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Medical image de-noising using Anisotropic Diffusion

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ABSTRACT : Image denoising is an important image processing task. Removing noise from the original image is still a challenging problem for researchers. Several algorithms have been published and each approach has its assumptions, advantages, and limitations. Wavelets give high quality results in image de-noising due to properties such as sparsity and multi resolution. Images get reduced due to presence of noise when they are retrieved, stored, transmitted or acquired. In this work, we give an idea to de-noise images by applying anisotropic diffusion and multilevel Discrete Wavelet Transform (DWT) on different types of noise. The different types of noise which we consider here are speckle noise and salt & pepper noise.
KEYWORDS -Anisotropic Diffusion, Multilevel Discrete Wavelet Transform (DWT)

I. INTRODUCTION

This technique gives us a digital image such as medical or remote sensing image despeckling technique using Anisotropic Diffusion method. Here we will apply this method on different noise such as salt & pepper noise. This is a widely used and safe medical diagnostic technique. It is non-interfering in nature, cheaper, and has capability of forming real time imaging along with improvements in image quality. The utility of ultrasound imaging is deprived by the presence of signal dependent noise known as speckle. In this technique, a new method for speckle reduction is explained. Here, a noisy image is decomposed into four 7 subbands in wavelet domain considering 2 level wavelet transform. The low frequency subband contains the low frequency coefficients having structural components with noise and high frequency subbands contain the high frequency coefficients of texture components with noise that can be easily eliminated using Anisotropic Diffusion method. Also, along with speckle noise, salt and pepper noise will be applied for testing and evaluation of signal to noise ratio.

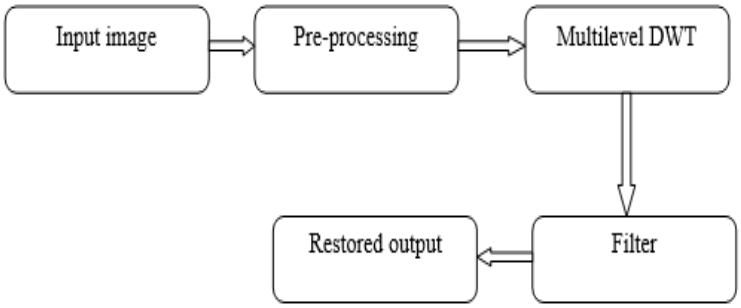

Fig 1: Tentative Model

The technique is compared with previous techniques as applied to simulated and unwanted parameters ie, mean square error and peak signal to noise ratio will be calculated for performance evaluation.

II. LITERATURE OVERVIEW

Image Denoising has remained a fundamental uncertainity in the stream of image processing.Various algorithms for denoising in wavelet domain were introduced in the last two decades. The advantages and usefullness of Wavelet Transform were better than Spatial and Fourier domain. Donoho's Wavelet based thresholding approach published in 1995 encouraged many others to publish papers in the denoising domain.[18] Although Donoho's work was not extraordinary, there was no requirement of tracking or comparing and realting of the wavelet maxima and minima over the number of scales as described by Mallat. [3]

Number of ways of calculating the parameters for the thresholding of wavelet coefficients were published by researchers. Also, a lot of effort has been invested in Bayesian denoising in Wavelet domain in recent research. Gaussian Scale Mixtures and Hidden Markov Models have also become well known resulting in publishing of more research work. There is a continued trend of focusing on using of different statistical models

for modelling the properties of the wavelet coefficients and its adjacent coefficients. In future, there will be a trend directed towards investigating more accurate and probabilistic models for the distribution of non-orthagonal wavelet coefficients.

Some more existing methods include total variation, wavelet and non-local means. The total variation method uses geometric features of the image, gives close match to the original signal or image, remove unwanted details while preserving important ones. The wavelet method utilizes the statistical features of the coefficients but the major drawback is that it is time consuming. The non-local mean method employs the mean value of group of pixels surrounding a target pixel to smooth the image.

III. WAVELET THEORY

A. WAVELET TRANSFORM

The Wavelets are known as DWT when they are sampled discretely. DWT is a multi-resolution decomposition structure. Utilizing DWT the primary image is decomposed into two subspaces of low frequency sub band and high frequency sub band. At every iteration of the DWT, the lines of the input image (obtained at the cessation of the precedent iteration) are high-pass filtered with a filter H and low-pass filtered with the filter L. There are two filters are decimated with a factor of two when the lines of the two images are obtained at the output. Then, the two columns of the images are low-pass filtered with L and high-pass filtered with H. The columns of those four images are additionally decimated with a factor of 2. This results in four incipient sub-images. The first sub image is denominated LL image or approximation sub-image. The other three are called detail sub-images: LH, HL and HH. For the next utterance, input is represented by LL image. In the given coefficients of DWT noted with $iDlm$, i represents the image. The resolution level or iteration represented by m and l=1 for HH image, l=2 for HL, l=3 for LH and l=4 for LL image. These coefficients are computed using eq. (1) to eq.(2). [1]

$$iD_m^l[n,p] = < i(\tau_1,\tau_2), \psi_{m,n,p}^l(\tau_1,\tau_2) > \quad (1)$$

where we can factorize the wavelets as:

$$\psi_{m,n,p}^l(\tau_1,\tau_2) = \alpha_{m,n,p}^l(\tau_1).\beta_{m,n,p}^l(\tau_2) \quad (2)$$

Using the proceeding relations and the scale function (τ) and mother wavelet (τ), the two factors can be computed using eq. (3) to eq. (4).

$$\alpha_{m,n,p}^l(\tau) = \begin{Bmatrix} \varphi_{m,n}(\tau), l = 1,4 \\ \psi_{m,n}(\tau), l = 2,3 \end{Bmatrix} \quad (3)$$

$$\beta_{m,n,p}^l(\tau) = \begin{Bmatrix} \varphi_{m,n}(\tau), l = 2,4 \\ \psi_{m,n}(\tau), l = 1,3 \end{Bmatrix} \quad (4)$$

Where,

$$\varphi_{m,n}(\tau) = 2^{-m/2}\varphi(2^{-m}\tau - n) \quad (5)$$

$$\psi_{m,n}(\tau) = 2^{-m/2}\psi(2^{-m}\tau - n) \quad (6)$$

B. DISCRETE WAVELET TRANSFORM

Discrete wavelet transform (DWT) is multiresolution decomposition of a signal. The low pass filter applied along a specific direction obtains the low frequency coefficients and the high pass filter obtains the high frequency coefficients of signal. [4]

In 2D applications, for every level of decomposition, the DWT is first performed in the vertical direction, followed by the DWT in the horizontal direction. After the first level of decomposition, there are 4 sub-bands: LL1, LH1, HL1, and HH1. For next each successive level of decomposition, in our approach the LH sub band of the precedent level is utilized as the input. Three levels of decomposition are performed on each component.

LH1, HL1, and HH1 contain the highest frequency bands present in the image section, while LL3 consists the lowest frequency band. [4]

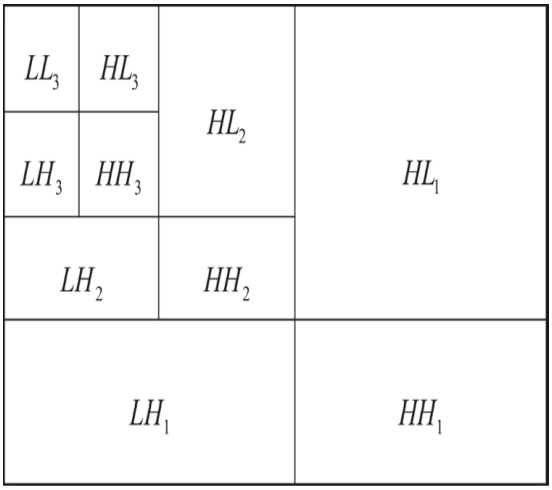

Fig 2: Three level DWT decomposition

IV. ANISOTROPIC DIFFUSION

It is a type of noise filtering technique. It was developed by Perona-Malik in 1987 and hence also called as Perona-Malik diffusion. It aims at reducing noise without removing significant parts of the image content, typically edges, lines or other details that are important for the understanding of the image.Anisotropic diffusion resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. This diffusion process is a non linear and space variant transformation of the original image.

V. ARTIFICIAL NEURAL NETWORK

ANN is similar to a biological neural network with a very competent information processing system. The special characteristics of ANN are its ability to learn, recall and generalize data and training patterns akin to that of human brain. Artificial Neurons or Neurons are the processing components of ANN and they are operated in parallel. [1]

ANN can be classified into two classes, namely Feed Forward and Feed-Back (FB). This classification is predicated on training pattern and network configurations. Here, we will focus on Feed Forward ANN. Here, the response is generated by processing the information in a forward pass. The weight and bias values for every neuron in this network is then upgraded by utilizing the back propagation supervised learning algorithm. [14]

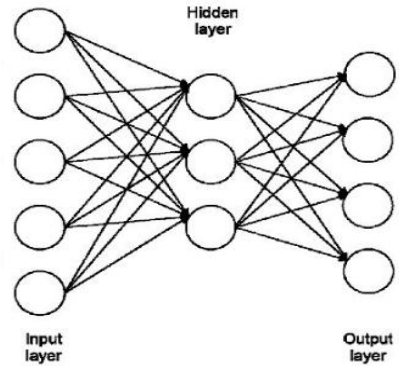

Fig 3: Architecture of FF ANN

A specific type of FF network known as Multi-Layer Perceptron (MLP) uses three or more layers of neurons. For non-linearly separable data they are able to co-relate training patterns with outputs. Fig 2 shows, an architecture of Feed Forward ANN.

VI. NOISE

Image noise is a random and unwanted variation of the information content of the image, and is generally an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise is an undesirable by-product of image capture that adds false and intrusive information.

Speckle noise

Speckle noise in an image means that some extra and unwanted pixels added in the image while taking a photograph through a digital camera. This degrades image quality and increases the size of image.

Salt and pepper noise

Salt and pepper noise is mostly seen on black and white images. it gives a grainy texture to image.

VII. RESULTS

We calculate the value for Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and Entropy for de-noised image. The calculated values apply for both types of noises i.e speckle noise and salt & pepper noise using equations,

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

Where,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2$$

Here, l is noisy image and K is the denoised image. m and n represent the dimensions of the images and *max* is the maximum pixel value.

TABLE 1

PSNR OF IMAGE-I WITH DIFFERENT NOISES FOR NOISE LEVELS 0.01

Types of noise	RMSE	PSNR	Entropy
Salt &pepper	5.40	40.80	7.10
Speckle	3.96	42.14	6.93

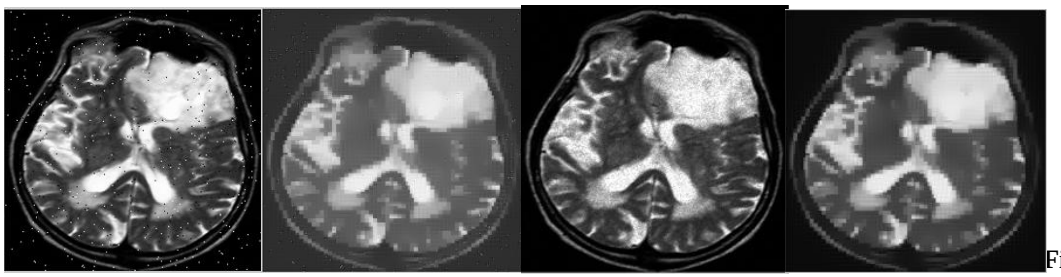

Fig 4: Noisy &De-noised Image with salt&pepper noise**Fig 5**: Noisy& De-noised image with speckle noise

TABLE 2

PSNR OF IMAGE-I WITH DIFFERENT NOISES FOR NOISE LEVELS 0.02

Types of noise	RMSE	PSNR	Entropy
Salt &pepper	17.85	35.61	7.18
Speckle	11.51	37.51	6.92

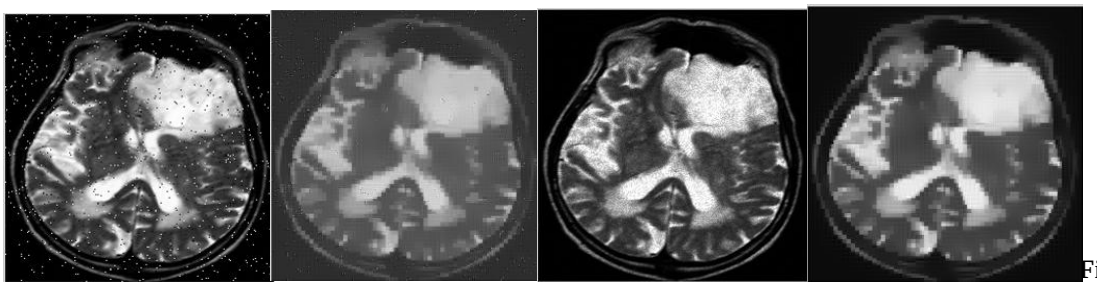

Fig 6: Noisy &De-noised Image with salt&pepper noise**Fig 7**: Noisy& De-noised image with speckle noise

TABLE 3
PSNR OF IMAGE-I WITH DIFFERENT NOISES FOR NOISE LEVELS 0.03

Types of noise	RMSE	PSNR	Entropy
Salt &pepper	28.31	33.61	7.25
Speckle	15.89	36.11	6.91

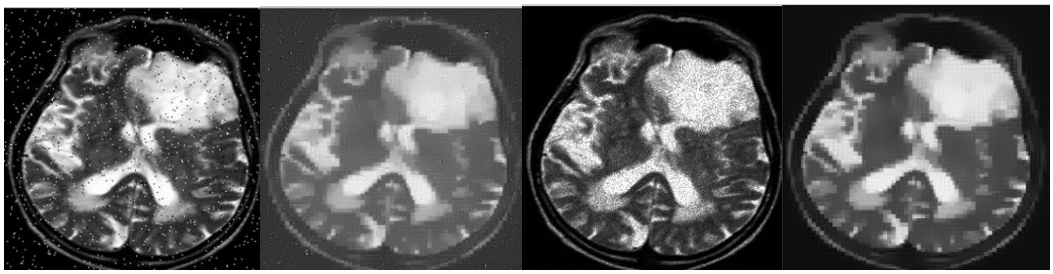

Fig 8: Noisy &De-noised Image with salt&pepper noise**Fig 9**: Noisy& De-noised image with speckle noise

TABLE 4
PSNR OF IMAGE-Il WITH DIFFERENT NOISES FOR NOISE LEVELS 0.01

Types of noise	RMSE	PSNR	Entropy
Salt &pepper	6.99	39.68	6.94
Speckle	4.04	42.06	6.92

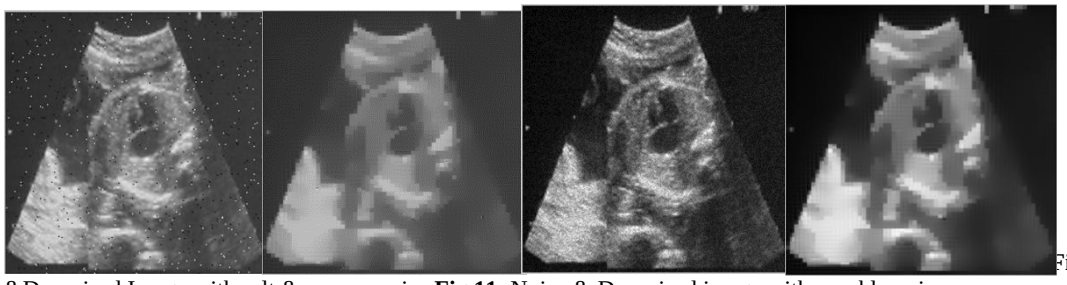

Fig 10: Noisy &De-noised Image with salt & pepper noise **Fig 11**: Noisy & De-noised image with speckle noise

TABLE 5
PSNR OF IMAGE-I WITH DIFFERENT NOISES FOR NOISE LEVELS 0.02

Types of noise	RMSE	PSNR	Entropy
Salt &pepper	6.75	39.83	6.96
Speckle	5.26	40.91	6.93

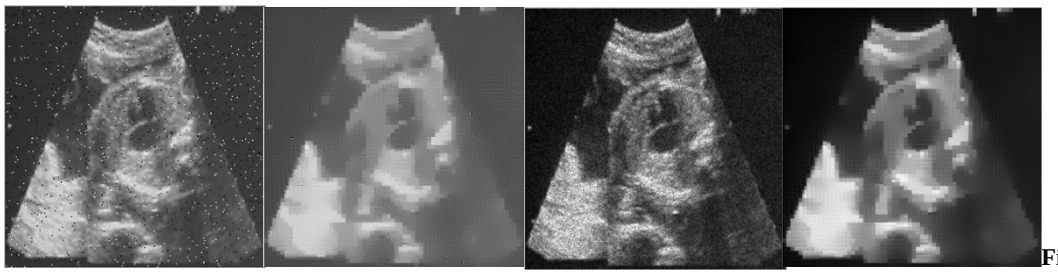

Fig 12: Noisy &De-noised Image with salt &pepper noise**Fig 13**: Noisy & De-noised image with speckle noise

TABLE 6
PSNR OF IMAGE-I WITH DIFFERENT NOISES FOR NOISE LEVELS 0.03

Types of noise	RMSE	PSNR	Entropy
Salt &pepper	7.56	39.34	6.99
Speckle	5.93	40.39	6.94

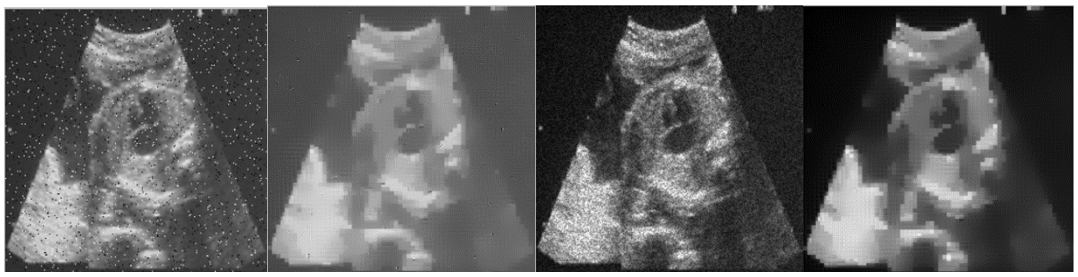

Fig 14:Noisy &De-noised Image with salt & pepper noise**Fig 15**:Noisy & De-noised image with speckle noise

VIII. CONCLUSION

The scope always exists for exploring innovative denominates of performing de-noising for enhancing image quality. Considering the precedence of image de-noising here, we present an approach to de-noise the images which is errored by the presence of noise. In this work we put together the advantages of anisotropic diffusion and DWT to obtain a competent image de-noising algorithm. Here, we utilize various test images, for speckle and salt and pepper noise with different noise level ranges. Our calculations are based on PSNR and Entropy. The PSNR of speckle noise is greater than that of salt and pepper noise. Whereas, Entropy levels are lower for speckle noise than salt and pepper noise.

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