CT Image Denoising using DTCWT with Level Dependent Thresholding

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Abstract— **This work aims at denoising CT images corrupted by Gaussian noise. In general, several types of noise degrade the image during acquisition and transmission. In this work, the Gaussian noise that corrupts the CT image is removed by using Bilateral Filter combined with Dual Tree Complex Wavelet Transform (DTCWT). The noisy image is filtered by using Bilateral Filter which comprises of two Gaussian Filter. These two filters serve to obtain the filtered image with required spatial and range properties. The difference between the filtered image and the noisy image results in method noise. The method noise has details in addition with noise. Then DTCWT is applied on the method noise to estimate the high frequency details by suppressing the noise effectively. The estimated wavelet coefficients are level dependent thresholded using Bayes Shrink Method which preserves the coefficient of details and discards noisy coefficients. The thresholding is implemented for each DWT in the DTCWT by thresholding separately to obtain the details efficiently. Then the fine details are added with the filtered image to get the denoised image with details. The proposed method gives very good PSNR value when compared with the other existing techniques. Furthermore, the UIQI and SSIM of the de-noised image depict the quality of the image. The denoised image is also visually pleasing.**

Keywords—CT image; Bilateral Filter; DTCWT; Wavelet Thresholding; BayesShrink; Method Noise.

I. Introduction

Denoising medical image that downgrades the signal has long been an area of research. In general, image gets corrupted by noise during acquisition and transmission. CT images are corrupted by noise in the reconstruction stage, where the influence of noise increases with decrease in the radiation dosage. In addition to this, CT images get blurred at the scanning stage. As the slice thickness increases, resolution of the image decreases. The photon fluctuations in the CT images contribute the quantum noise. Due to this quantum noise, attenuation coefficients of tissue voxels that belong to the same tissue vary [1],[2]. Many studies have proved that CT images are more commonly affected by Gaussian noise [2]. Further, CT image gets degraded by many other factors such as flaws in photon counting, duration to radiation exposure, dosage of the radiation and error that occurs in the device [3]. Furthermore, CT images can also get distorted due to scattering of X-rays projected on the patient, movements in the patient during scan like respiratory movements, peristaltic motion and heart beat. The noise affected CT images are less luminous and loses fine details [3]. All these issues contribute to corruption of CT image and complicate diagnosis. 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 algorithms have been proposed in the recent past to reduce 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. This computational complexity was reduced by frequency domain methods. They make use of Fourier transform wherein convolution in spatial domain was simplified to multiplication in frequency domain. Low pass filter is used for denoising, as noise is spread throughout the image at wide range of frequencies. This method fails in preserving the fine details that are dominated by noise and results in smoothened image [4].Another drawback of frequency domain method is the use of infinite length window. To overcome the shortcomings of the former techniques, Short Time Fourier Transform (STFT) was designed with a fixed length window. The use of fixed length window fits best for periodic signals. In case of aperiodic signals, fixed window cannot be used because the window that effectively works on high frequency will be less effective for low frequencies [7].Thus, a window with variable length is required. Wavelet transform makes use of variable window for denoising. Thus, many researches were made on wavelet transform. Wavelet transform gives a time-frequency analysis where the convolution of the wavelet and the signal gives many number of coefficients which are used back in its inverse form to obtain the signal of interest. However, many signals are discrete in nature which does not require continuously varying parameters. Hence, the discrete wavelet transform with discrete time wavelet came into use. Discrete wavelet transform (DWT) being invertible produces efficient results. DWT is a flexible tool and has good data compression. DWT fails to give an output that has shift invariance and good directional sensitivity for diagonal features. This makes DWT unsuitable for many signal applications. Several algorithms were proposed to compensate these limitations. One of the methods is the Shift Invariant wavelet transform (SIWT). This algorithm reduces shift variance of the denoised image by oversampling DWT, but fails in making it better in terms of directional sensitivity [6]. Another method proposed by Gopinath uses N number of filter banks that are parallel and phase shifted to each other reduces shift variance in a much better way. This algorithm is found to be more effective when two filter banks [7] are used, based on which Dual Tree Wavelet Transform (DTWT) was proposed. In DTWT the image to be denoised is decomposed as real values. DTWT was not popular as it does not completely overcome the limitations of DWT; in addition to this DTWT has the effect of aliasing and oscillations [8]. Having two parallel filter trees, the DTCWT decomposes the input as like the earlier proposed transform methods. In DTCWT the image is decomposed as complex values. The use of real and imaginary values aids DTCWT to lessen the effect of aliasing on Fourier Transform coefficients, achieve shift invariance and also makes it directional. This makes DTCWT a significant transform for many applications [9].

The Gaussian affected CT images when denoised by Weiner filter exhibit agreeable results with reasonable PSNR and reduced MSE, but the images obtained are blurred at the edges. Hasan Koyuncu et al proposed a Block Matching and 3D Filtering which outperforms other denoising techniques and also removes noise in micro CT images. The main disadvantage of using BM3D is that it produces clearly visible artifacts in low frequency regions of the denoised image [12]. The Dual Domain Image Denoising (DDID) algorithm designed by Knaus et al makes use of STFT in transform domain and Bilateral filter in spatial domain. When CT images are denoised with DDID algorithm, the resultant image gives better PSNR results than BM3D.This method preserves more details and also overcomes the blurring effect [10]. As stated earlier, drawback in STFT is its invariable window. DDID makes use of Bilateral filter for denoising in spatial domain, whose main advantage is that it considers both spatial and intensity information which makes it to preserve the edges. Bilateral filter removes the noisy pixel by averaging the nearby pixels except at the regions where noise exceeds the edge contrast [4]. The bilateral filter has two major hindrances: staircase effect and gradiant reversal. The staircase effect gives the denoised image a cartoonistic look. Gradient reversal results in duplication of edges [4]. Bilateral filter along with method noise thresholding gives better PSNR and IQI values but its computational complexity is more [11]. The use of method noise thresholding with bilateral filter minimizes gradient reversal but staircase effect still exists. When bilateral filter is used along with DTCWT the limitations of the former method can be reduced to a great extend. This method also aids in retrieving the fine details that gets filtered by bilateral filter and results in visually pleasing denoised image.

II. Bilateral Filter with Dual Tree Complex Wavelet Transfrom and it's Thresholding

A. *Bilateral Filter*

The Bilateral filter is a nonlinear filter proposed by Tomasi and Manduchi [12]. It makes use of two Gaussian filters: spatial filtering and range filtering. The spatial filter deals with pixel location while the range filter deals with pixel intensities. Spatial filtering is similar to the conventional methods, where the neighboring pixels that are present in the vicinity have influence on each other. Spatial filter is the Gaussian filter which can be implemented with different kernel size (say 5x5, 7x7, 11x11). The kernel size 5 x 5 of a Gaussian filter is illustrated below

$\frac{1}{273}$

1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

As Gaussian distribution is non-linear, the kernel size for the Gaussian filter cannot be pre-determined but can be applied with specific kernel size based on the characteristics of the image. Theoretically Gaussian distribution is non-zero for an infinite range and will require a kernel of infinite length for convolution. In practice as the kernel length increases, the standard deviation becomes negligible. Hence, the effective kernel size is chosen as per the requirements.

The range filtering is non-linear. The range filter assigns higher weightage to the pixel which has intensity similar to the centre pixel. At the edges, where there is a large variation in the intensity of the pixels, range filtering reduces the influence of the distant pixels thereby preserving the edges.

For a pixel m, the output of bilateral filter can be represented as:

$$X_f(m) = \frac{1}{w}\sum_{n\in s} C\sigma_s(\|m-n\|)C\sigma_r(|X(m)-X(n)|)X(n) \qquad (1)$$

Where, $C\sigma_s(\|m-n\|) = e^{-\frac{m-n^2}{2\sigma s^2}}$, is the closeness of nearby pixels.

$C\sigma_r(|X(m)-X(n)|) = e^{-\frac{|X(m)-X(n)|^2}{2\sigma r^2}}$ is the gray level similarity in range filter

$W=\sum_{n\in S} C\sigma_s(\|m - n\|)\ C\sigma_r\ (|X(m) - X(n)|)$ is the normalization constant

The bilateral filter makes use of two parameters namely, spatial standard deviation σ_s and range standard deviation σ_r which determine the fall of weights in spatial domain and range domain, respectively. Optimal use of these values gives better results. The spatial domain σ_s value is nearly insensitive to noise variance when compared to range standard deviation σ_r, so σ_r has to be adjusted according to the noise variance σ_n^2. Smoothness of the image depends on σ_s where the optimum values is chosen between 1.5 to 2 [4]. As the σ_s is the smoothing factor, the blurring effect in the image increases with increase in σ_s value. The optimum value of σ_r is determined by high frequency details of the image to be filtered. The σ_r is represented by the standard deviation of high frequency details which is obtained by the decomposition of the image using DWT. The increasing value of σ_r results in the flattening of Gaussian distribution curve, so the Bilateral Filter behaves as Gaussian Filter which can be preserved by iterating.

B. Dual Tree Complex Wavelet Transform

The Dual Tree structure implementation of wavelet transform has two versions such as the real DTWT and complex DTWT. The real DTWT is the two critically sampled DWTs using oscillating real wavelets. Unlike the real DTWT, DTCWT is based on the complex oscillating wavelets and it is the advantageous version of the real DTWT. The real DTWT is twice expansive than DWT (for N point signal it results in 2N number of wavelet coefficients) but the complex DTWT is four times expansive than the DWT.

The one-dimensional DTCWT is the implementation of two critically sampled DWT (Discrete Wavelet Transform). As far as image is concerned, the 2-D DTCWT is implemented with four critically sampled 2-D DWT. The 2-D DWT is implemented with analysis Filter Banks (FBs) and down sampling in forward transform while synthesis Filter Banks and up sampling in inverse transform. These filter banks are responsible for the Perfect Reconstruction (PR) conditions and are designed jointly such that the transform is analytic. The DTCWT has two different set of filters as there is no advantage if the filters in the upper and lower DWTs are same. The image is decomposed into low frequencies and high frequencies sub bands. The sub bands of the upper DWT are interpreted as the real part of the transform and the lower DWT sub bands are as the imaginary part of the transform. There are two wavelets associated for each direction where the DTCWT gives rise to six directions such that one of the two wavelets are real part of 2-D wavelet while another is the imaginary part. The complex wavelets associated with the upper and lower DWTs are Hilbert transform to each other and results with analytic property. The wavelet filters and the scaling functions are also responsible for the analytic property of the complex wavelets. The filters used in DTCWT are real and so there is no complex arithmetic involved in implementation of DTCWT.

The forward transform results with the sub bands of real and imaginary parts by the continuous decomposition of the high frequency bands till the desired decomposition level is reached. The inverse transform is implemented by the application of the four parallel inverse DWTs of real and imaginary parts which then averaged to obtain the original image. The original image can be retrieved by taking either the real or imaginary part alone.

The DTCWT has two sets of filter banks in the upper tree aligned in rows and columns. They are $h_0(n)$ and $h_1(n)$ where the $h_0(n)$ is the low pass filter and the $h_1(n)$ is the high pass filter. Similarly, the lower tree has its own low pass $g_0(n)$ and high pass $g_1(n)$ filters. Then each pair of low pass and high pass filters gives the sub bands of each decomposition level. The wavelet associated with the upper tree is $\varphi_u(t)$ is real part of complex wavelet and the wavelet associated with the lower tree is $\varphi_l(t)$ is the imaginary part of the complex wavelet. The complex wavelet is illustrated as $\varphi_u(t)+j\varphi_l(t)$, where $\varphi_u(t)=HT(\varphi_l(t))$. The implementation of Inverse DTCWT is as given in fig.3. The filter banks are used to reconstruct the image from the real and imaginary part of the transform. The conditions for the filters are same as with the forward transform. The recovered bands are averaged to get the original image.

C. Wavelet Thresholding

Thresholding is the technique by which the noisy coefficients are removed from the image. Thresholding can be carried out in two ways: hard thresholding, soft thresholding. Hard thresholding is the keep or kill procedure where the coefficients above threshold value are preserved and the coefficients below the threshold value are discarded. Hard thresholding introduces artifacts in the output. Soft thresholding overcomes the shortcomings of hard thresholding. Soft thresholding is smoothening activation function, wherein thresholding is performed on the determined threshold value. In hard thresholding the coefficients are either preserved or eliminated whereas in soft thresholding the range for thresholding is determined as follows:

$$tmp = (abs(x) - t) \quad (2)$$
$$soft\_t = (tmp + abs\ (tmp))/2 \quad (3)$$
$$yw = sign(x).*soft\_t \quad (4)$$

where, x is the image on which thresholding is performed, t is the determined threshold value, soft_t is the soft threshold value, sign(x) is the signum function.

In wavelet decomposition the image is decomposed into four subbands, namely HH, LL, HL and LH. The HH subband (diagonal subband) contains the high frequency details of the image; LL subband is the low resolution subband which can be further split (HH, LL, HL and LH) at higher levels of decomposition. The wavelet coefficients comprise of noisy coefficients and coefficients of details. Wavelet thresholding is an effective technique used for denoising the signal in transform domain. Wavelet thresholding has to remove the noise and preserve the details, for which many thresholding techniques like BayesShrink, SureShrink, VisuShrink have been proposed. VisuShrink applies global threshold method for thresholding the decomposed wavelets. VisuShrink thresholding technique results in an overly smoothed image thereby losing the high frequency details. Further, this thresholding technique do not adapt well at the edges. SureShrink technique thresholds each subband by adaptive thresholding method. SureShrink produces better results than VisuShrink. The sharp edges are also preserved by this method. BayesShrink thresholding method is an adaptive data driven threshold where the optimal threshold value is obtained from the diagonal subband. BayesShrink method smoothen the image while preserving the edges, thereby resulting a visually pleasing image. BayesShrink technique outperforms SureShrink in terms of MSE [13].

In literature, global thresholding is performed on DTCWT. DTCWT is the implementation of four DWTs (real and imaginary). Hence, any one of the DWTs is chosen to find the optimum threshold value and the thresholding is implemented on DTCWT. The shortcoming of using global thresholding can be explained with the standard deviation (from HH1 band) chosen for thresholding. When the DWT with lowest standard deviation is chosen for thresholding DTCWT, the DWTs with higher standard deviation preserves noise along with the details. Similarly, when the DWT with higher standard deviation is chosen for thresholding, the DWTs with lesser standard deviation will lose their details. To overcome this shortcoming, this work finds an optimum threshold value for each DWT and BayesShrink soft thresholding is performed on it. This method of thresholding removes noise in all the DWTs, thereby obtaining a denoised image with more details.

III. Bilateral Filter and Method Noise Thresholding.

This framework depicts the idea proposed for denoising CT images as suggested [4]. The CT image that is affected by Gaussian noise is given to the bilateral filter. Bilateral filter denoises the image and preserves the edges of the filtered image. The filter tends to lose some of the fine details during denoising. Hence, the difference between the original image and filtered image illustrates the method noise, which is given by:

$$MN = X - X_f \tag{5}$$

Where, X is the noise affected image, X_f is the filtered image and MN is the method noise.

Hence, the method noise contains Gaussian noise G that degrades the signal of interest and details of the image D_i. This can be represented as:

$$MN = D_i + G \tag{6}$$

CT image has to provide all the details of the scanned body part very clearly. Hence it is necessary to preserve as much details as possible. The fine details of the image are highly influenced by noise. Thus, details that are superimposed by noise have to be retrieved, for which wavelet transform is used. The DTCWT is applied on the method noise which results in coefficients of noise as well as coefficients of details. It is given by

$$P = W_c + N \tag{7}$$

where N is the Gaussian noise, W_c is the wavelet coefficient that contains detail and P is the noisy wavelet coefficient. So it is evident that the Gaussian noise N that prevails in P has to be suppressed to acquire the details W_c. Wavelet thresholding is done to remove N from filtered image P. Wavelet thresholding proposed by Donoho is an effective method for denoising. Wavelet thresholding thresholds the image at all subbands. This suppresses the coefficients of noise effectively. It provides an optimal threshold value when compared to universal thresholding. In this work, BayesShrink is used for thresholding as it provides better thresholding than other wavelet thresholding methods. BayesShrink is an adaptive thresholding method, in which soft thresholding is performed on the subbands. The noise level in the subband is estimated using Robust median estimator. Based on the parameters obtained, thresholding is done. In which, soft thresholding is preferred as it does not produce visible artifacts like hard thresholding. On thresholding, maximum noise gets suppressed and provides true wavelet coefficient W_t .

When inverse DTCWT is performed on the wavelet coefficient W_t, it gives the detail image D_t which was secured on thresholding. The filtered image X_f and the details D_t obtained from IDTCWT when put together gives denoised image X_d as output. As the filtered out details are added back to the output of filtered image X_f , more details are preserved in the denoised image X_d.

IV. Results and Discussion.

Bilateral with DTCWT is experimented on various CT images of the brain as shown in the Fig 2. The gray scale images are resized to 256 x 256 and are corrupted by Gaussian noise with standard deviation ranging from 10 to 50.

The performance of the proposed method is compared with other denoising techniques like Gaussian filter, Wiener filter, Non local mean filter and Bilateral filter in terms of method noise, PSNR, Universal Image Quality Index (UIQI), VFI and SSIM. The denoising methods in literature like Gaussian filter, Wiener filter, Non Local Mean filter and Bilateral filter are implemented using the parameter values recommended by

Sheryamsha Kumar. Bilateral filter with DTCWT uses debuchies8 (db8) wavelet for decomposition of the image. The image is decomposed into three stages and the noisy coefficients are thresholded using the BayesShrink soft thresholding method. On decomposing the image using wavelet transform, the high frequency details are present in the diagonal subband. These high frequency details have less intervention of noise and gives lower standard deviation. Hence, the diagonal subband is opted for determining the standard deviation. In this work first level HH band is used to determine the standard deviation in both spatial domain and transform domain. The parameters used in various denoising methods are stated below

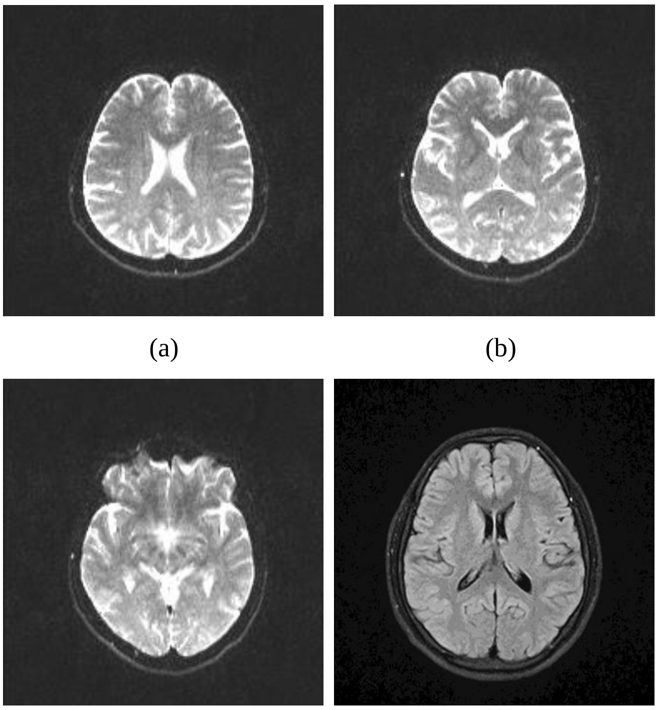
TABLE I. VARIOUS TYPE OF BAYESSHRINK THRESHOLDING METHOD.

SIGMA	10	20	30	40	50
Hard thresholding	34.29	30.50	27.41	25.33	23.66
Trimmed thresholding	35.06	30.64	27.89	25.85	24.08
Soft thresholding	34.91	30.67	28.05	26.01	24.16

Bilateral filter: σs =1.8, σr =5σn, kernel size=11 × 11
Gaussian filter: σs = 1.8, kernel size = 11 × 11
Bilateral Filter with Method Noise Thresholding: σs =1.8, σr =5σn, kernel size =11 × 11

The BayesShrink thresholding method is of three types: Hard thresholding, Soft thresholding, Trimmed thresholding. The Table 1 depicts the PSNR value of Bilateral DTCWT using different types of thresholding. From this table it can be inferred that BayesShrink Hard thresholding removes details along with noise on thresholding and results in a smoothed image. For σ 10, Trimmed thresholding gives higher PSNR than soft thresholding, but for other σ values (20, 30, 40, 50 and above) Trimmed thresholding cannot preserve details as effectively as soft thresholding.

An efficient denoising algorithm should remove noise and preserve the details of the image. When the denoising technique is applied on a noiseless image, the texture of the image must not get altered. The effectiveness of the filter can be identified using the method noise. In the Fig. 3 the method noise of various denoising methods like Gaussian filter, Wiener filter, Non Local Mean filter and Bilateral filter have been compared with the proposed filter for the original image(d) influenced by Gaussian noise of standard deviation 20. From Fig. 3(b), (c) and (e) it can be observed that more details are present at the edges of the method noise image. This depicts that the filters do not preserve the details rather



(a) (b) (c) (d)

Fig.2. Original CT images of brain used for experiment.

discard the details along with noise. In Fig. 3(c) the details are visible at the centre of the image (near the thalamus region) and near the meninges. Fig, 3(e) illustrates the method noise of bilateral filter which has fewer details when compared to the former methods, but the grooves of the brain like fissures, sulci can still be noted. The proposed work performs wavelet thresholding on the method noise and adds the details to the denoised image i.e. it restores the removed details. As the details are transferred to the denoised image, the method noise of Bilateral filter with DTCWT do not have much details as like other denoising methods.

The quality of the image can be determined by two methods: visiblity of noise in the filtered image, preservation of details. The original image is corrupted by Gaussian noise of different standard deviation levels and are denoised using various denoising methods. Figure 4 and 5 shows the denoised image of denoising methods at σ = 20 and 40. The denoised image of Wiener filter at Fig. 5(c) shows that the filter flattens the grayscale on denoising. The Gaussian filtered and Bilateral filtered images in Fig. 5(b) and (e) depicts that the filter smoothen the image on denoising. In Bilateral fiter with DTCWT, due to wavelet thresholding the details near the thalamus region and at the edges are well preserved.

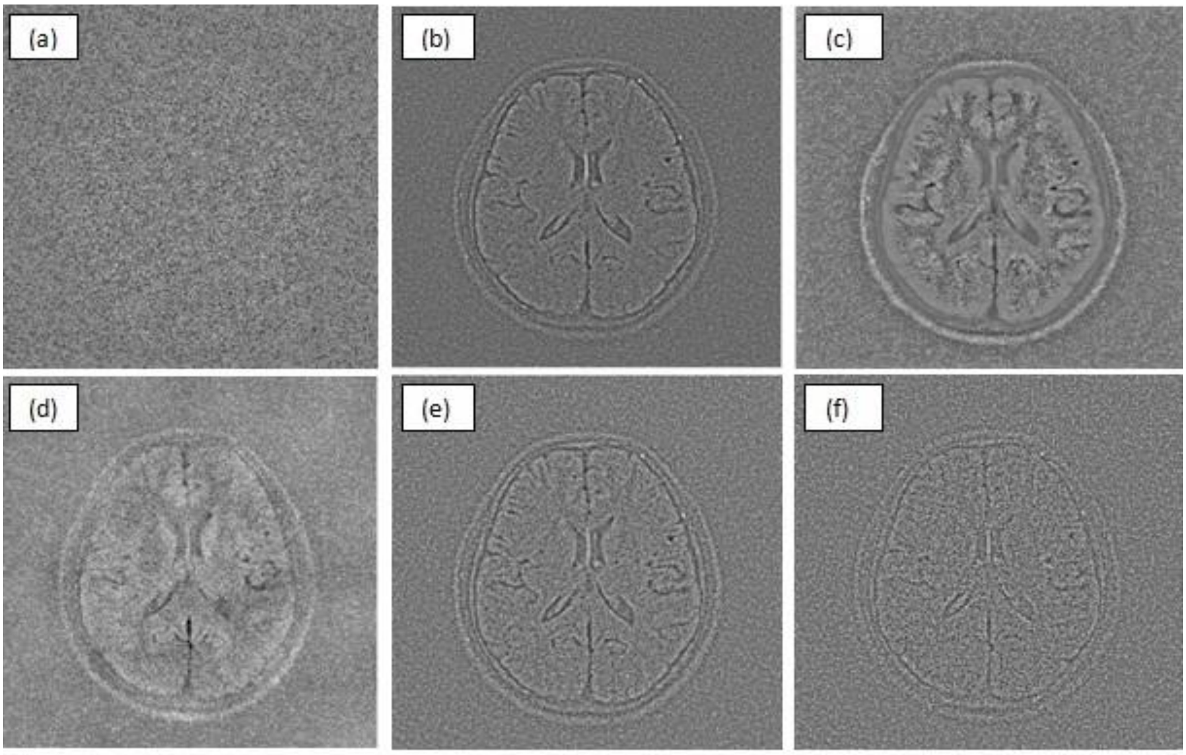


Fig. 3. Method noise of the original CT image (d) affected by Gaussian noise with sigma 20. (a) Method noise of noisy image. Method noise of denoising filters (b) Gaussian filter (c) Wiener filter (d) NLM filter (e) Bilateral filter (f) Bilateral filter with DTCWT

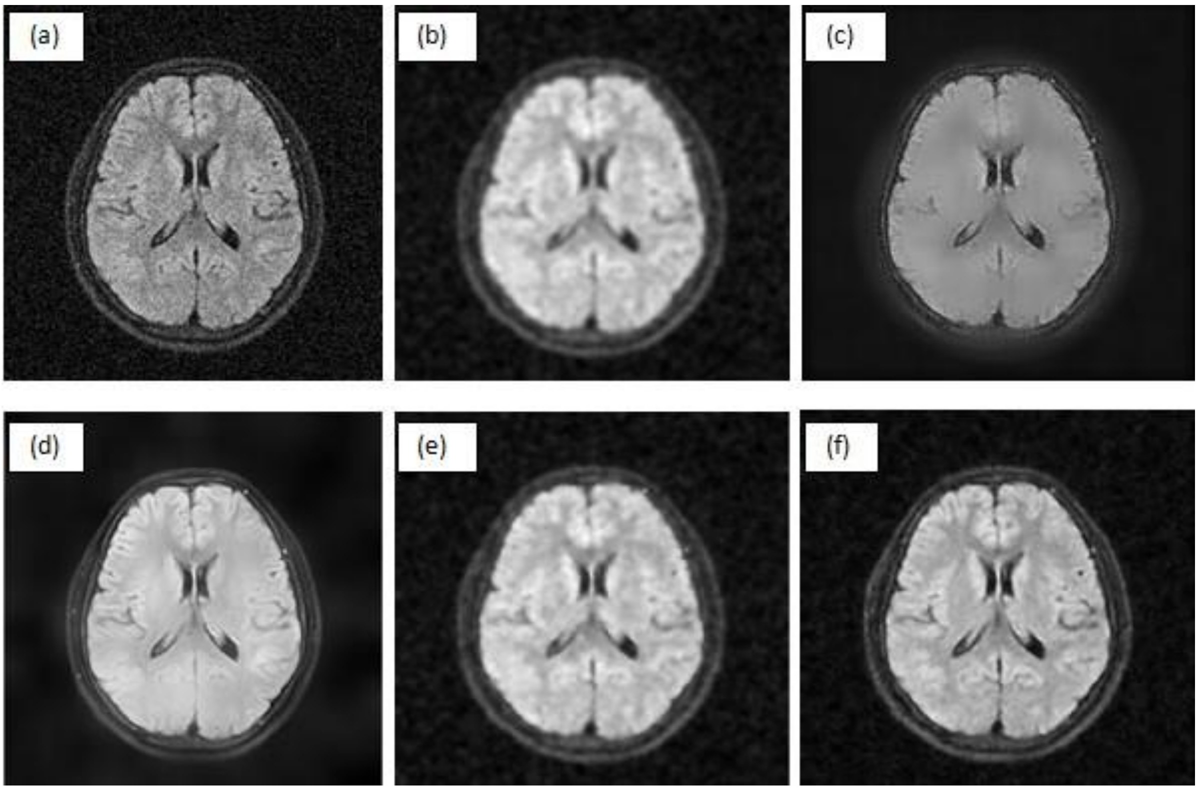


Fig. 4. (a) Original CT image(d) corrupted by Gaussian noise with sigma 20. Denoised images of (b) Gaussian filter, (c) Wiener filter, (d) NLM filter, (e) Bilateral filter and (f) Bilateral filter with DTCWT.

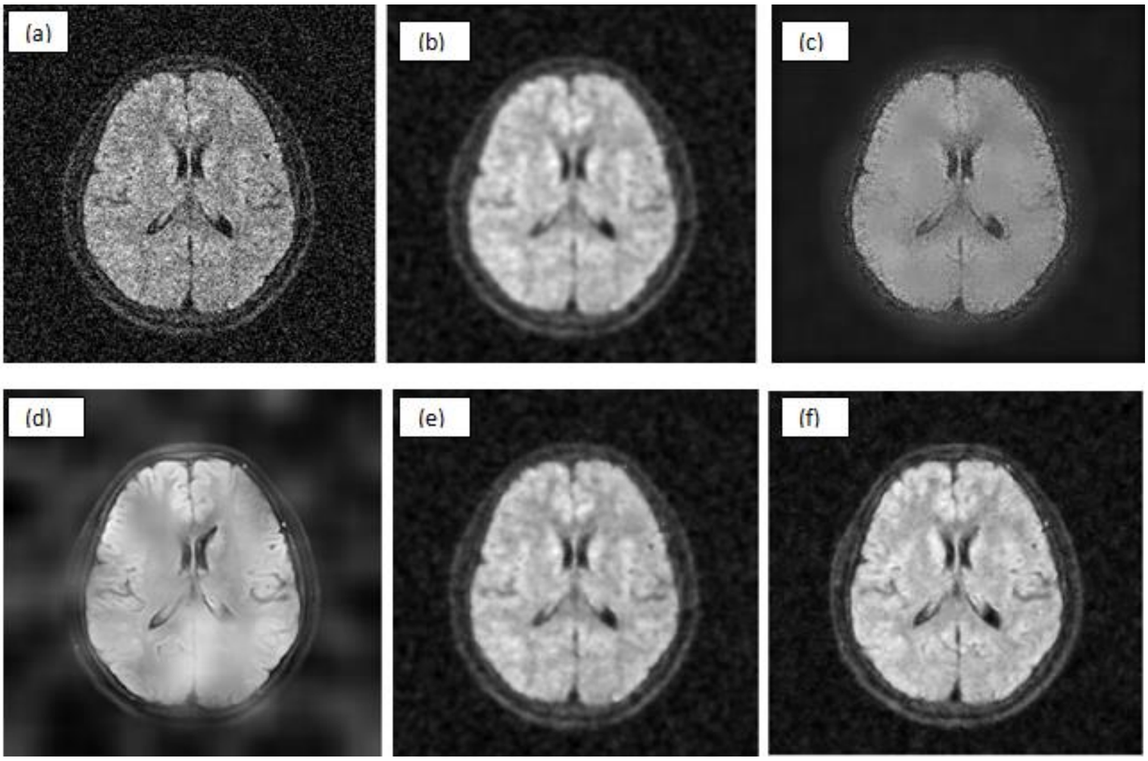


Fig. 5. (a) Original CT image(d) corrupted by Gaussian noise with sigma 40. Denoised images of (b) Gaussian filter, (c) Wiener filter, (d) NLM filter, (e)Bilateral filter and (f) Bilateral filter with DTCWT.

TABLE II. PSNR COMPARISON OF DIFFERENT DENOISING METHOD

Sigma	10	20	30	40	50
Gaussian filter	27.56	26.32	25.28	24.61	21.99
Wiener filter	28.17	26.95	25.59	24.26	22.81
NLM filter	29.22	27.69	26.55	25.79	24.01
DWT and Thresholding	31.26	30.46	27.15	25.23	23.62
Bilateral filter	31.61	29.07	27.40	25.89	24.34
Bilateral with DWT	32.25	30.58	28.26	26.61	25.49
DTCWT and thresholding	33.12	30.78	28.89	27.53	26.30
Proposed method	34.91	30.67	28.08	26.01	24.36

TABLE III. PERFORMANCE OF VARIOUS FILTERS IN TERMS OF UIQI

Sigma	10	20	30	40	50
Gaussian filter	0.9633	0.9617	0.9606	0.9555	0.9531
Wiener filter	0.9731	0.9645	0.9584	0.9497	0.9439
NLM filter	0.9787	0.9658	0.9631	0.9605	0.9497
DWT and thresholding	0.9309	0.9003	0.8793	0.8617	0.8554
Bilateral filter	0.9825	0.9736	0.9687	0.9622	0.9531
Bilateral with DWT	0.9886	0.9790	0.9725	0.9649	0.9603
DTCWT and thresholding	0.9918	0.9821	0.9734	0.9659	0.9616
Proposed method	0.9949	0.9864	0.9784	0.9696	0.9628

The performance of the denoising algorithm is compared in terms of PSNR and UIQI to analyze the results quantitatively and compared with other algorithms. The PSNR value of the

TABLE IV. PERFORMANCE OF VARIOUS FILTERS IN TERMS OF SSIM

Sigma	10	20	30	40	50
Gaussian filter	0.7888	0.751	0.7222	0.699	0.681
Wiener filter	0.811	0.810	0.799	0.755	0.655
DWT and thresholding	0.6319	0.4621	0.3607	0.2844	0.2276
Bilateral filter	0.8704	0.7801	0.702	0.6903	0.6711
Bilateral with DWT	0.8745	0.8213	0.7088	0.6985	0.6717
DTCWT and thresholding	0.7901	0.6940	0.6483	0.6016	0.5734
Proposed method	0.9001	0.8861	0.8351	0.8201	0.8011

proposed algorithm is the highest for standard deviation σ values 10,20,30,40 and 50. The IQI value of the proposed work ranges from 0.99 to 0.96. The SSIM gives the structural similarity between the original image and denoised image. The SSIM value of the proposed method is higher. This proves that the denoised image retains the structure of the original image on denoising. This shows that Bilateral DTCWT has better quality image than other denoising filters in the literature.

CONCLUSION AND FUTURE WORK

In this paper, CT image denoising using bilateral filter and its method noise thresholding using DTCWT has been proposed. The performance of this method is compared with Gaussian filter, Wiener filter, bilateral filter, various wavelet transforms and DDID methods. The proposed work has better PSNR values and provides visually pleasing images. The proposed work has less computational complexity.

The performance of the proposed method can be improved by enhancing the transform as rotational invariant with the help of steerable wavelet transform. It may be possible to improve the results further in spatial domain filtering which may also helps with visual inspections of medical images.

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