curvelets are multi scale ridgelets that comprises of spatial band pass filtering operation. The ridgelets have global length and variable widths, curvelets in addition has variable width, variable length and so a variable anisotropy. The curvelet are non- adaptive transform that has many applications in image processing and computer vision. The image denoising by curvelet transform preserves edges and curve singularities in the image much better than the wavelet and ridgelet transform. The curvelet is an extension of wavelet transform, it comprises of band pass filtering and thresholding in transform domain. Monika Shukla et al proposes a comparative analysis of wavelet and curvelet for image denoising, curvelet produces efficient restoration results for poisson, Gaussian and speckle noise because of its sparsity and multiresolution property.

Spatial Domain Filtering

Spatial domain refers to image plane and image processing methods based on the direct manipulation of pixels in an image. Spatial filtering is a form of finite impulse response (FIR) filtering. It consists of a neighborhood and a predefined operation that is performed on the image pixels encompassed by the neighborhood. The filter is actually a mask of weights arranged in a rectangular pattern. It is classified as linear and non-linear filters.

In linear spatial filter, the filtered value of the target pixel is obtained by the linear combination of pixel values in its neighborhood. It comprises of mean filters and Wiener filters. Most probably mean filter is a low pass linear filter and it introduces a threshold. If the magnitude of the change in pixel value lies below its threshold, mean filter replaces current pixel value with the mean of its neighborhood pixels. Thus the mean filter is efficient for removing Gaussian noise and it is not effective for removing salt and pepper noise. Wiener filter needs the knowledge about the spectra of noise and original image. It works well only if the underlying details are smooth. In [19], Anjali Malvia makes use of Wiener filter in order to achieve efficient noise reduction when its variance is less.

In non-linear spatial filter, the filtered value will be the non-linear operation on neighborhood pixels. It includes median filter, spatial median filter and weighted median filter. In median filter, the corrupted pixel value of noisy image is replaced by median value of corresponding window. This filter is more robust to outliers and does not create a new unrealistic pixel value. Also, it helps in preventing edge blurring and loss of image detail. In spatial median filter, spatial depth of each pixel is determined within the pixel followed by sorting these spatial depths in descending order. Weighted median filter yields more weight to some values within the kernel. Thus median filters eliminate salt and pepper noise.

Guido Gerig et.al, proposes a simple non-linear anisotropic spatial filter having the merit of object boundary blur ringing and fine structural detail suppression [20]. Yu-Li You et.al, illustrates that the anisotropic diffusion is the steepest descent method which performs smoothing and edge enhancement with the help of orthogonal decomposition of diffusion operator [21]. Michael J. Black et.al [22], uses new edge-stopping function based on Turkey's biweight robust estimator. It reveals that the addition of spatial coherence constraint edges enhance the continuity of recovered edges. S. Vijaya Kumar [23] proposes different hybrid filtering techniques for the elimination of Gaussian noise and salt and pepper noise. Filters are considered by means of a finite set of certain estimation and neighborhood building operations. It is based on the analysis of nonlinear filters.

Transform Domain Filtering

Depending on the basis function transform domain filtering is subdivided into non-data adaptive transform domain filtering and data adaptive transform domain filtering.

The non-data adaptive transform filtering is classified as spatial frequency domain filtering and wavelet domain filtering. Low pass filter is used with the help of Fast Fourier Transform. It relies on cut off frequency which is time engrossing and produces artificial frequencies in the processed image. Filtering process in wavelet domain is divided into linear filtering, non-linear threshold filtering and wavelet coefficient model filtering.

Wiener filter is a linear filter which is based on wavelet coefficients. The wavelet coefficients are conditionally independent Gaussian random variables. Even though this filtering approach diminishes the mean square error, the filtering image is more displeasing than the original noisy image. When the image is corrupted by additive white Gaussian noise, Nevine Jacob et.al enlightens that Wiener filtering on wavelet coefficients is the most appropriate for image denoising. It uses both hard and soft threshold techniques [24].

Non-linear threshold filtering is the most scrutinized domain in wavelet denoising. It exploits the property of wavelet transform. The method where small coefficients are removed leaving other coefficients untouched is called hard thresholding. Its harvest spurious blips are called artifacts. To avoid this artifact soft thresholding is used. In soft thresholding, coefficients whose magnitude is greater than the selected threshold value become shrinks towards zero and others set to zero. This filtering is categorized as non-adaptive and adaptive thresholding. VISU shrink is a non-adaptive universal threshold. The threshold value is obtained from the standard deviation of noise. It utilizes global thresholding scheme. This means that the single value of threshold is applied globally to all wavelet coefficients. This method provides smoothed image. It accords with additive noise and does not accord with mean square error minimization. By using this method speckle noise is not removed. Both SURE shrink and Bayes shrink belong to adaptive threshold. SURE shrink works on the principle of Stein's Unbiased Risk Estimator (SURE). In wavelet transform, the threshold value for each resolution level is known as level dependent thresholding. It suppresses the noise by thresholding empirical wavelet coefficient. The main benefit of SURE shrink is the minimization of mean square error. The threshold level in Bayes shrink is selected at each band of resolution in the wavelet decomposition. The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink.

Table 1. Characteristics of Shrink

Shrink Type	Threshold Formula	Threshold Rule	Threshold Value
VISU	$t = \sigma\sqrt{2\log n}$ σ is the noise variance n is the size of the image	Hard thresholding	Universal threshold
SURE	$t_s = min\left(t, \sigma\sqrt{2\log n}\right)$ t is the value that reduces SURE shrink σ is the noise variance n is the size of the image	Soft thresholding	Sub band dependent threshold
Bayes	$t_b = \frac{\sigma^2}{\sigma_s}$ σ^2 is the noise variance σ_s is the signal variance	Soft thresholding	Sub band dependent threshold

A Azzalini et.al, introduces a new recursive algorithm to estimate the variance of noise in images. The nonlinear thresholding of wavelet coefficients is an efficient method for denoising signals with isolated singularities [25]. Wei Liu et.al [26], incorporates both wavelet image threshold and edge detection method. Initially, with the help of wavelet edge detection, edges are obtained which is followed by wavelet image threshold denoising technique.

Wavelet coefficient model filtering approach focuses on multiresolution properties of wavelet transform. Although the output of this approach is excellent, it is computationally complex and expensive. Modelling of wavelet coefficients can either be deterministic or statistical. In deterministic modelling method, tree structure of wavelet coefficients is formulated. The level of the tree structure expresses the transformation scale and wavelet coefficient node. Statistical modelling approach deals with the properties of multiscale correlation between wavelet coefficients and local correlation between neighbourhood coefficients. Two techniques involved in this method are marginal probabilistic model and joint probabilistic method. Gaussian Mixture Model (GMM) and Generalized Gaussian Distribution (GGD) constitute the marginal probabilistic model. When comparing both GMM and GGD, GMM is simple and GGD is more accurate. Hidden

Markov Model (HMM) and Random Markov Field (RMF) form the joint probabilistic model. RMF is not describing the local structures but HMM is used to capture higher order statistics.

Independent Component Analysis (ICA) is a data adaptive transform filtering method for finding underlying factors or components from multivariate (multi-dimensional) statistical data. It is based on the principle of nonlinear decorrelation and maximum non-gaussianity. It is very difficult to obtain the noise free training data and its cost is expensive. It is used for blind source separation problem.

CONCLUSION

This paper analyzes evolution of restoration models and features of different filters are also discussed. The filter selection depends upon the noise model and the filtering efficiency is evaluated for a specific application. Medical image noises are removed by using both spatial domain filters and transform domain filters. Linear techniques possess mathematical simplicity but have the drawback of introducing blurring effect. To diminish this blurring effect we can use non-linear filters like median filter. Image denoising using wavelet techniques is effective because of its ability to capture the energy of signal in a few high transform values.

REFERENCES

[1] A. Aboshosha, M. Hassan, M. Ashour, and M. El Mashade, Image denoising based on spatial filters, An analytical study, In Computer Engineering & Systems, 2009. ICCES 2009. International Conference on 2009 Dec 14: 245-250

[2] Rekha, Ch Kranthi, V. Vijaya, and B. Sreedevi. Comparison of higher order diffusion filters for speckle noise reduction. In Computer Applications and Industrial Electronics (ICCAIE), 2010 International Conference on, IEEE, 2010: 697-701.

[3] Yousuf, M. A., and M. N. Nobi. A new method to remove noise in magnetic resonance and ultrasound images. Journal of scientific research 2010; 3(1): 81.

[4] Geusebroek, J.M., Smeulders, A.W. and van de Weijer, J., 2002, May. Fast anisotropic gauss filtering. In European Conference on Computer Vision, Springer Berlin Heidelberg: 99-112.

[5] Buades, A., Coll, B. and Morel, J.M., A review of image denoising algorithms, with a new one. Multiscale Modeling & Simulation, 2005; 4(2):490-530.

[6] Sivakumar, R., Denoising of computer tomography images using curvelet transform. ARPN Journal of Engineering and Applied Sciences, 2007; 2(1): 21-26.

[7] Bao, Z.C., You, X.G., Xing, C.F. and He, Q.Y., August. Image denoising by using non-tensor product wavelets filter banks. In Machine Learning and Cybernetics, 2007 International Conference on IEEE. 2007; 3: 1734-1738.

[8] Sijbers, J., den Dekker, A.J., Van der Linden, A., Verhoye, M. and Van Dyck, D., Adaptive anisotropic noise filtering for magnitude MR data. Magnetic resonance imaging, 1999; 17(10): 1533-1539.

[9] Nath, A., Image denoising algorithms: A comparative study of different filtration approaches used in image restoration. In Communication Systems and Network Technologies (CSNT), 2013 International Conference on IEEE.2013, April; 157-163.

[10] Huang, D.A., Kang, L.W., Wang, Y.C.F. and Lin, C.W., Self-learning based image decomposition with applications to single image denoising. IEEE Transactions on multimedia, 2014; 16(1): 83-93.

[11] Liu, Han, Yong Guo, and Gang Zheng. Image denoising based on least squares support vector machines. In Intelligent Control and Automation, 2006. WCICA 2006. The Sixth World Congress on IEEE, 2006; 1: 4180-4184.

[12] Pok, G., Liu, J.C. and Nair, A.S., Selective removal of impulse noise based on homogeneity level information. IEEE Transactions on Image Processing, 2003; 12(1): 85-92.

[13] Xu, X., Miller, E.L., Chen, D. and Sarhadi, M., Adaptive two-pass rank order filter to remove impulse noise in highly corrupted images. IEEE Transactions on Image Processing, 2004; 13(2): 238-247.

[14] Yu, Y. and Acton, S.T., Speckle reducing anisotropic diffusion. IEEE Transactions on image processing, 2002; 11(11): 1260-1270.

[15] Pizurica, A., Wink, A.M., Vansteenkiste, E., Philips, W. and Roerdink, B.J., A review of wavelet denoising in MRI and ultrasound brain imaging. Current medical imaging reviews, 2006; 2(2): 247-260.

[16] Raj, V.P. and Venkateswarlu, T., Denoising of medical ultrasound images using spatial filtering and multiscale transforms. International Journal of Computer Science & Information Technology, 2012; 4(6): 169.

[17] Foi, A., March. Noise estimation and removal in MR imaging: the variance-stabilization approach. In Biomedical Imaging: From Nano to Macro, 2011 IEEE International Symposium on IEEE 2011; 1809-1814.

[18] Aelterman, J., Goossens, B., Pižurica, A. and Philips, W., Removal of correlated rician noise in magnetic resonance imaging. In Signal Processing Conference, 2008 16th European IEEE 2008; 1-5.

[19] Malviya, A., Fractal based spatial domain techniques for image de-noising. In Audio, Language and Image Processing, 2008. ICALIP 2008. International Conference on IEEE 2008; 1511-1516.

[20] Gerig, G., Kubler, O., Kikinis, R. and Jolesz, F.A., Nonlinear anisotropic filtering of MRI data. IEEE Transactions on medical imaging, 1992; 11(2): 221-232.

[21] You, Y.L., Xu, W., Tannenbaum, A. and Kaveh, M., Behavioral analysis of anisotropic diffusion in image processing. IEEE Transactions on Image Processing, 1996; 5(11): 1539-1553.

[22] Black, M.J., Sapiro, G., Marimont, D.H. and Heeger, D., Robust anisotropic diffusion. IEEE Transactions on image processing, 1998; 7(3): 421-432.

[23] S. Vijaya Kumar, Hybrid filters for medical image reconstruction, African Journal of Mathematics and Computer Science Research, 2013; 6: 177-182.

[24] Jacob, N. and Martin, A., Image denoising in the wavelet domain using wiener filtering. Unpublished course project, University of Wisconsin, Madison, Wisconsin, USA. 2004; 1-21.

[25] Azzalini, A., Farge, M. and Schneider, K., Nonlinear wavelet thresholding: A recursive method to determine the optimal denoising threshold. Applied and Computational Harmonic Analysis, 2005; 18(2): 177-185.

[26] LIU, W. and MA, Z., Wavelet image threshold denoising based on edge detection [J]. Journal of Image and Graphics, 2002; 8: 008.