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Spectral Domain Denoising Technique for Effective Removal of Noise in Medical Images

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Abstract
In general, various types of noise degrade the image during acquisition and transmission. In this work, the Gaussian noise that corrupts the CT image is removed by Fast Guided filter combined with Dual Tree Complex wavelet Transform . Guided filter is for edge aware image filtering that simply speed up from 0(N) time to 0(N/s2) time for a sub sampling ratio 's'. The filtered image is subtracted from the noisy image and results in method noise. The method noise has details in addition with the noise. The DTCWT is applied on the method noise to estimate the high frequency details by suppressing the noise effectively. The estimated noisy coefficients are removed and preserved with details by Bayes Shrink thresholding method and are discarded. Level dependent thresholding is carried out to preserve more details. Then the details are added with the filtered image to get the denoised image with details. The proposed method aims at increasing PSNR value when compared with the other existing techniques. Furthermore, the SSIM of the de-noised image will be improved.

Keywords**:** *Image filtering, Thresholding of wavelets, PSNR, DTCWT*

I INTRODUCTION

Medical image denoising has long been an area of research. In general, image gets corrupted by noise when acquired and transmitted. Distortion because of noise in CT images in the reconstruction stage, influences the increase of noise with decrease in the radiation dosage. The photon fluctuations in the CT images contribute the quantum noise, attenuation coefficients of tissue voxels that belong to the same tissue vary. Many studies have proved that CT images are more commonly affected by Gaussian noise. As CT images provide fine medical information, it is evident to provide clear images. To attain this many denoising techniques have been carried out. Several techniques have been proposed to decrease the noise in CT images. The spatial filtering is more successful in removal of high frequency noise but it has a high computational complexity while carrying out convolution. computational complexity was reduced by frequency domain methods. They make use of Fourier transform wherein convolution in spatial area was improved to increase in recurrence space. Low pass filter is used for denoising, as noise is spread throughout the image at wide range of frequencies. In our proposed work, Dual Tree Complex Wavelet Transform (DTCWT) which is a kind of complex valued wavelet transform is utilized. Compared to real valued wavelet transform, a complex valued wavelet transform find better characteristics within denoising application [14]. Table.1 exhibit the contrast in between the real valued wavelet transform along with complex valued wavelet transforms. From the table it shows very clear that, DTCWT have better features compared to the other transforms like DWT, LWT etc.

Table 1: Comparison of Real Valued Wavelet Transform and Complex Valued Wavelet Transform

Real Valued Wavelet Transforms	**Complex Valued Wavelet Transforms**

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Real filters with real coefficients are used in Real valued wavelet transform	Complex valued filters with complex valued coefficients are used in complex valued wavelet transform
Examples of Real Valued Wavelet Transform are Discrete Wavelet Transform (DWT)	Examples of Complex Valued Wavelet Transform are Dual Tree Complex Wavelet Transform (DTCWT)
Stationary Wavelet Transform (SWT) Multi Wavelet Transform (MWT) Lifting Wavelet Transform (LWT)	Daubechies Complex Wavelet Transform (DCWT)
Computation efficiency of a real valued wavelet transforms is achieved based on its better sparse representation	Two real DWT are used in parallel in DTCWT. For generation of real part one DWT is used and for imaginary part generation another DWT is used in DTCWT.
The main drawbacks of Real Valued Wavelet Transforms are they suffer from Shift Variance Lack of Directionality Absence of Phase Information Oscillation and Aliasing	The main properties which makes Dual tree complex wavelet transform favorable over other transforms are Shift Invariance High Directionality Perfect Reconstruction Computational Efficiency

II Proposed Methodology

The steps involved in the proposed spectral domain denoising technique for effective removal of noise in medical images are displayed in Figure 1.

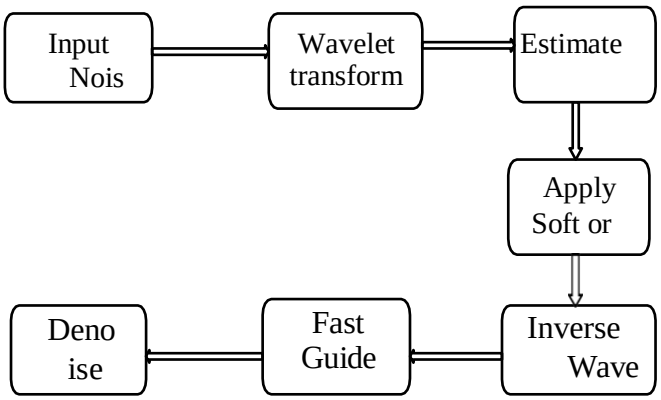

Fig .1. Block Diagram of Spectral Domain Denoising Technique

DTCWT is applied over the input noisy image over which thresholding is applied. Thresholding is the technique of removing the noisy coefficients from the wavelet coefficients. It is a non-linear technique, which works on each wavelet coefficient in turn. In its most essential structure, every coefficient is threshold by contrasting against the threshold. On the off chance that the coefficient is littler than the threshold value, it is set to zero in any case kept or altered. Exchanging the noisy coefficients by zero and taking inverse wavelet transform on the outcome prompts regeneration with basic sign attributes and with less noise. For a Thresholding algorithm to be really effective, it should preserve logical and semantic content.

Soft Thresholding overcomes the shortcomings of hard Thresholding. Soft Thresholding is smoothening activation function, wherein Thresholding is performed on the determined threshold limit. In hard Thresholding the attributes are either preserved or eliminated whereas in soft Thresholding the range for Thresholding is determined as follows:

tmp = (abs(x)-t) soft_t = (tmp+abs(tmp))/2
yw = sign(x)*soft_t

Where, x is the image on which Thresholding is performed, the determined thresholding value is

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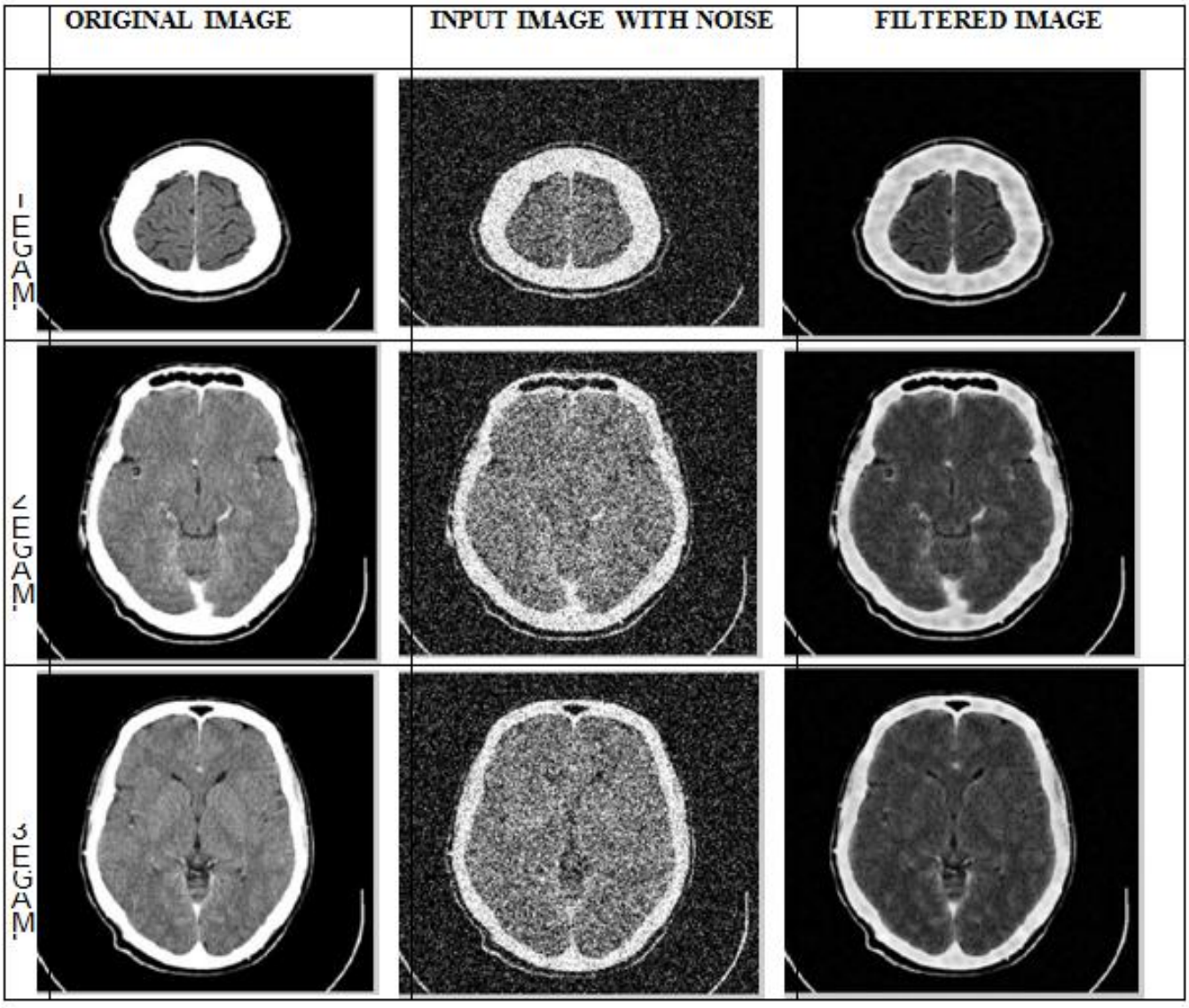
given by t, soft_t is soft thresholding value, sign(x) is the signum function [11].

III EXPERIMENTAL RESULTS

Fast guided filter with DTCWT is applied on various CT images [15] of the brain as shown in Table 1. The gray scale images are resized to 256 x 256 and are degraded by electronic noise with standard deviation varying from 10 to 50. The achievement of the proposed design is contrasted with other denoising techniques. Within the transform domain, comparison is done between DWT and DTCWT. Based on the comparison fast guided filter and DTCWT have been chosen the best in terms of Peak Signal to Noise Ratio and Structural Similarity Index Measure. The thresholding technique is also compared with other existing techniques such as hard, soft and trimmed thresholding, from which the soft thresholding is implemented for better results. The proposed algorithm uses daubechies(db8) wavelet for decomposition of the image. The parameters of fast guided filter are chosen as, Fast guided filter: epsilon=0.01, win_size=5.

Table 1: Comparison of the Original Image, With noise and Filtered Image



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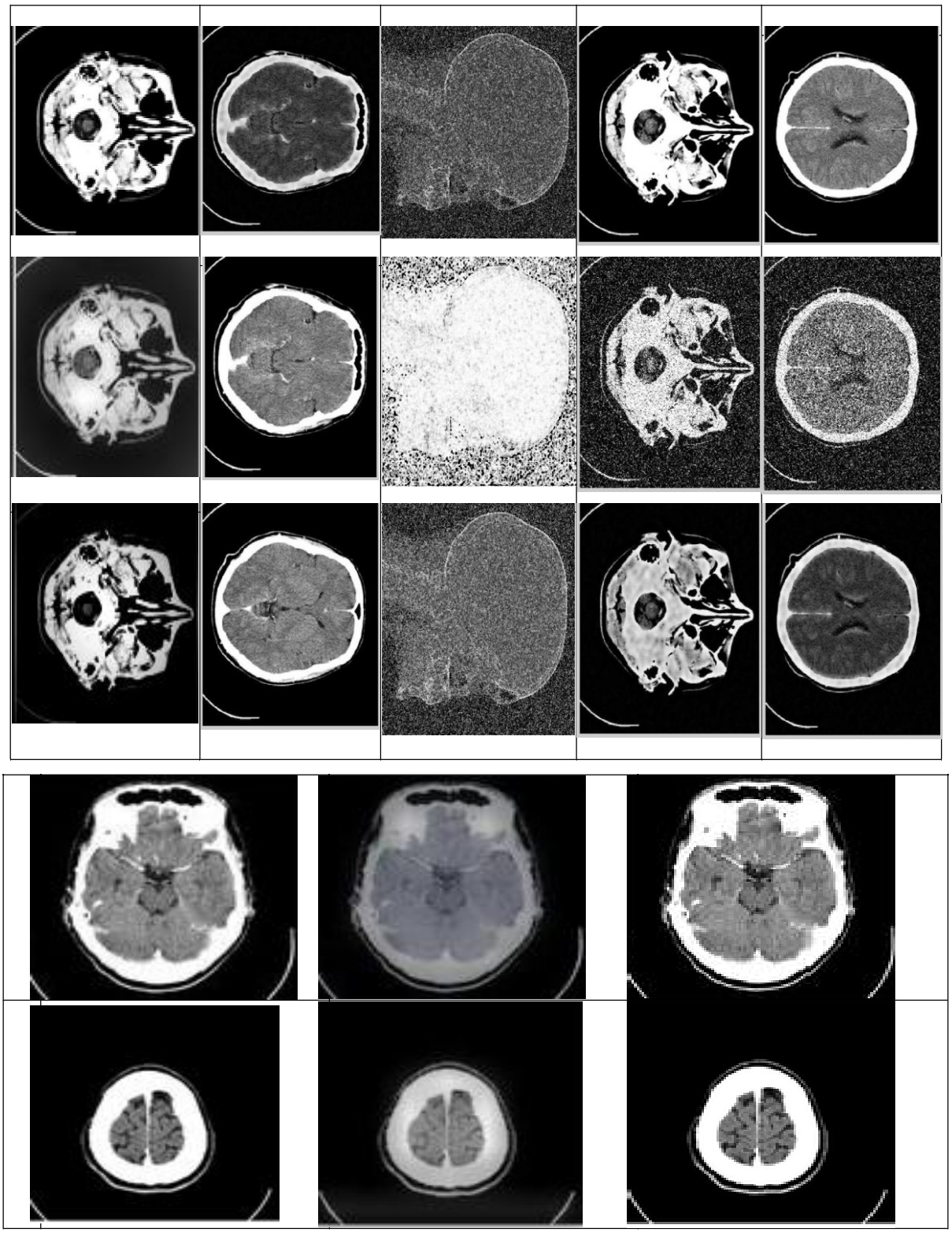

Table 2: Values for PSNR, SSIM and MSE in accordance with attenuation

SAMPLE NO.	dB	PSNR	SSIM	MSE
	10	61.579	0.053	0.05
IMAGE 1	20	64.146	0.0528	0.03
	30	69.425	0.5702	0.01
	40	72.812	0.6504	0

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	50	72.961	0.6541	0
IMAGE2	10	61.107	0.0282	0.05
	20	64.593	-0.0156	0.02
	30	65.323	0.2553	0.02
	40	65.844	0.2987	0.02
	50	65.887	0.2998	0.02
IMAGE 3	10	61.117	0.0301	0.05
	20	64.951	-0.0144	0.02
	30	65.432	0.263	0.02
	40	65.858	0.3067	0.02
	50	65.909	0.3074	0
IMAGE 4	10	61.256	0.0336	0.05
	20	65.11	-0.0076	0.02
	30	66.053	0.308	0.02
	40	66.65	0.3572	0.01
	50	66.712	0.3587	0.01
IMAGE 5	10	61.174	0.0324	0.05
	20	63.075	0.0434	0.01
	30	68.029	0.427	0.01
	40	70.854	0.4928	0.01
	50	71.056	0.4965	0.01
IMAGE 6	10	62.118	0.0301	0.05
	20	64.951	-0.0144	0.02
	30	66.998	0.263	0.02
	40	67.118	0.3067	0.02
	50	68.232	0.3074	0.02
IMAGE 7	10	61.256	0.0336	0.05
	20	65.11	-0.0076	0.02
	30	68.23	0.308	0.02
	40	71.92	0.3572	0.01
	50	73.69	0.3587	0.01
IMAGE 8	10	61.174	-0.0144	0.05
	20	66.232	0.0301	0.01
	30	68.029	0.263	0.01
	40	72.12	0.3067	0.01
	50	73.56	0.3074	0.01
IMAGE 9	10	61.256	-0.0156	0.05
	20	65.11	0.0282	0.02
	30	72.63	0.2553	0.02
	40	74.36	0.2987	0.01
	50	75.88	0.2998	0.01
IMAGE 10	10	61.174	0.053	0.05
	20	65.23	0.0528	0.01
	30	68.029	0.5702	0.01
	40	70.854	0.6504	0.01
	50	73.69	0.6541	0.01

For various attenuation values PSNR is calculated and plotted in Figures 3 to 7. It has been observed that the PSNR value will vary with respective to the attenuation values (10 dB to 50 dB). The varying PSNR values will depend on the pixel value of the images.

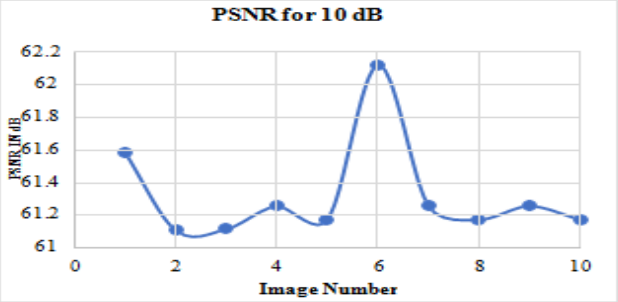

Fig 3: Graph for PSNR Vs attenuation

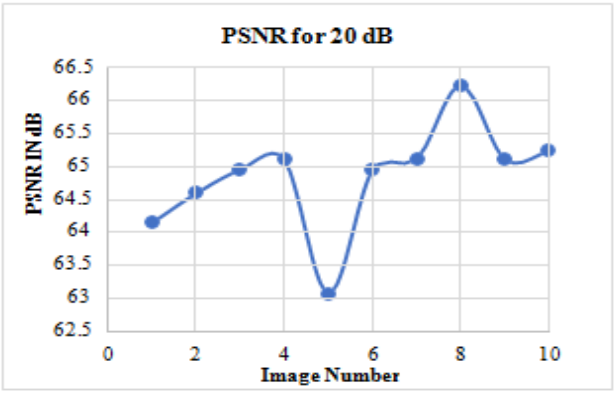

Fig 4: Graph for PSNR Vs attenuation

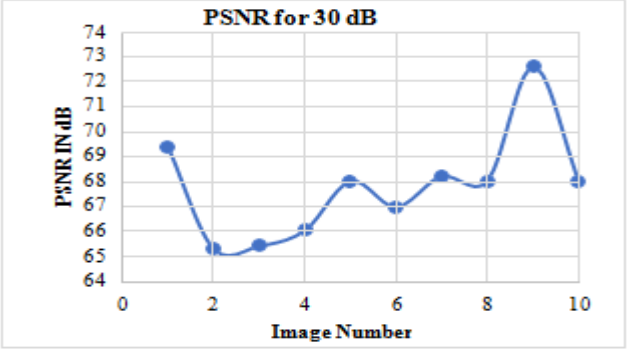

Fig 5: Graph for PSNR Vs attenuation

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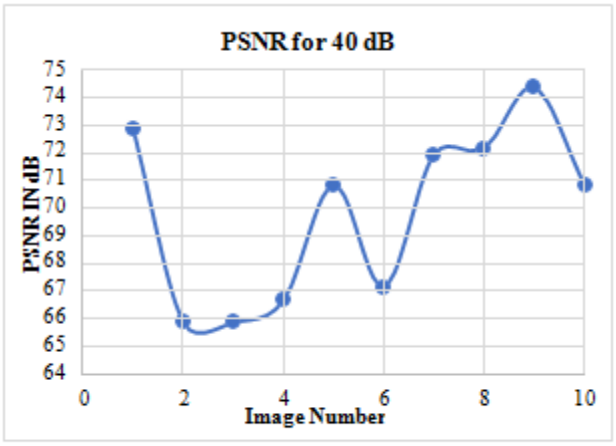

Fig 6: Graph for PSNR Vs attenuation

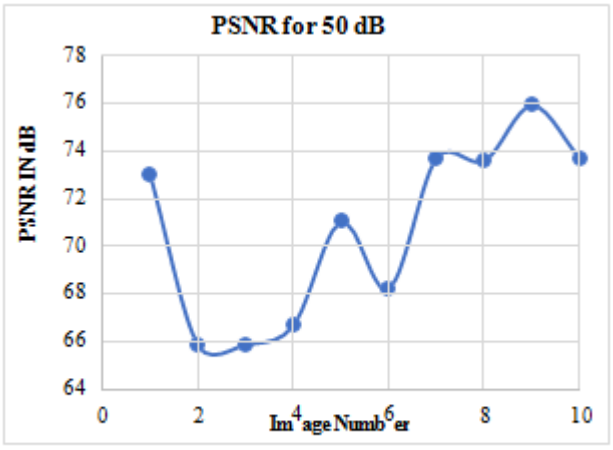

Fig 7: Graph for PSNR Vs attenuation

Figures 8 and 9 are plotted for various images and their calculated SSIM values for 10 dB and 20 dB attenuation. The change in SSIM value is similar to all the images for variable attenuation values.

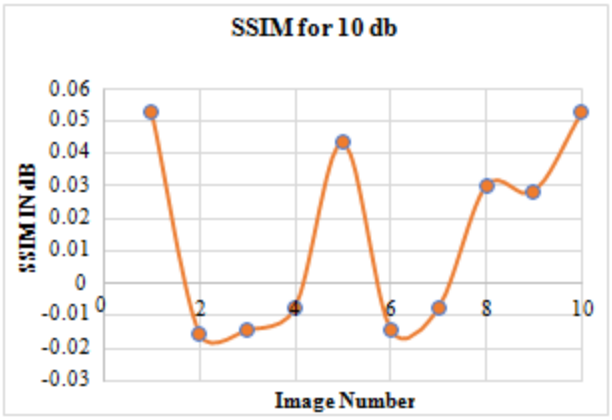

Fig 8: Graph for SSIM Vs attenuation

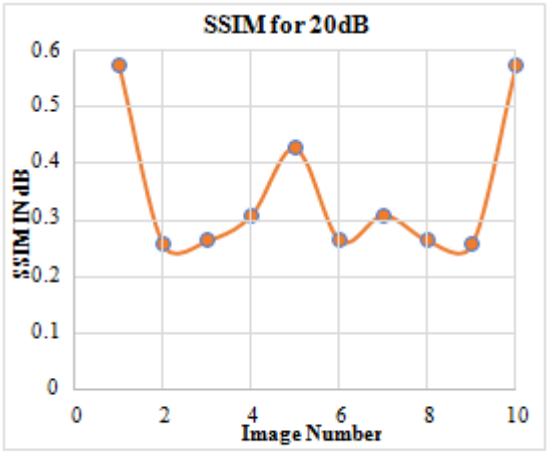

Fig 9: Graph for SSIM Vs attenuation

Figures 10 and 11, shows the relation of attenuation and MSE for two images (Image 1 and Image 2). From the figures it is inferred that the values of MSE goes on decreasing gradually with respect to the increase in the attenuation from 10 dB to 50 dB.

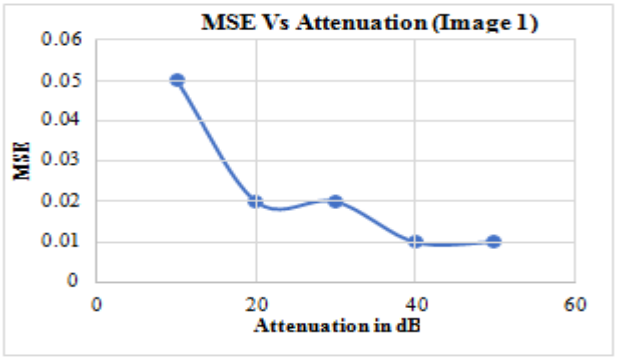

Fig 10: Graph for MSE Vs Attenuation for Image 1

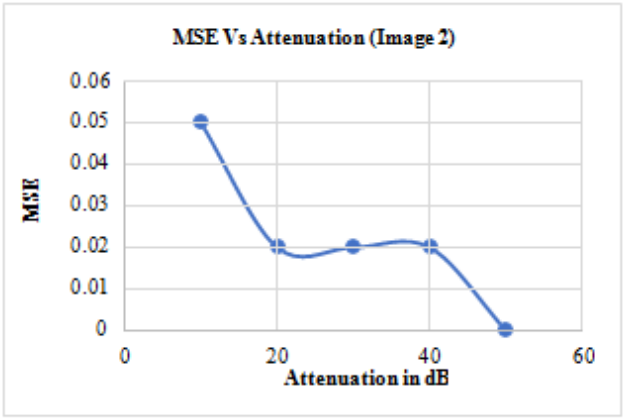

Fig 11: Graph for MSE Vs Attenuation for Image 2

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IV CONCLUSION

In this paper, to carry out denoising DTCWT is utilized. By the utilization of hard and soft thresholding functions for the shrinkage of wavelet coefficients and analyzed their effectiveness of denoising the pictures dependent on Peak Signal to Noise Ratio, Structural Similarity Index Measure and SSIM map. The following observations were also made from our proposed work: The value of PSNR will change in accordance with the pixel value of the image. Different images with different pixel values tend to vary in the PSNR value. PSNR value varies with the attenuation, the change in SSIM value is similar to all the images for variable attenuation values and MSE goes on decreasing gradually with respect to the increase in the attenuation from 10 dB to 50 dB.

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