Medical Image Denoising Based on ICM PCNN

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Abstract- **Image denoising is the crucial task in the area of image processing and computer vision. During the image acquisition, versatile intrinsic and extrinsic stimuli effectuate superfluous signals that lead to noisy image. Especially in medical images the quality of the image is never compromised as it is a life-sustaining issue in diagnosis. It is critical and most important to decimate the occurrence of noise in medical images. DWT (Discrete Wavelet Transform) and ICM PCNN (Intersecting Cortical Model Pulse Coupled Neural Network) model are employed to extinguish the occurrence of noise in medical images. DWT decomposes the input image into detailed and approximate coefficients at three levels resulting in best localization of the given image. The proposed jointure of ICM PCNN with DWT model classifies the image variance and detail variance without commoving the original image data. Filters are introduced to eliminate the noise that corrupted the input image. Wiener Filter, Adaptive Bilateral Filters and Boundary Discriminative Noise Detection (BDND) are used to denoise the speckle noise and salt and pepper noise present in the CT scan and Ultra Sound image. Results are assessed by estimating Peak Signal to Noise Ratio (PSNR), SSIM (Structural Similarity Index Measure), CoC (Coefficient of Correlation) and EPI (Edge Preserving Index) for Medical images corrupted with noise.**

Keywords- PCNN, PCNN ICM, DWT, BDND, ABF

1. INTRODUCTION

In image processing one of the chore is image denoising. Image denoising is a substantial task to provide the anatomical references that are concealed inside the noisy image. It aims at equipoise the blemishes, alters the original image without depriving image details and also upholds the abuts and quality of image.

Medical imaging is the approach of making visual representations of the internal structure of a body for clinical analysis and medical intercession. Biological imaging associates radiology which uses the imaging technologies of X-ray, radiography, magnetic resonance imaging, medical ultrasonography or ultrasound, endoscopy, electrography, tactile imaging, thermography, medical photography and nuclear medicine functional imaging techniques as Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography(SPECT).

Medical ultra-sonography uses high frequency broadband sound waves in the megahertz range that are reflected by tissue to varying degrees to produce (up to 3D) images. It is employed to analyze the internal body structure such as muscle, joints, vessels and internal organs. To view soft tissues of the human body such as internal organs and muscles, ultra-sonograms uses high-frequency sound waves. The ultrasound images are captured in real-time, it pictures the movement of the body's internal organs as well as blood flowing through blood vessels. CT (Computerized Tomography) scan is also called X-ray computed tomography. It is a combination of many x-ray images take from different angle to produce cross sectional images of specific areas of the scanned image to see inside the object without cutting.

Noise is the ergodic variation in image and the presence of unwanted signals may extend to blender the image details during image acquisition. Noises can inhibit details in the captured image and thus in turn leads to false diagnosis. Fourier Transforms are introduced to extinguish the various noises. FT gives only the frequency representation of the signals and not the time details. It is average in finding out the continuities in an image. To surmount these shortcomings DWT is employed to decimate the artifacts of images effectively than Fourier Transforms.

DWT analyses the signal at distinct resolutions called multiresolution. It affirms the multiresolution decomposition by decomposing of original image with approximation and detail coefficient. And it will retain all signal features irrespective of the frequency components. It maintains the acuity of an image and preserves the image details comfortably.

PCNN ICM is an excel tool for image denoising. It is a multiresolution proficiency for decomposition of an image. It decomposes the image based on noisy details and detail coefficient. It ousts the noisy pixels without agitating the neighboring pixel of an image. Faster computation efficiency and reduction in the number of equations than PCNN is achieved with PCNN ICM. And it also foregrounds the image details expeditiously.

Filtering is used to decimate the presence of noise in an image. It removes only the noise and take accounts of not affecting the contour details of image. It is exerted by either linear filtering or nonlinear filtering. Both high pass and low pass filtering are used to expel the corrupted pixel.

1.1. Related Works

Images are one of the most popular way of convey information in modern science and technologies, for e.g. in the medical field, communication, military purposes etc. So, it is very important that images should be of high quality and should not be affected because of any reasons. To improve the image quality, Denoising and Deblurring are the essential steps (Kaur & Mittal, 2016).

Image denoising is a process in image processing which eliminate noise from the image, enhance the image quality and recover fine details that may be hidden in the image (R.Coifman & Donoho, 1998). The image denoising algorithms have to tradeoff between the two parameters i.e. effective noise removal and preservation of image details (Grover, 2016). Image denoising algorithm deals with the elimination of the noisy components while preserving the important signal as much as possible. Image restoration is the process of diminution of the degraded images which are incurred while the image is being acquired (Rani, Nisha, & Sathik, 2016).

The technologies for acquiring digital medical images continue to improve and resulting in images of higher resolution and quality but removal of noise in these digital images remains one of the major challenges in the study of medical imaging because they could mask and blur important features in the images and many proposed de-noising techniques have their own problems. Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images (Kaur & Bansal, 2016).

The principal sources of noise in digital images arise during image acquisition and/or transmission (Gonzalez & Woods, 2008). Noise represents unwanted information which destroys the image quality (Shettar, Maini, S.Shreelakshmi, & Raj, 2013). Depending on a source, the noises are categorized into six types: acoustic noise; thermal and shot noise; electromagnetic noise; electrostatic noise; channel distortions, echo and fading; processing noise (JandKuosmanen, 1997).

Wavelet transform is a mathematical technique that decomposes the signal into series of small basis function called wavelets. It allow the multiresolution analysis of image and is well localized in both time and frequency domain. As a result of wavelet transform the image is decomposed into low frequency and high frequency components. The information content of these sub images that corresponds to Horizontal, Vertical and Diagonal directions implies unique feature of an image (L.Renjini & R.L.Jyothi, 2015).

Pulse Coupled Neural Network (PCNN) is another important image processing tool. It is a visual cortex-inspired network characterized by global coupling and pulse synchronization of neurons (Johnson, Ranganath, Kuntimad, & Caulfield, 1998), and has been widely applied in intelligent computing including image processing. 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 (Yide, Lian, & Yayu, 2006) (Kuntimad & Ranganath, 1999). PCNN has the characteristics of neurons synchronize with similar excitation, adaptive, generating an output pulse train. By using these attributes the impulse noise can be detected exactly. In order to filter noise, and meanwhile preserve image details and edge information effectively, the PCNN ignition matrix was adopted to detect and locate the noise (Han & Wu, 2015).

The Intersecting Cortical Model, ICM is a new visual cortex model that has the important biological background, compared with the PCNN, it has less unknown parameters and the computational complexity is significantly reduced, and has a superior image processing performance (Ling, 2013).

Filtering is a vital part of any signal processing system, which entails estimation of signal degradation and restoring the signal satisfactorily with its features preserved intact. The filters having good edge and image detail preservation properties are highly desirable for visual perception (Song, 1991) (JandKuosmanen, 1997). Generally, filters are divided into two groups as linear and non-linear. Linear filters have simple design and encoding and they are intended for general aim. These filters can be used to smooth the images or enhance the edges but they have weak capacity for noise elimination (Sun & Neuvo, 1994).

Objective quality measures are based on a mathematical comparison of the original and processed or enhanced image and can give an immediate estimate of the Perceptual quality of an image enhancement algorithm (Mohideen, Perumal, & Sathik, 2008).

1.2. Motivation and Justification

Image denoising is a technique for extinguishing artifacts introduced by the acquisition of an image. These artifacts constitute the degradation in medical images. As the medical images comprises of contextual information, the noise in an image may peril to false clinical diagnosis which further leads to severe complications. To avert such scenarios the decimation of image noise is indispensable. Image de-noising is a process which crusades until the artifacts are expelled. While removing the noise, retaining the actual pixels without disturbing them is requisite.

Fourier transform (FT) uses sinusoids for basic functions like decomposition, transformations etc. The Fourier transforms incorporates only frequency information. Temporal information is lost in the transformation process. To overcome these shortcomings, wavelet transforms are introduced in this work for the decimation of image noises.

Wavelet transform is one of the most powerful tool for Signal representation. DWT is a new scheme for multiresolution analysis. Multiresolution analysis allows image decomposition at various levels of coefficients to preserve infinitesimal information exists in an image. It efficiently addresses both the lower frequency components and higher frequency components in the process of decomposition. The resultant coefficients of different images can be aggregated to incur new coefficients.

The propose PCNN ICM is a prominent aid for image processing. An image may be polluted either only on partial picture elements or randomly distributed all over the image. PCNN has excellent capability to restore the image by modifying algorithm strategies. As it employs the time matrix to denoise the images, the restoration of the image properties is preserved to a greater extent. PCNN relies on multi-resolution decomposition for excerpting the features of interest in images by decimating image artifacts. A simplified PCNN with ICM is projected against the impulse noise to decimate effectively by keeping the details of the image. The use of simplified PCNN also reduces the time consumption of the entire work and the use of filters will help in curbing the noise. It showed a greater superiority in image processing compared to conventional algorithms. It has other various significant merits including the robustness against noise and the independence of geometric variations in input patterns. The attributes of the synchronous neuronal burst and the different firing fashion to different neurons can be utilized to situate the noise precisely. Motivated by these facts, discrete wavelet transform and the proposed work of PCCN ICM is exerted for denoising medical images.

1.3. Organization of the paper

The remaining paper is organized as follows. Methodology which include the proposed work of, Discrete Wavelet Transform, PCNN ICM model and filtering are represented in section 2. Experimental results are shown in section 3. Performance evaluations are discussed in section 4. Conclusion in Section 5.

2. METHODOLOGY

2.1. Outline of the proposed work

To overcome the artifacts present in input image is conceded to have with wavelet and PCNN ICM transformed to decompose the image and find out noise pixel. After identification of noise pixel filter is applied to remove the noise and reconstruct the image through inverse transformation process.

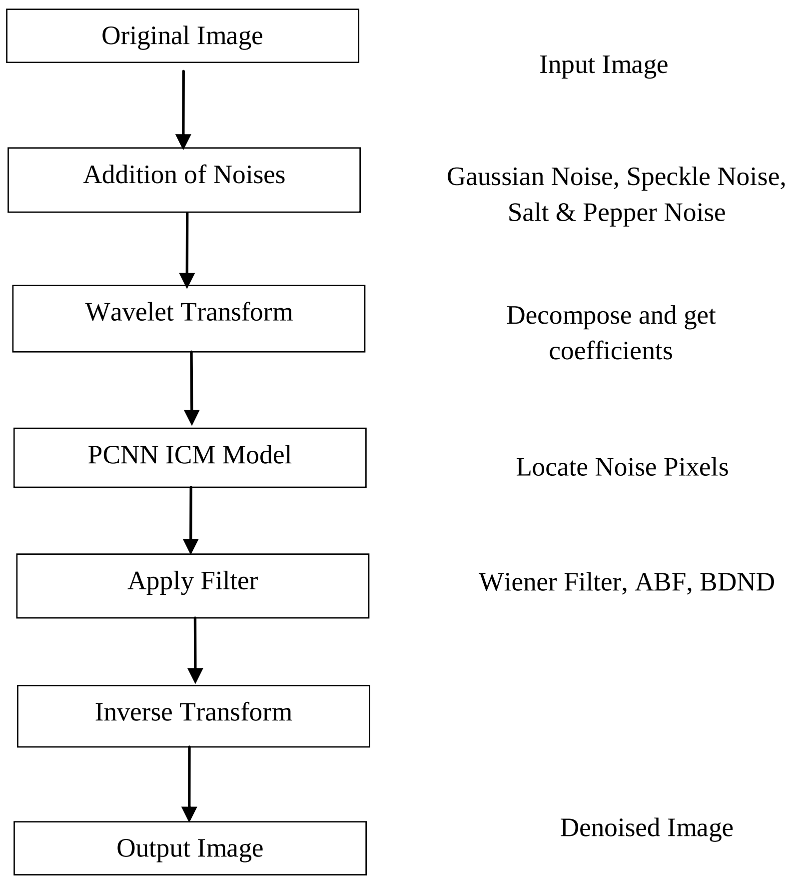

Figure 1. Image Denoising Block Diagram Using Wavelet and PCNN ICM Model

The restored image measured with metrics values like PSNR, COC, SSIM, EPI and UQI. Figure 1 illustrates the overall process of the proposed method.

2.2. DWT

Wavelet denoising attempts to remove noise which is present in the signal while retaining all the signal characteristics regardless of its frequency contents. Discrete wavelet transform decompose the original cover image into four frequency sub-bands namely LL, HH, LH and HL. LL frequency sub-band establishes the estimate details. The frequency sub-band LH is used to constitute the vertical details of the image, HL contains the horizontal details of the image and the HH sub-band contains the diagonal details of the image.

The LL sub-band that is the approximation of the digital image could be further decomposed with the use of discrete wavelet transform to get any level of decomposition of the digital content and it will generate the further four sub-bands. Thus multiple levels of decomposition could be obtained by applying the discrete wavelet transform on the approximation part, that is, on the LL part of the digital content as desired by the application. These sub band are the decomposition of original image. Sub band LL caries approximate element of image, LH contain the vertical element of image, HL contain the horizontal element of image and HH contains diagonal element of image. Thus the information of image is stored in decomposed form in these sub bands (Singh). Figure 2 show the wavelet decomposition at level 1.

LL1	HL1
LH1	HH1

Figure 2. Wavelet decomposition at level 1

The role of decomposition in the analysis of N*N image can be explained as:

- Initial low pass filtering of the rows blurs the image values along each row followed by low pass filtering along the columns which result in a low pass approximation of the whole image.
- Low pass filtering of the rows followed by high pass filtering of the columns highlights the changes that occur between the rows - horizontal details
- Initial high pass filtering of the original rows of the image highlights the changes between elements in any given low. Subsequent low pass filtering of the columns blurs the changes that may occur between the rows thus providing the vertical details
- High pass filtering of the rows followed by high pass filtering of the columns only changes that are neither horizontal are emphasized. This sequence gives the diagonal details of the original image.

2.3. PCCN basic model

The PCNN is single layered, two-dimensional, laterally connected neural network of pulse-coupled neurons, which are connected with image pixels each other.

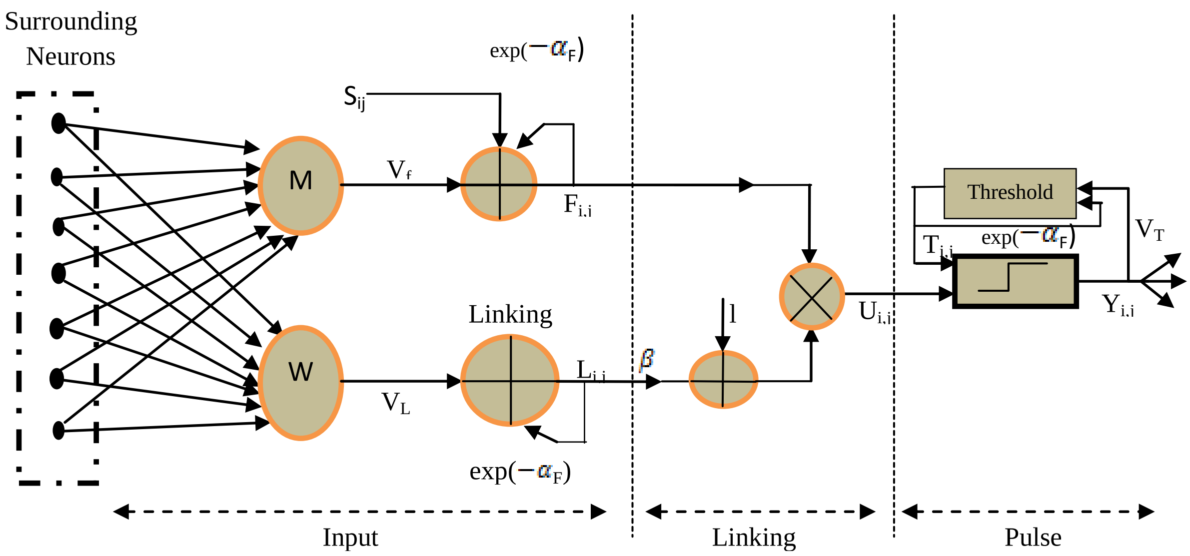

Figure 3. PCNN's Neuron model

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 Figure. 3. 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. The standard PCNN model is described as iteration by the following equation

$$F_{ij} = e^{\alpha} F_{ij}\left[n-1\right] + V_F \sum\nolimits_{k,i} W_{i,j,k,i} y_{i,j}\left[n-1\right] + S_{i,j} \tag{1}$$

$$L_{i,j} = e^{-\alpha f} L_{ij}[n-1] + V_L \sum\nolimits_{k,i} m_{i,k,i} y_{i,j}[n-1] \tag{2}$$

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

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

$$T_{i,j}[n] = e^{-\alpha_T} T_{i,j}[n-1] + V_T y_{i,j}[n] \tag{5}$$

In these equations (1-5), $S_{i,j}$ is the input stimulus such as the normalized gray level of image pixels in (i,j) position, $F_{i,j}[n]$ is the feedback input of the neuron in (i ,j) and $L_{i,j}[n]$ is the linking item. $U_{i,j}[n]$ is internal activity of neuron, and $T_{i,j}[n]$ is the dynamic threshold. $Y_{i,j}[n]$ 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 (Ranganath, Kuntimad, & Johnson, 1995) (Sattar, Floreby, Salomonsson, & Lovstrom, 1997).

2.4. PCNN ICM

Intersecting Cortical Model (ICM) and finds that there exist defaults in the frame structure and parameters determination. It improves the electronic nerve components of the classic ICM and uses the thinking in the new image de-nosing algorithm based on the PCNN timed matrix for reference, then it introduces the timed matrix T to determine adaptively the iteration times. On the above foundation, it put forward the Adaptive Image de-nosing Algorithm and gives the detailed steps. First of all, we improved the Intersecting Cortical Model (ICM), and gained the Timed matrix information on basis of the improved IICM, then determined the specific location of the pixels polluted by the impulse noise. We used the adaptive image de-noising algorithm to do the de-nosing process on these pixels, and then gave the specific steps of the adaptive image de-noising algorithm.

In which, the subscript (i, j) is the coordinate of each pixel; W_{ij} is the link matrix between neurons, Y_{ij} is the output value of the corresponding, which is either 1 or 0; F_{ij} ,S_{ij},θ_{ij} respectively represents the dendrites state value corresponding pixel value of the input image and the dynamic threshold of the neuron; f and g respectively represents the dendritic attenuation coefficient and the threshold attenuation coefficient of the corresponding iteration; h is the threshold amplitude constant; (f, g) and h are all scalar factors, and meet g<f<1, in order to ensure that a dynamic threshold value will be lower than the state value of neurons as the iteration continues. The structure of a basic ICM neurons and its discrete mathematical expression is as in the figure 4.

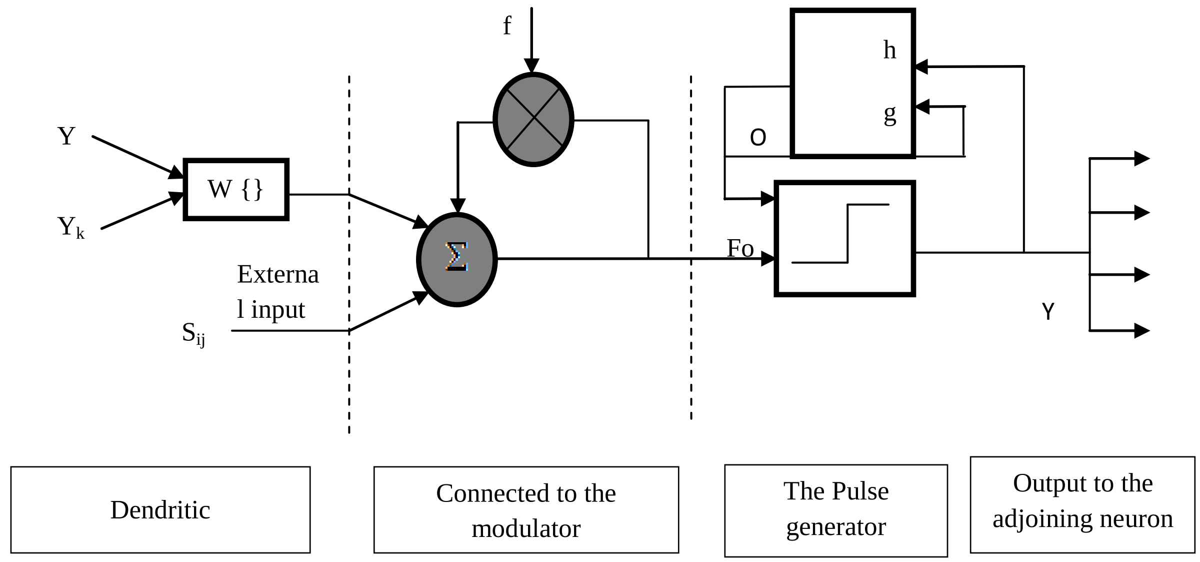

Figure 4: The structure of the ICM neuron

$$F_{i,j} = fF_{ij}(m-1)+S_{ij}+w_{ij}\{t[n-1]\} \tag{6}$$

$$Y_{ij}[n]=\begin{cases}1 & ifF_{ij}[n]\succ\theta_{ij}[n-1] \\ 0 & then\end{cases} \tag{7}$$

$$\theta_{ij} = g\theta_{ij}[n-1]+hy_{ij}[n] \tag{8}$$

Usually h is a big scalar value to ensure that after ignition each neuron can quickly enhance its dynamic threshold value to ensure that the neural will not be activated in the next iteration (Sampat, Wang, Gupta, Bovik, & Markey, 2009).

2.5. Noise Models

The noise is individuated by its pattern and with its probabilistic characteristics. There is a wide range of noise types are; Gaussian noise, salt and pepper noise, Poisson noise, impulse noise, speckle noise.

2.5.1 Gaussian Noise

Gaussian noise is the statistical noise which has its probability density function equal to that of a normal distribution, which is called as the Gaussian distribution. In the different words, the noise values can take on being Gaussian distributed. A different case is white Gaussian noise, values at any pair of the times are identically distributed and also statistically independent. In applications, Gaussian noise is normally used as additive white noise to the yield additive white Gaussian noise (Kuntimad & Ranganath, 1999)

$$g(x,y)= f(x,y)+n(x,y) \tag{9}$$

where g(x,y) is the output of the original image function f(x,y) corrupted by the additive Gaussian noise n(x,y)

Probability density function for Gaussian noise given below

$$p(g)=\sqrt{\frac{1}{2\Pi\sigma^2}}e^{\frac{-(g-\mu)^2}{2\sigma^2}} \tag{10}$$

where g represents the grey level, μ the mean value and σ the standard deviation.

2.5.2 Salt and Pepper Noise

Pepper and Salt noise are a form of the noise classically seen on the images. Salt and pepper noise represents itself as randomly happening black and white pixels. A real noise reduction technique for this kind of noise includes usage of the median filter, contra harmonic mean filter or a morphological filter. Pepper and Salt noise creeps into images in circumstances where quick transients, such as defective switching, take place. Salt and pepper noise is random in nature, it distributed randomly in the image pixel values (Umbaugh, 1998).

2.5.3 Speckle Noise

Speckle is a complex phenomenon, which degrades image quality with a backscattered wave appearance which originates from many microscopic diffused reflections that passing through internal organs and makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations. This type of noise occurs in almost all coherent systems such as SAR images, Ultrasound images, etc. The source of this noise is random interference between the coherent returns. The speckle noise follows a gamma distribution (Donoho, 1995).

$$g(x,y) = f(x,y) * n(x,y) \tag{11}$$

where g(x,y) is the result of the original image function f(x,y) corrupted by the multiplicative noise n(x,y).

2.6. Filtering Techniques

2.6.1 Wiener filter

Wiener filters are a class of optimum linear filters which involve linear estimation of a desired signal sequence from another related sequence. It is not an adaptive filter. The wiener filter's main purpose is to reduce the amount of noise present in an image by comparison with an estimation of the desired noiseless image. It is usually applied in the frequency domain (by taking the Fourier transform) (Kaur & Bansal, 2016), due to linear motion or unfocussed optics Wiener filter is the most important technique for removal of blur in images. The goal of the Wiener filter is to filter out noise that has corrupted a signal. Wiener filters are characterized by the following:

1. Assumption: signal and (additive) noise are stationary linear random processes with known spectral characteristics.
2. Requirement: the filter must be physically realizable,
3. I.e. causal (this requirement can be dropped, resulting in a non-causal solution).
4. Performance criteria: minimum mean-square error. Wiener Filter in the Fourier Domain as in Equation

$$f(u,v) = \left[\frac{H(u,v)}{H(u,v)^2 + \left[\frac{S_n(u,v)}{S_f(u,v)} \right]} \right] G(u,v) \tag{12}$$

where H(u,v) is the degradation function $H(u,v)^*$ is its conjugate complex and G(u,v) is the degraded image. Functions $s_f(u,v)$ and $s_n(u,v)$ are power spectra of the original image and the noise (Vijayalakshmi, C.Titus, & Beaulah, 2014).

2.6.2 Boundary Discriminative Noise Detection (BDND)

The boundary discriminative process consist of two iterations, in which the first iteration is essentially a noise detection step which is based on clustering the pixels in the image in a localized window into three groups, namely; lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. The clustering is based on defining two boundaries using the intensity differences in the ordered set of the pixels in the window. The pixel is classified as uncorrupted if it belongs to the middle cluster. Otherwise it is a noisy pixel. This noise detection mechanism showed impressive detection accuracy under different impulse noise models and the second iteration will only be invoked conditionally.

Step 1. Impose a 21x21 window, which is centered on the current pixel.

Step 2. Sort the pixels in the window according to the ascending order and find the median, med, of the sorted vector Vo.

Step 3. Compute the intensity difference between each pair of adjacent pixels across the sorted vector Vo and obtain the difference vector VD.

Step 4. For the pixel intensities between 0 and med in the Vo, find the maximum intensity difference in the VD of the same range and mark its corresponding pixel in the Vo as the boundary b1.

Step 5. Likewise, the boundary b2 is identified for pixel intensities between med and 255; three clusters are, thus, formed.

Step 6. If the pixel belongs to the middle cluster, it is classified as uncorrupted pixel, and the classification process stops; else, the second iteration will be invoked in the following.

Step 7. Impose a 3x3 window, being centered on the concerned pixel and repeat Steps 2–5

Step 8. If the pixel under consideration belongs to the middle cluster, it is classified as uncorrupted Pixel, otherwise corrupted (Gayathri, 2014).

$$F_{mn} = median\{B_{m-p,n-u} \mid (p,u) \in v \wedge B_{m-p,n-u} \in Z_c \tag{13}$$

$$V = \{(p,u) \mid -(V_y - 1)/2 \le (p,u) \le (V_y - 1)/2\} \tag{14}$$

2.6.3 Adaptive Bilateral Filter

In order to increase the sharpness of the image some modifications to the bilateral filter is to be done, a new method for both sharpening and smoothing the image is been proposed here. The response at [m0, n0] of the proposed shift-variant ABF to an impulse at [m, n] is given by:

$$h(m_0, n_0; m, n) = r_{m_0,n_0}^{-1} \exp\left\{ -\frac{(m-m_0)^2 + (n-n_0)^2}{2\sigma_d^2} \exp(-(g[m,n] - g[m_0,n_0] - \zeta[m_0 n_0]^2) \right. \tag{15}$$

where $[m_0,n_0]]$ is the center pixel of the window σd and σr are the standard deviations of the domain and range Gaussian filters, respectively.

The ABF retains the general form of a bilateral filter, but contains two important modifications. First, an offset ζ is introduced to the range filter in the ABF. Second, both ζ and the width of the range filter σr in the ABF are locally adaptive. The combination of a locally adaptive ζ and σr transforms the bilateral filter into a much more powerful filter that is capable of both smoothing and sharpening. Moreover, it sharpens an image by increasing the slope of the edges. It determines how selective the range filter is in choosing the pixels that are similar enough in gray value to be included in the averaging operation (Shettar, Maini, S.Shreelakshmi, & Raj, 2013).

3. EXPERIMENTAL RESULTS

The ultra-scan image to be denoised is shown in figure 5. The noises like Speckle Noise, Salt & Pepper Noise and Gaussian Noise is chosen. Figure 6 shows denoised of an ultra sound image for speckle noise, Gaussian noise and salt & pepper noise.

Figure 5. Original image of ultra-scan image

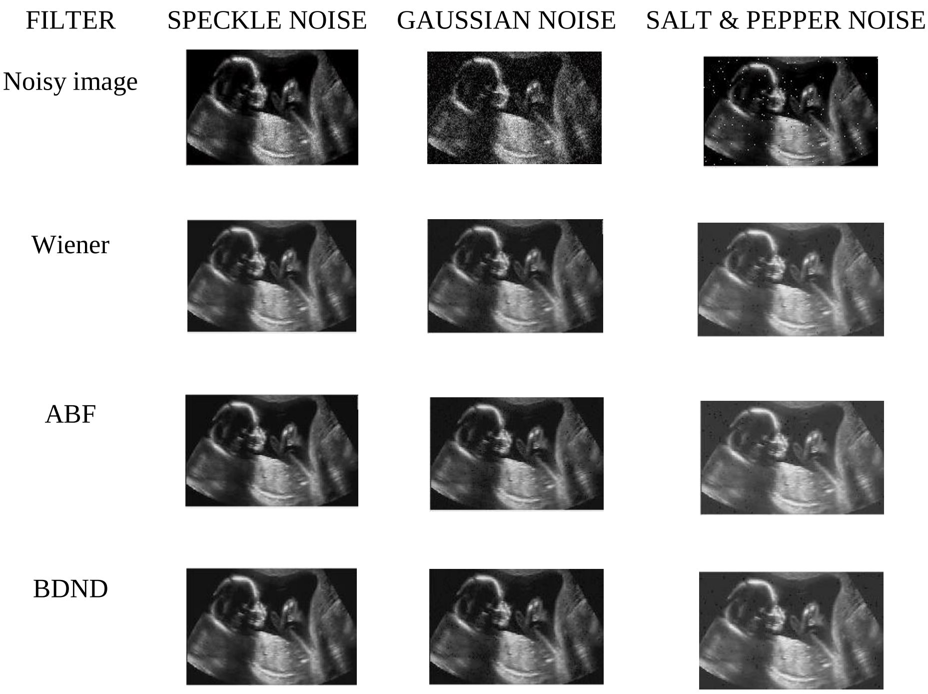

Figure 6. Denoised ultra sound images

3.1. Performance Metrics

3.1.1 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 using the equation (16).

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{16}$$

where MSE is mean square error and MAX is the maximum pixel value of image (Shettar, Maini, S.Shreelakshmi, & Raj, 2013).

3.1.2 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 using equation (17).

$$SSIM = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} c2)}{(\mu^2 x + \mu^2 y + c1)(\sigma^2 x + \sigma^2 y + c2)} \tag{17}$$

where

µx the average of x;
µy 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 (Yoshino, Dong, Washizawa, & Yamashita, 2010).

3.1.3 Edge Preservation Index (EPI)

$$EPI = \frac{\sum(\Delta x - \overline{\Delta x})(\Delta y - \overline{\Delta y})}{\sum(\Delta x - \overline{\Delta x})^2 (\Delta y - \overline{\Delta y})^2} \tag{18}$$

where, $\overline{\Delta x}$ and $\overline{\Delta y}$ are the high pass filtered versions of images x and y, obtained with a 3×3 pixel standard approximation of the Laplacian operator. The $\overline{\Delta x}$ and $\overline{\Delta y}$ are the mean values of the high pass filtered versions of Δx and Δy respectively.

3.1.4 Correlation Coefficient (CoC)

$$CoC = \frac{\sum(x - \overline{x})(y - \overline{y})}{\sqrt{\sum(x - \overline{x})^2 (y - \overline{y})^2}} \tag{19}$$

where, x and y are the mean of the original and denoised image respectively. The CoC is used to measure the similarity between the original image and despeckled image.

3.1.5 Universal Quality Index (UQI)

Universal quality index (Mohideen, Perumal, & Sathik, 2008) is the new parameter for comparison of quality of the image. Let x= {xi|i=1,2,…,N} and y={yi|i=1,2,…,N} be the original and the test image signal respectively. The quality index Q is defined as:

$$Q = \frac{4\sigma_{xy} xy}{(\sigma x^2 + \sigma y^2)[(\overline{x})^2 + (\overline{y})^2]} \tag{20}$$

Where

$$\overline{x} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

$$\overline{y} = \frac{1}{N} \sum_{i=1}^{N} y_i$$

$$\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2$$

$$\sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \overline{y})^2$$

$$\sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})(y_i - \overline{y})$$

The range of Q is [-1, 1]. The ideal value Q=1 will achieve iff $y_i=x_i$ for all i=1, 2,…,N, i.e. both images are same (Yide, Lian, & Yayu, 2006) .

3.2. Performance Evaluation

The performance evaluation of a proposed work, the Wavelet, PCNNICM transform is performed and filtering is applied to oust the noise present in an input image. Performance is calculated by PSNR, SSIM, COC, EPI and UQI. In Table 1 presents Speckle noise of ultrasound image with metrics. Table 2 presents Gaussian noise of ultrasound image with metrics. Table 3 presents Salt & pepper noise of ultrasound image with metrics.

Table : 1 Speckle noise of ultrasound image with metrics

SPECKLE NOISE FOR ULTRA SOUND IMAGE						
FILTERS	METRICS	PSNR	SSIM	COC	UQI	EPI
	WIENER	55.5087	0.99973	0.99996	0.92822	1.0065
	ABF	**57.3836**	0.99977	0.99998	0.91287	1.0058
	BDND	57.1542	0.99971	0.99998	0.93308	1.0058

Table : 2 Gaussian noise of ultrasound image with metrics

GAUSSIAN NOISE FOR ULTRA SOUND IMAGE						
FILTERS	METRICS	PSNR	SSIM	COC	UQI	EPI
	WIENER	**36.8368**	0.90294	0.99719	0.72414	1.2263
	ABF	36.4461	0.90326	0.99728	0.73041	1.2234
	BDND	35.5495	0.90437	0.99732	0.72825	1.2215

Table : 3 Salt & Pepper noise of ultrasound image with metrics

SALT & PEPPER NOISE FOR ULTRA SOUND IMAGE						
FILTERS	METRICS	PSNR	SSIM	COC	UQI	EPI
	WIENER	37.5147	0.92542	0.99779	0.80572	1.1366
	ABF	37.6023	0.92515	0.99783	0.80782	1.1375
	BDND	**38.432**	0.94211	0.99819	0.8214	1.1091

4. CONCLUSION

The wavelet and the proposed method of PCNN ICM constituted for removal of noise with filtering offers high quality. Wavelet used to decompose the image. PCCN Icm Model will help to locate the noisy pixel. By applying filters like ABF, BDND and wiener are used to remove the noisy pixel without loss of edge details in images.

The performance Metrics like PSNR, SSIM, UQI, EPI, COC are used to measure the denoised images. Wiener filter works well against speckle noise. ABF filter works well against Gaussian Noise. BDND filter works well against Salt & pepper Noise.

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