ISSN 2319-2720

Volume 7, No.2, April – June 2018

International Journal of Computing, Communications and Networking

Available Online at http://www.warse.org/ijccn/static/pdf/file/ijccn03722018.pdf

https://doi.org/10.30534/ijccn/2018/03722018

Medical Image Denoising using Unit Linking PCNN Model

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Abstract— *Image Denoising is tranquil challenges for many researchers. Image Denoising has a main aim to retain the important details and dislodge the noises as far as possible. Noise is the error in the image, its displays the disparate intensity values in lieu of true intensity values. It is an usual, the medical images contain some noises during some unavoidable reasons. Low contrast and poor quality are the major problems in medical images. In this work Gaussian noises and Speckle noises are added to MRI and X-Ray images. Contourlet transform and Unit Linking PCNN model is a best transformation function and it is used for decomposition. Contourlet is used to sustain the edges and contour regions. Unit Linking PCNN model is used to lessen the intricacy for picking the parameters. To diminish the noises some threshold function are used such as Bayes shrink,Block shrink and Neigh shrink. Performance of denoised image are appraised by Image Quality Index(IQI), Structural Similarity Index(SSIM), Normalized Cross Correlation(NCC), Peak Signal to Noise Ratio(PSNR).*

Keywords—*denoising,MRI,X-Ray,PCNN*

1. INTRODUCTION

Image denoising is a substantial task in image processing and image analysis. Image denoising is used to remove the unwanted noises as well as to restore the original image content. The main objective of image denoising is to achieve the noise reduction and conserve the image clarity. Image denoising is an important step in Medical Field. There are different approaches for generating medical images such as MRI, X-Ray, Computed Tomography(CT), Poistron Emission Tomography(PET), Ultra Sound(UV). MRI is a medical image technique and it is used in processes of radiology and physiological of body in both diseases and health. To form images of the body, MRI use powerful magnetic fields and radio waves.It is painless, harmless and non-invasive. X-ray is used to show a bones images and some tumors images. It can help to cure a diseases and detect the broken bones and cancers etc. The medical images habitually have a problems of high levels of noises during poor scanning and transmission. Medical images can interrupted by different types of noises.The common type of noises are (i)Additive noise (ii) Multiplicative noise (iii) Impulse noise. Additive noise is gaussian noise and salt & pepper noise. Impulse noise is amplifier noise and Multiplicative noise is speckle noise and rician noise. In medical images multiplicative noises is utmost corrupted. MRI images are interrupted with speckle and rician noises and X-Ray images are interrupted with poisson noise.

Contourlet Domain is Multidimensional and Multiscale image representation model. It is formulated by Laplacian Pyramid(LP) and Directional Filtering Bank(DFB). It can clearly detects the shapes and edges. Unit Linking PCNN model is a simplified version of PCNN model with fewer parameters. Unit Linking PCNN model can be effectively work on image processing. Unit Linking PCNN model has a free learning process and invariant to geometrical transformation. Unit Linking PCNN model can produce sequence of binary pulses that contains more information of features such as texture and edges. Thresholding is one of the best technique in image processing. Many thresholding techniques are used in the image processing such as bayes shrink, sure shrink, neigh shrink, neighsure shrink, bivariate shrink, block shrink, smooth shrink, normal shrink, minmax shrink, maxmin shrink. These techniques are used to eradicate the noises and enhance the image content

1.1 .Related Works

Image denoising is one of the classical problems in digital image processing, and has been studied for nearly half a century due to its important role as a pre – processing step in various electronic imaging applications. Its main aim is to recover the best estimate of the original image from its noisy versions [17]. Medical images are typically corrupted with noise, which hinder the medical diagnosis based on these images. There has been substantial interest in the problem of denoising of images in general. Tools from traditional image processing field have been applied to denoised MR images [47]. However, the process of noise suppression must not appreciably degrade the useful features in an image. Noise is present in an image either in an additive or multiplicative form. An additive noise follows the rule $w(x, y) = s(x, y) + n(x, y)$,While the multiplicative noise satisfies $w(x, y) = s(x, y)\times n(x, y)$,Where $s(x,y)$ is the original signal, $n(x,y)$ denotes the noise introduced into the signal to produce the corrupted image $w(x,y)$, and (x,y) represents the pixel location. The above image algebra is done at pixel level. Image addition also finds applications in image morphing [39].By image multiplication, we mean the brightness of the image is varied. The classification of noise relies mainly on the characterizing probabilistic specifications.There are the four types of noise categories in image processing [52].The Gaussian noise can be modelled in terms of amplifier noise, which is additive Gaussian, and hence independent at each pixel and intensity of the signal. This noise follows probability distribution function and is most frequently occurring in digital images [6]. Mean gray level is increased in speckle noise from local area of an image. Imageinterpretation and recognition is very difficult in this type of noise. Mean and Variance of local area and single pixel are proportional to each other values. Speckle is also known as or type of granular noise[3].Contourlet transforms is by introducing basis functions which are local,directional, and with multiresolution expansion.This representation has two basic building blocks, the Laplacian pyramid (LP) and the Directional Filter Bank (DFB).A computationally efficient iterative double filter bank structure proposed in [24,28] uses Laplacian pyramid [50] to capture the point discontinuities, followed by a directional _filter bank [45] to connect point discontinuities into linear structures. contourlet Transform achieves perfect reconstruction if the LP and DFB use perfect reconstruction filters with redundancy ratio of 4/3 [28]. Contourlet frames are compactly supported with flexible anisotropy. The threshold method, developed by Donoho [41] in 1995, provides a viable treatment option for the wavelet coefficients of nonlinear processing and, consequently, significantly advanced the field of image denoising.Bayes shrink was proposed by Chang, Yu and Vetterli [35]. The objective of this technique is to minimalize the Bayesian risk, and therefore named as BayesShrink. It uses soft thresholding and is subband-dependent, which meant that thresholding in the wavelet decomposition is done at each subband of resolution. This shrinkage technique includes the use of neighboring coefficients. The window sizes used for the neighborhood window could vary being 3X3, 5X5, 7X7, 9X9, etc. amongst them3X3 serves the best[36]. the threshold value calculated using universal shrinkage technique but since this does not provide an optimal output. Block Shrink is a completely data-driven block thresholding approach and is also easy to implement [19]. It can decide the optimal block size and threshold for every wavelet sub band by minimizing Stein’s unbiased risk estimate (SURE).Pulse coupled neural networks (PCNN) were proposed based on the sync pulse distribution phenomenon in the brain's visual cortex in various mammals, such as cats and monkeys [48]. PCNN has many advantages over traditional image processing. Since put forward, PCNN have been used extensively for image segmentation, image denoising, image enhancement, and image fusion [22-38].Pulse Coupled Neural Network (PCNN), was a model derived from a neural mammal model. Johnson andhis colleagues [37] had modified the model of the initial PCNN, which was applicable to calculate in the computer more easily. The existed algorithm of PCNN is often applied to the fields of segmentation of gray image [27],edge detection of gray image [29] , or binary image [30] respectively, Liang Zhou et al. expand the application of PCNN model and put forward a new algorithm based on PCNN [18] , which is a simplified algorithm of color image processing based on PCNN and the computer simulations are satisfied. In Liang Zhou’s algorithm, the same model of PCNN is used for image segmentation and image edge detection, which can improve the effect of the image processing, however, the same PCNN is fit for edge detection more than image segmentation according to the simulation results, because the edge pixels and central pixels are dealt with unfairly in different regions. The pulse coupling neural network is an artificial neural network, which was founded in the last century 90's, completely different from artificial neural networks. Eckhorn and his colleagues found that the synchronized shake phenomenon appeared in the local areas of different positions caused by similar stimulus input [44] in the study of the cat visual cortex. Later, in the experiments on monkeys they gained the same result [14]. Then Eckhorn bring out pulse coupling neural network model. Because this model is highly nonlinearity and complex reciprocity, it is difficult to use mathematical methods to control and interpret the results of neuronal behaviour. So in 1999 Johnson transformed Eckhorn’s model into PCNN model [31].PCNN is used in the field of image processing, target recognition, feature extraction, speech recognition, combinatorial optimization, compressed encoding, etc. In the meanwhile, favorable application effect has been achieved by combining it with Genetic Algorithm, Mathematical Morphology, Wavelet Theory, etc. Ma Yide, et al achieved the PCNN algorithm of automatic image segmentation [34]ULPCNN is a simplified version of the basic PCNN with fewer parameters [23]. There are many parameters which are difficult to assign in PCNN and the assignment of them has direct effect on the performance.To solve this problem, many simplified PCNN models are proposed by researchers, including the intersecting cortical model [25], the spiking cortical model (SCM) [15] and the unit-linking PCNN model [32], among which, Unit-Linking PCNN(UL-PCNN) has attracted many researchers by virtue of its simple assignment of parameters and better performance of segmentation and has been applied in some fields such as edge detection[26] and feature extraction [10] etc. But the solid value 0.2 of linking coefficient b cant reflect the linking relation between neurons accurately. In fact, the linking relation between neurons will vary as they are in different regions, of different gray value.ULPCNN neurons are inspired by directional contrast revealing the prominence of each directional subband, and such a ULPCNN is expected to possess good sensitivity to directional information of objects in images. The linking range is also determined by corresponding directional contrast. In this way, the global coupling character of the ULPCNN is better represented than that with constant linking range, especially for the strong stimulus. In our fusion rules, the first firing time of each neuron is chosen as the salience measure.[4].Unit-linking PCNN (ULPCNN) algorithm had better performance for image segmentation, but with application limitation for low contrast or complicated gray distribution images[44]. Through the statistic characteristics of neurons, stimulated number to optimize PCNN parameters,but it did not further explain how to strengthen the interaction between neurons to improve the image segmentation effect[37].

1.2.Motivation and Justification

Wavelet transform is decomposed into vertical and horizontal directions, it retains the limited direction of information. Contourlet dispense all degree of directionality and describes all the curves and the countover regions. Wavelet cannot lucidly describes the edges and curves but Contourlet is more adpt for storing the edges and curves. Wavelet wont suitable for recognizing the anisotropic elements. Contourlet can clearly recognizing the anisotropic elements. Contourlet performance is abundant better than Wavelet. Contourlet can accompolish higher PSNR than wavelet based methods. In Wavelet, cost of computing is high but In Contourlet cost of computing is low. Wavelet based filter can yields the blurred image and noises near the edges. Contourlet based filter can not yield any blurred image as well as near the edges noises are removed so strong edges are detained and their weak edges are also embellished. It can not take long compression time but Wavelet can take a long compression time. Wavelet transform does not dispense a accurate information and their result is sometimes doubtful for geometrical structures. Contourlet provide more adequate information and their result is more accurate for smoothen geometrical structures because it has fast implementation process. In PCNN model, created features are not invariant to geometrical transform. Unit Linking PCNN model can increasing the invariance of created features against rotation, translation and dilation of images. PCNN model has slow processing because it has large number of iterations and its computational is too complexity. Unit Linking PCNN model reduces the number of iterations and its also reduces the complexity. PCNN model cannot preserve the high recognition precision but Unit Linking PCNN model preserve the high recognition precision. PCNN model takes a long time for computation. Unit Linking PCNN model take very less time for computation process.

1.3. Organization of the Paper

The rest of the paper is classified as follows. Methodology includes outline of the proposed method,Contourlet,UL PCNN Model and Thresholding Shrinkages Techniques are presented in Section II. Experimental results are shown in Section III. Performance Evaluation are discussed in Section IV. Atlast Conclusion is presented in Section V.

2.METHODOLOGY

2.1. Outline of the proposed Method

The New Proposed Denoised method that uses the combination of Contourlet and UL PCNN Model. The System is expressed in Fig 1.The input images are added with Speckle,Gausssian, and Poisson noises. The corrupted images are decomposed with Contourlet and UL PCNN Model.Then apply some threshold function to denoise the noisy coefficients and then apply inverse transform to get a denoised image

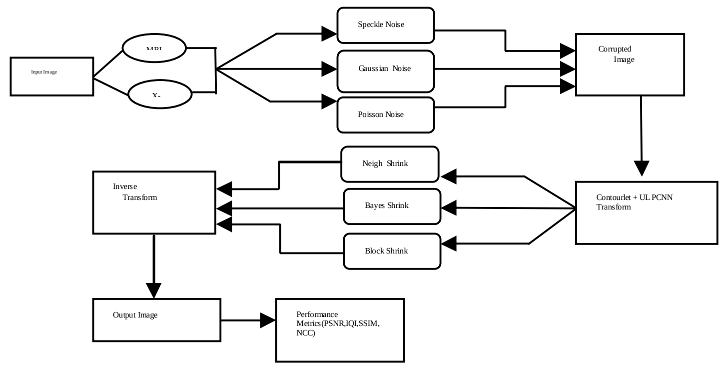


Fig 1. Block diagram of Image Denoising with Contourlet and UL PCNN Model

2.2. The Contourlet Transform

The Contourlet Transform (CT) is a directional multiresolution image representation scheme proposed by Do and Vetterli, which is effective in representing smooth contours in different directions of an image, thus providing directionality and anisotropy [28]. The framework of the contourlet transform in (Fig.2)The method utilizes a double filter bank (Fig.3) in which, first the Laplacian Pyramid (LP) [50] detects the point discontinuities of the image and then the Directional Filter Bank (DFB) [45] links point discontinuities into linear structures. The LP provides the means to obtain multiscale decomposition. In each decomposition level it creates a downsampled lowpass version of the original image and a more detailed image with the supplementary high frequencies containing the point discontinuities. This scheme can be iterated continuously in the lowpass image and is restricted only by the size of the original image due to the downsampling. The DFB is a 2D directional filter bank that can achieve perfect reconstruction. The simplified DFB used for the contourlet transform consists of two stages, leading to *2l* subbands with wedge-shaped frequency partitioning [43]. The first stage is a two-channel quincunx filter bank [17] with fan filters that divides the 2D spectrum into vertical and horizontal directions. The second stage is a shearing operator that just reorders the samples. By adding a shearing operator and its inverse before and after a two-channel filter bank, a different directional frequency partition is obtained (diagonal directions), while maintaining the ability to perfectly reconstruct the original image.

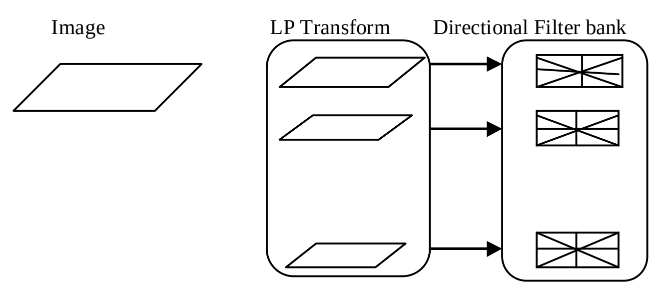


Fig.2 The Contourlet Transform Framework

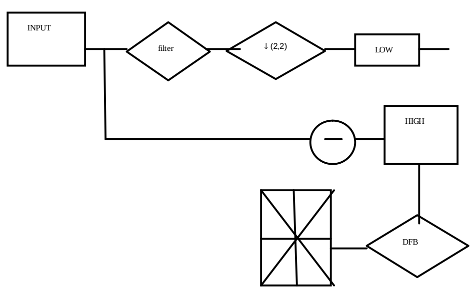


Fig. 3 The Contourlet Filter Bank.

By combining the LP and the DFB, a double filter bank named Pyramidal Directional Filter Bank (PDFB) is obtained. Bandpass images from the LP decomposition are fed into a DFB in order to capture the directional information. This scheme can be repeated on the coarser image levels, restricted only by the size of the original image. The combined result is the contourlet filter bank. The contourlet coefficients have a similarity with wavelet coefficients since most of them are almost zero and only few of them, located near the edge of the objects, have large magnitudes [20]. In this work, the Cohen and Daubechies 9-7 filters [46] have been utilized for the Laplacian Pyramid. For the Directional Filter Bank, these filters are mapped into their corresponding 2D filters using the McClellan transform as proposed by Do and Vetterli in [28]. The creation of optimal filters for the contourlet filter bank remains an open research topic.

2.3. The PCNN model

Here we introduce the basic knowledge about the PCNN, mainly including the structure of the PCNN neuromime and its software implementation in Matlab.[12]

Neuromime structure

As mentioned above, the PCNN is single layered, two-dimensional, laterally connected neural network of pulse-coupled neurons, which are connected with image pixels each other. Because each image pixel is associated with a neuron of the PCNN, the structure of the PCNN comes out from structure of input image, which will be processed. The PCNN neuron's structure is shown in Fig. 4. The neuron consists of an input part, linking part and a pulse generator. The neuron receives the input signals from feeding and linking inputs. Feeding input is the primary input from the neuron's receptive area. The neuron receptive area consists of the neighboring pixels of corresponding pixel in the input image. Linking input is the secondary input of lateral connections with neighboring neurons. The difference between these inputs is that the feeding connections have a slower characteristic response time constant than the linking connections.

$$F_{i,j}[n]=e^{-\alpha_F}F_{ij}[n-1]+V_F\sum_{k,l}M_{i,j,k,l}Y_{k,l}[n-1]+S_{i,j} \tag{1}$$

$$L_{i,j}[n]=e^{-\alpha_L}L_{i,j}[n-1]+V_L\sum_{k,l}W_{i,j,k,l}Y_{k,l}[n-1] \tag{2}$$

$$U_{i,j}[n]=F_{i,j}[n].(1+\beta L_{i,j}[n]) \tag{3}$$

$$Y_{i,j}[n]=\begin{cases}1; & U_{i,j}[n]>T_{i,j}[n]\\ 0; & otherwise\end{cases} \tag{4}$$

$$T_{i,j}[n]=e^{-\alpha_\theta}T_{i,j}[n-1]+V_TY_{i,j}[n] \tag{5}$$

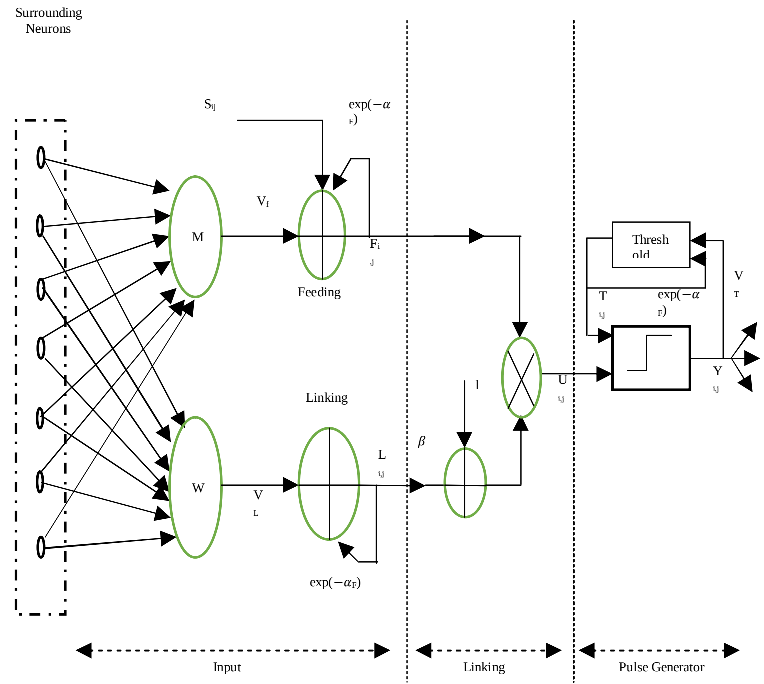


Fig 4 The basic PCNN Model

In these equations, S_{ij} is the input stimulus such as the normalized gray level of image pixels in (i,j) position, $F_{ij}[n]$ is the feedback input of the neuron in(i,j), and $L_{ij}[n]$ is the linking item. $U_{ij}[n]$is the internal activity of neuron, and $T_{ij}[n]$is the dynamic threshold. $Y_{ij}[n]$ stands for the pulse output of neuron and it gets either the binary value 0 or 1. The input stimulus (the pixel intensity) is received by the feeding element and the internal activation element combines the feeding element with the linking element. The value of internal activation element is compared with a dynamic threshold that gradually decreases at iteration. The internal activation element accumulates the signals until it surpasses the dynamic threshold and then fires the output element and the dynamic threshold increases simultaneously strongly. The output of the neuron is then iteratively fed back to the element with a delay of one iteration. The inter-connections M and W are the constant synaptic weight matrices for the feeding and the linking inputs, respectively, which dependant on the distance between neurons. Generally, M and W (normally W=M) refer to the Gaussian weight functions with the distance.β is the linking coefficient.α_F, α_L and α_T are the attenuation time constants $F_{ij}[n]$, $L_{ij}[n]$ and $T_{ij}[n]$, respectively. V_F,V_L, and V_T denote the inherent voltage potential of $F_{ij}[n]$, $L_{ij}[n]$ and $T_{ij}[n]$, respectively. Clearly, the standard PCNN has many parameters. A good algorithm using PCNN can make each parameter perform its own functions and further finish the task of data processing very well.Hence, we give a brief explanation about the functions of these parameters in the following.

For the feeding channel, α_F determines the rate of decay of the feeding channel. Larger α_F causes faster decay of the feeding channel.V_F can enlarge or reduce the influence from surrounding neurons.Matrix W refers to the mode of inter-connection among neurons in the feeding receptive field. Generally, the size of W denotes the size of the feeding receptive field. The value of matrix element w_{ijkl} determines the synaptic weight strength. In most cases, this channel is simplified via α_F=0 and V_F =0. Different from the feeding channel, the link channel usually keep itself as it is. The lin channel also has three parameters (α_L; V_L, and M) that have the same function to the parameters(α_F; V_F, and W) respectively. It is noteworthy that the mode of inter-connection should be designed carefully according to the task of data processing (e.g. image denoising), for it has a great effect on the output of PCNN. Usually, the inter-connection employs the Gaussian weight functions with the distance.

The linking coefficient β is an important parameter, because it can vary the weighting of the linking channel in the internal activity. Hence, its value is usually depended on different demands. For example, if much influence from the linking channel is expected, β should be given larger value. All neurons often have the same value of β. It is not absolute. Each neuron can have its own value of β. For the pulse generator, α_T indicates the rate of decay of the threshold in the iterative process. Because it directly decides the firing time of neuron, α_T is a significant parameter. Smaller α_T can make the PCNN work in a meticulous way but it will take much time to finish the processing. On the contrary, larger α_T can decrease more running time of PCNN. V_T decides the threshold value of fired neuron. If expecting that neuron just fires one time, you can give α_T a huge value.

2.4. Unit Linking PCNN MODEL

PCNN is qualified to imitate the biological features of HSV and hence apply to image processing [9],[10],[11]; however, so many parameters in the model should be set during use. So far, the relation between model parameters and network outputs is still ambiguous, and it is really difficult to determine the proper PCNN parameters. Therefore, ULPCNN is presented to simplify the PCNN by means of decreasing parameters and making the linking inputs of ULPCNN neurons uniform [23]. Fig. 3 displays the simplified model for a single ULPCNN neuron.

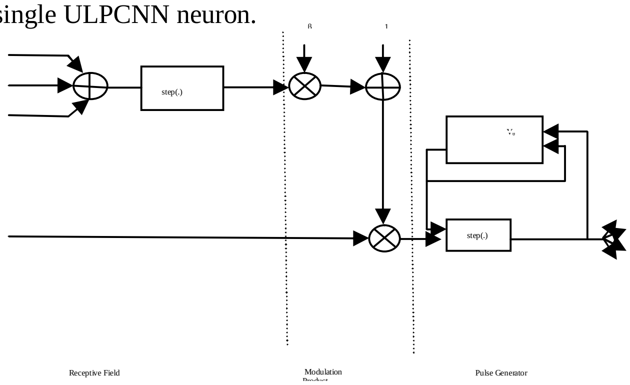


Fig 5 Unit Linking PCNN Model

The processes of a single ULPCNN neuron are displayed as

$$F_{ij}(n) = S_{ij} \tag{6}$$

$$L_{ij}(n) = \begin{cases} 1, & \sum_{kl} Y_{kl}(n-1) > 0 \\ 0, & otherwise \end{cases} \tag{7}$$

$$U_{ij}(n) = F_{ij}(n).(1+\beta L_{ij}(n)) \tag{8}$$

$$Y_{ij}(n) = \begin{cases} 1, & U_{ij}(n) > \theta_{ij}(n-1) \\ 0, & otherwise \end{cases} \tag{9}$$

$$\theta_{ij}(n) = e^{-\alpha_\theta}\theta_{ij}(n-1) + V_\theta Y_{ij}(n) \tag{10}$$

According to (7), if any neuron in the $k \times l$ neighborhood fires, L_{ij} will have a unity input, and then the centered neuron will be encouraged to fire. Obviously,impulse expanding behavior is much clearer and more controllable with much fewer parameters than the basic PCNN.

2.5. Thresholding Techniques

Thresholding is a technique used for signal and image de-noising. The shrinkage rule defines how we apply the threshold [51].[7]It is clearly proved that highest PSNR value is achieved at lowest standard deviation and lowest PSNR at highest Standard Deviation.Most of the real time and online applications require these types of filters with less execution time.

i) Block Shrink

Block Shrink is a completely data-driven block thresholding approach and is also easy to implement[19]. It can decide the optimal block size and threshold for every subband by minimizing Stein's unbiased risk estimate (SURE). The block thresholding simultaneously keeps or kills all the coefficients in groups rather than individually, enjoys a number of advantages over the conventional term-by-term thresholding. The block thresholding increases the estimation precision byutilizing the information about the neighbor waveletcoefficients. The local block thresholding methods all have the fixed block size and threshold and samethresholding rule is applied to all resolution levels regardless of the distribution of the coefficients.[19]. For every subband, we need to divide it into a lot of square blocks. Block Shrink can select the optimal block size and threshold for the given subband by minimizing Stein's unbiased risk estimate.

ii) Bayes Shrink

Bayes Shrink is a sub band adaptive data driven thresholding method. This method assumes that the coefficients are distributed as a generalized Gaussian distribution in each sub . Bayes Shrink was proposed by Chang, Yu and Vetterli.The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink [35]. The Bayes threshold is defined as

$$\lambda = \frac{\sigma_{noise}^2}{\sqrt{\max(\sigma_y^2 - \sigma_{noise}^2, 0)}} \tag{11}$$

This method defines the rules for applying the threshold to the coefficients.The threshold is compared to all coefficients of the contourlet domain and when the coefficients are less than the threshold value they are assigned zero values, otherwise they are kept unaltered. The reason behind it is that small coefficients are supposed to be not of signal elements and so can be modified to zeroes. The large coefficients are supposed to be of important signal features band. It also finds a threshold which minimizes the Bayesian risk. σ^2 is the noise variance and σ is the signal variance

iii) Neigh Shrink

The method NeighShrink thresholds the coefficients according to the magnitude of the squared sum of all the coefficients, i.e., the local energy, within the neighborhood window[2].The neighborhood window size may be 3×3, 5×5, 7×7, 9×9,etc. But, the authors have already demonstrated through the results that the 3×3 window is the best among all window sizes.The neighboring window of size 3* 3 centered at the coefficient to be shrinked.The shrinkage function for *NeighShrink* of any arbitrary 3×3 window centered at (i,j) is expressed as:

$$T_{ij} = 1 - \frac{T_u^2}{S_{ij}^2} \tag{12}$$

where, $T^2{}_u$ *is* the **universal threshold** and $S^2{}_{ij}$ is the squared sum of all wavelet coefficients in the respective 3×3 window given by:

$$S_{ij}^2 = \sum_{n=j-1}^{j+1} \sum_{m=i-1}^{i+1} Y_{m,n}^2 \tag{13}$$

2.6. Noise Models

i) Gaussian Noise or Amplifier Noise

This noise has a probability density function [pdf] of the normal distribution. It is also known as Gaussian distribution. It is a major part of the read noise of an image sensor that is of the constant level of noise in the dark areas of the image.[5]

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(z-\mu)^2}{2\sigma^2}} \tag{4}$$

ii) Speckle noise

A different type of noise in the coherent imaging of objects is called speckle noise. This noise is, in fact, caused by errors in data transmission [40, 42]. This kind of noise affects the ultrasound images [19]. Speckle noise follows a gamma distribution and is given as

$$F(g) = \frac{g^{\propto -1}}{(\propto -1)!a^{\propto}} e^{\frac{g}{a}} \tag{5}$$

where, $a^{\propto}$ is the variance, $\propto$ is the shape parameter of gamma distribution and g is the gray level.

iii) Poisson Noise

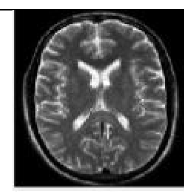
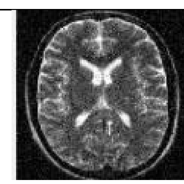
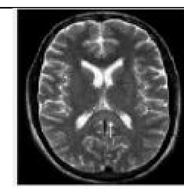
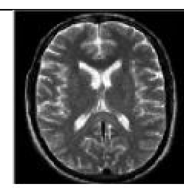
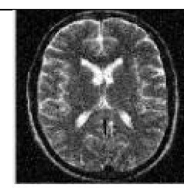
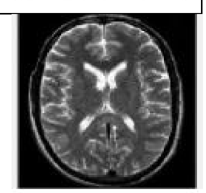
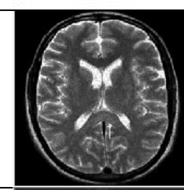
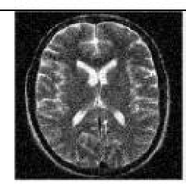
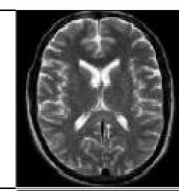
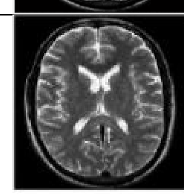
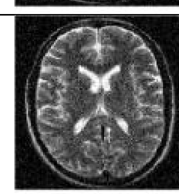
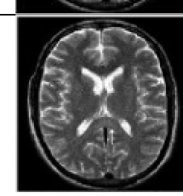
This noise mainly occurs in medical application like X-ray imaging and Infra-red imaging.[1] A Poisson noise can be stated in terms such that each pixel y of an image f(y) is derived from Poisson distribution function with parameter c=f(y)
where c is the original image to be drawn.

3.EXPERIMENTAL RESULT

Experiments were conducted in MRI Slicing brain image and X-Ray image is shown in Fig 6. Speckle,Gaussian and Poisson noise were considered.Noisy image are also presented in Fig 7 and Fig 8. Different threshold function are performed in MRI Image,X-ray images and their results of denoised image is shown in Fig 7 and Fig 8.

Fig 6 Original Image of MRI and X-RAY

Fig 7 Denoised image for new proposed method in MRI image

Noises	Speckle	Gaussian	Poisson
Noisy Image			
Neigh			
Bayes			
Block			

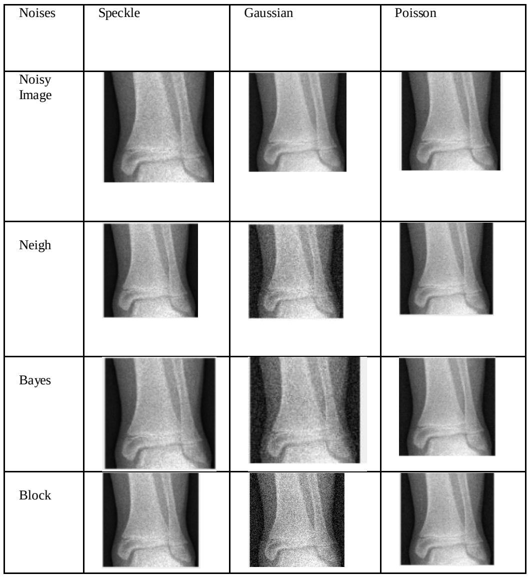


Fig 8 Denoised image for new proposed method in X-RAY image

4.PERFORMANCE ANALYSIS

4.1. Performance Metrics

i) Peak Signal to Noise Ratio (PSNR)

It is the ratio between maximum possible power of a signal and the power of corrupting noise that affects the quality and reliability of its representation. PSNR is calculated as

$$PSNR = 10Log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (14)$$

Where MSE is mean square error and MAX is the maximum pixel value of image [8].

ii) Structural Similarity Index (SSIM)

It is a method for measuring the similarity between two images. The SSIM measure the image quality based on an initial distortion-free image as reference.

$$SSIM=\frac{(2\mu_x\,\mu_{y+C_1})(2\sigma_{xy}C_2)}{(\mu_x^2+\mu_y^2+C1)(\sigma_x^2+\sigma_y^2+C2)} \qquad (15)$$

μ_x the average of x;
μ_y the average of y;
σx^2 the variance of x;
σy^2 the variance of y;
σ_{xy} the covariance of x and y;
$C_1= (k1L)^2$ and $C2 = (k2L)^2$

are two variables to stabilize the division with weak denominator. L the dynamic range of the pixel-values k1 = 0.01 and k2 = 0.03 by default. The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two identical sets of data.[16]

iii)Normalized Correlation (NC)

Normalized correlation is calculated by

$$NK = \sum_{I=1}^{M}\sum_{J=1}^{N}(g(i,j).g'(i,j)]/\sum_{i=1}^{M}\sum_{J=1}^{N}\big(g(i,j)\big)^2 \qquad (16)$$

If the normalized cross correlation tends to 1, then the image quality is deemed to be better.[3]

iv) Image Quality Index(IQI)

The Image Quality Index (IQI), Q, is proposed by Wang and Bovik [46] as a product of three different factors: loss of correlation, luminance distortion, and contrast distortion and is defined as

$$Q=\frac{\sigma_{fg}}{\sigma_f\sigma_g}\cdot\frac{2\bar{f}\bar{g}}{\bar{f}^2+\bar{g}^2}\cdot\frac{2\sigma_f\sigma_g}{\sigma_f^2+\sigma_g^2} \qquad (17)$$

The first component of eqn. (10) is the correlation coefficient between f and g, which measures the degree of linear correlation between f and g and its dynamic range is [-1,1]. The second component, with a value range of [0,1], measures how close the mean luminance is between f and g. σ_f and σ_g can be viewed as estimate of the contrast of f and g, so the third component with a value range of [0,1] measures how similar the contrasts of the images are.Thus, Q can be rewritten as

$$Q=\frac{4\sigma_{fg}\bar{f}\bar{g}}{(\sigma_f^2+\sigma_g^2)(\bar{f}^2+\bar{g}^2)} \qquad (18)$$

4.2. Performance Evaluation

The performance of new proposed work for combining Contourlet & UL PCNN model and thresholding techniques were studied using PSNR, SSIM, IQI, NCC.The first experiment is conducted to evaluate the performance of our new proposed work .Results are shown in Table I and Table II .Considering all the metrics, it is clearly observed in Table I removal of speckle noise gives better result than other noises and in Table II removal of poisson noise gives better than other noises The results are enhanced by applying thresholding techniques. Experimental results are analayed with 50,000 iterations

Table I Proposed work Contourlet and UL PCNN Model for denoised MRI image

THRESHOLD TYPE	SPECKLE	GAUSSIAN	POISSON	METRIC
NEIGH	45.8497	44.7137	45.8189	PSNR
BAYES	45.8527	44.7167	45.8176	
BLOCK	45.8538	44.7075	45.8083	
NEIGH	0.88711	0.40852	0.87252	SSIM
BAYES	0.89236	0.41053	0.87678	
BLOCK	0.89205	0.40835	0.87696	
NEIGH	0.72412	0.44189	0.70364	IQI
BAYES	0.78251	0.44411	0.74713	
BLOCK	0.78184	0.40835	0.74715	
NEIGH	0.99156	1.0150	0.99359	NCC
BAYES	0.99564	1.0183	0.99705	
BLOCK	0.99568	1.0184	0.99867	

Table II Proposed work Contourlet and UL PCNN Model for denoised X-Ray image

THRESHOLD TYPE	SPECKLE	GAUSSIAN	POISSON	METRIC
NEIGH	45.2805	44.6474	45.5197	PSNR
BAYES	45.2820	44.6445	45.5231	
BLOCK	45.2795	44.6477	45.5217	
NEIGH	0.47866	0.17038	0.50437	SSIM
BAYES	0.47987	0.16935	0.50688	
BLOCK	0.47980	0.17011	0.50629	
NEIGH	0.32710	0.13224	0.32468	IQI
BAYES	0.32979	0.13165	0.32789	
BLOCK	0.32846	0.13203	0.32609	
NEIGH	0.99685	1.0124	0.99697	NCC
BAYES	0.99930	1.0148	1.00070	
BLOCK	1.0004	1.0144	0.99970	

Experimental results demonstrate that the superiority of the proposed method,in the field of image quality. Table I shows the denoising results in MRI image and Table II shows the denoised results in X-Ray image. The results of our new proposed method has higher PSNR and IQI. From Table I and Table II, it found that new proposed work are best suitable for Speckle noise and Poisson noise in MRI and X-Ray images.

5.CONCLUSION

In this paper,we provide a new image denoising method based on Contourlet and UL PCNN Model. We have observed the experimental results with three shrinkages such as Neigh, Bayes and Block. These Thresholding function is used to reduces the noises and enhanced the image data. The achieved results were evaluated by the commonly used performance metrics such as PSNR,SSIM,IQI and NCC. Experimental results are illuminate that the Contourlet & UL PCNN method outperforms than other methods in both visual quality and preserving edges capabilities of the other approaches. The quality of the denoised image is better than original image. In MRI Image, Speckle noise is well suitable for Block shrink and Poisson noise is well suitable for Neigh Shrink. In X-Ray image, Speckle noise and Poisson noise is better suited for both Bayes shrink

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