An Efficient Hybrid Filtering Method for Noise and Artifacts Removal in Effective Medical Image Segmentation

S.Karthikeyan[1,*], V.V.Gomathi[2] and M.Hemalatha[3]

[1] Department of Information Technology,
College of Applied Sciences, Sohar, Oman

[2] Research and Development Centre
Bharathiar University, Coimbatore, Tamilnadu, India

[3]School of Science
SNS Arts and Science College, Coimbatore, Tamilnadu, India

[*]*Corresponding author's email: skaarthi [AT] gmail.com*

ABSTRACT—*Medical imaging technology is becoming a key element for accurate diagnosis in medical domain. Noise and artifacts are the biggest obstacles in processing the medical images. Medical image pre-processing is a challenging task in the Computer-aided Diagnostic systems. It is very significant, particularly in tumor region segmentation and identification. The exact tumor segmentation is possible if the image is preprocessed accurately. In this paper, we propose a novel Hybrid Filtering method by the combination of wavelet filtering and curvelet filtering technique to reduce the noise and artifacts in Computer Tomography images for effective segmentation. The performances of Hybrid filtering method is evaluated by using various quantitative measures. It has been found that the Hybrid filtering method performs well in terms of performance metrics, visual quality and also reduces the over segmentation in accurate tumor identification.*

Keywords— Artifact, Computer tomography, Curvelet Filter, Hybrid Filter, Noise, Segmentation, Wavelet Filter

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1. INTRODUCTION

Computer Tomography (CT) is one of the most important modalities in medical imaging. Two important characteristics of the computer tomography (CT) image that affect the ability to visualize anatomic structures are noise and artifacts. This paper presents the reduction of noises and artifacts on different slices of Computer Tomography images using Hybrid filtering technique for increasing the visual quality and effective segmentation.

Segmentation of organs is very complex process. It presents many challenges. Many artifacts and noises can occur in CT scans. CT images are normally affected by Gaussian noise, Poisson noise, Quantum noise, Random noise and streak artifacts. This research work examines wavelet transform, curvelet transform and proposes a Hybrid filtering algorithm for noise reduction in the CT images. The performances of wavelet transform, curvelet transform and Hybrid filtering technique are compared in terms Mean Square Error (MSE), Mean Absolute Error (MAE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), Laplacian Mean Square Error (LMSE), Correlation Coefficient (COC) and Structural Similarity Index (SSI).

This paper is organized as follows. Section II describes methodology. Section III presents Computational Results and Discussions finally Concluding Remarks are given in Section IV.

2. METHODOLOGY

2.1 Wavelet Transform Filtering Technique

Wavelet transform is realized by means of the statistical models of both noise and signal. It deals with the smooth area of image but is not so perfect in high frequency areas such as the edges. It is very effective because of its ability to capture the energy of a signal in few energy transform values. It handles different type of noises which is present in an image. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale [1]. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes [2]. It can be very useful for blur as well as noise removal from images, by preserving important details. For example here we have described Discrete Wavelet Transform decomposition in one level.

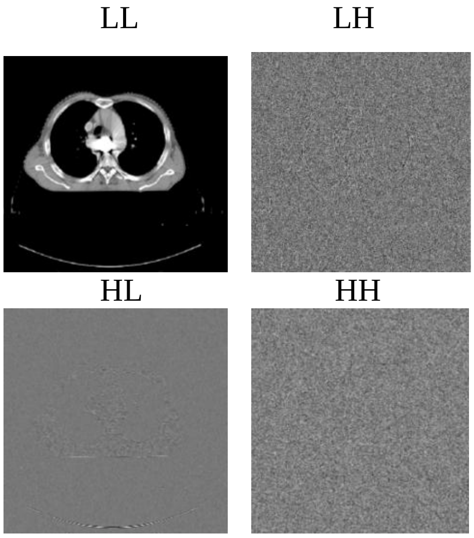

Figure 1: Discrete Wavelet Transform for Streak artifacts CT Image in one level decomposition

Advantages:

- Its simplicity and its potential to benefit from a greater range of orthogonal and bi-orthogonal filters. It also brings the possibility of extracting edge information, which provides essential visual cues in the clinical interpretation of images. The wavelet has the ability to approximate an image with just a few coefficients independent of the original image resolution and, thus, makes possible the comparison of images of different resolutions [3].

Drawbacks:

- Wavelet Transform filtering smooth areas are partitioned by edges, and while edges are irregular across, they are classically smooth curves.
- Wavelet transform is many wavelet coefficients are needed to account for edges i.e. singularities along lines or curves which results into relatively high mean squared error (MSE) [4].
- The wavelet coefficients amplitude differs largely [5].
- The DWT cannot distinguish between the contrasting diagonal directions [5]
- It is not efficient for two-dimensional singularities [6].

2.2 Curvelet Transform Filtering Technique

Curvelet transform as a recently developed mathematical transform is often used as time-frequency and multiresolution analysis tool in the signal and image processing domain. Curvelet transform is a multi-scale geometric wavelet transforms, can represent edges and curves singularities much more efficiently than traditional wavelet. Meanwhile Candes and Donoho [7] develeped a new theory of multi resolution analysis called the curvelet transform. This mathematical transform differs from wavelet and related other mathematical transform. The curvelet transform as a multiscale transform has directional parameters occurs at all scales, locations, and orientations [8]. It is superior to wavelet in the expression of image edge, such as geometry characteristic of curve and beeline, which has already obtained good research results in image denoising. It has good orientation characteristic [9]. It is developed to overcome the intrinsic limitation of conventional multiresolution techniques and has better directional and edge representation facilities.

The Curvelet transform recovers the original image from the noisy one using lesser coefficients than denoising using the Wavelet transform. The curvelet transform is made up of a sequence of steps. It uses a wavelet transform algorithm to decompose an n by n image I into J+1 subband arrays of size n x n.

Advantages:

- The curvelet transform represents edges better than wavelets, and is therefore well-suited for multiscale edge enhancement [13].

- The curvelet transform, there is better detection of noisy contours than with other methods.
- Curvelet Transform gives a superior performance in image denoising due to properties such as sparsity and multiresolution structure.

Drawbacks:

- Curvelet transform filter performs well when considering the other existing filters. Few limitations were observed while implementing the curvelet transform. Jiang Taoa and Zhao Xinb(2008)[9] ; Jianwei Ma and Gerlind Plonka (2010) [10] both are mentioned few drawbacks in their paper. The following are the Observed Limitations
- The discrete curvelet transform is highly redundant.
- They are not optimal for sparse approximation of curve features.
- The denoising effects were good in curvelet transform, but more radial stripes produced after using curvelet transform.
- Curvelet method is performing effective with gray scale images not binary images in point of intensity level and also random size images.

2.3 Proposed Hybrid Filtering Algorithm

Hybrid Filtering Algorithm is proposed to avoid the drawbacks of the wavelet transform and curvelet transform. Here Hybrid filtering algorithm is designed to avoid the above said limitation and filter efficiently.

Step I: Consider the noisy Single Dicom image or slices of Dicom images

Step II: Apply the 2D FFT and obtain Fourier samples $\hat{f}[n_1, n_2], -n/2 \leq n_1, n_2 < n/2$

Step III: For each scale j and angle ℓ, form the product $\tilde{U}_{j,\ell}[n_1, n_2]\hat{f}[n_1, n_2]$

Step IV: Wrap this product around the origin and obtain $\hat{f}_{j,\ell}[n_1, n_2] = W(\tilde{U}_{j,\ell}\hat{f})[n_1, n_2]$, Where the range for n_1 and n_2 is now $0 \leq n_1 < L_{1,j}$, and $0 \leq n_2 < L_{2,j}$ (for θ in the range $(-\pi/4, \pi/4)$).

Step V: Apply the inverse 2D FFT to each $\hat{f}_{j,l}$, hence collecting the discrete coefficients $c^D(j, \ell, k)$.

Step VI: Apply the Wavelet Transform.

Fast Fourier transform is applied to the input image with noise, where the Fourier sample data are obtained for the image. Wrapping is performed. 2D IFFT is involved, to obtain the discrete coefficients. This process are performed again with the discrete coefficient data, where instead of wrapping, unwrapping is done in similar method. Curvelets are designed to handle curves using only a small number of coefficients. Wavelet transform involves in down sampling the image during the initial stage of the process. Wavelet filter shall be decided as daubechies or Haar transform. The next step of the process involves in low pass filtering and high pass filtering. The low pass filter and high pass filter kernel values are dependent upon the wavelet filter selected for the process. The input image shall be involved to both low pass and high pass filter and each result again performed with both the filter to obtain LL, LH, HL and HH. The LL components are the approximation coefficients and LH, HL, HH are the diagonal coefficients. These LL components shall have the smooth component data's of every pixel and rest of the coefficients shall have the contrast information of LL. Only these LL components are considered for the final output. The output of curvelet filter shall be directly given to wavelet. The wavelet transform unsharpened the curve value and also involves segregating the information pixel. Approximation coefficient information of the every pixel shall be the output. Thus the proposed method results shall give the quality metrics value.

2.4 Medical image quality metrics (MIQM) for performance evaluation of denoised images

Medical Image quality assessment is a complex problem due to the subjective nature of human visual perception. Medical Image Quality Metric (MIQM) is vital in the development of Medical image processing algorithms such as enhancement, deblurring, denoising etc., as it can be used to evaluate their performances in terms of the quality of the processed image. Quality of a medical image can be assessed either subjectively through human evaluation or objectively through computer calculation. MIQM is to produce an objective metric which can predict the image quality as closely to the human subjectivity as possible. The easiest way of quality assessment perhaps is by direct pixel comparison between the two images [11].

Different kinds of statistical measurement such as Mean Square Error (MSE), Mean Absolute Error (MAE), Signal-to-Noise Ratio (SNR), Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), Laplacian Mean Square

Error (LMSE), Correlation Coefficient (COC), Structural Similarity Index (SSI) are used to evaluate the performance of the filtering techniques.

2.4.1 Mean Square Error:

The simplest and most widely used image quality measurement is Mean Square Error (MSE), computed by averaging the squared intensity differences of distorted and reference image pixels, along with the related quantity of Peak Signal-to-Noise Ratio (PSNR). The large value of MSE means that the image is of poor quality. MSE measures the average of the squares of the errors. The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. MSE is defined as follow:

$$MSE = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} \left(I(x,y) - \bar{I}(x,y) \right)^2 \quad \text{------------------(1)}$$

where $I(x,y)$ and $\bar{I}(x,y)$ are the reference image and the test image with coordinate (x, y) and size $M \times N$ respectively.

2.4.2 Mean Absolute Error:

The Mean Absolute Error (MAE) measures the average magnitude of the errors or noise. It measures accuracy for continuous variables.

The mean absolute error function is given by

$$MAE(t) = \frac{1}{n} \sum_{i=1}^{k} f_i |x_i - t| = \sum_{i=1}^{k} p_i |x_i - 1| \quad \text{--------------(2)}$$

Where xi, t denotes the restored and original image. As the name suggests, the mean absolute error is a weighted average of the absolute errors, with the relative frequencies as the weight factors.

2.4.3 Signal-to-Noise-Ratio:

Signal-to-Noise Ratio (SNR) is a measure to quantify how much a signal has been corrupted by noise. SNR is defined as the image contrast divided by the standard deviation of the image densities in the selected area.

$$SNR(dB) = 10 \log_{10} \left(\frac{\sum_{i,j} x(i,j)^2}{\sum_{i,j} \left(x(i,j) - y(i,j) \right)^2} \right) \quad \text{-----------(3)}$$

for $0 \le i \le M-1$ and $0 \le i \le N-1$, where $x(i,j)$ denotes pixel (i,j) of the original (“clean”) image and denotes $y(i,j)$ denotes pixel (i,j) of the noisy image.

In Image processing, the SNR of an image is usually calculated as the ratio of the mean pixel value to the standard deviation of the pixel values over a given neighborhood. If the SNR value is high the image quality will be high. The SNR value of the noisy image is low compared to the original image.

2.4.4 Peak Signal-to-Noise Ratio:

Peak Signal-to-Noise Ratio (PSNR) is the most popular and widely used objective image quality metric but it does not correlate well with the subjective assessment [12]. The ratio is between the maximum possible power of a signal and the power of corrupting noise. The small value of PSNR means that image is of poor quality. PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is defined as

$$PSNR = 10.\log_{10} \left(\frac{MAX_1^2}{MSE} \right) \quad \text{------------------ (4)}$$

Here,

MAX_1 - The maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255.

MSE - Mean Squared Error

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{i=1}^{N} \left[g(i,j) - f(i,j) \right]^2$$

Where

Where, M and N are the total number of pixels in the horizontal and the vertical dimensions of image. g denotes the noise image and f denotes the filtered image.

2.4.5 Root Mean Square Error:

The Root Mean Square Error (RMSE) is used to find the total amount of difference between two images. It indicates the root of average difference of the pixels throughout the image. It gives the measure of prediction accuracy and prediction error respectively. To construct the root mean square error, the determination of residuals is important. Residuals are the difference between the actual values and the predicted values.

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \quad \text{-------------------(5)}$$

Where y_i is the observed value for the ith observation and $\hat{y}_i$ is the predicted value. Squaring the residuals, averaging the squares, and taking the square root gives the r. m .s error.

2.4.6 Laplacian Mean Square Error:

This measure is based on the importance of edges and objective boundaries in images for the human observer. The large value of Laplacian Mean Square Error (LMSE) means that image is of poor quality [13]. LMSE is defined as follow:

$$LMSE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[L(x(m,n)) - L(\hat{x}(m,n))\right]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[L(x(m,n))\right]^2} \quad \text{-----------(6)}$$

Where, L (m, n) is laplacian operator

$$L(x(m,n)) = x(m+1,n) + x(m-1,n) + x(m,n+1) + 4x(mn)$$

2.4.7 Correlation Coefficient:

Correlation Coefficient (COC) represents the strength and direction of a linear relationship between two variances. The COC is used to measure the similarity between the original image and despeckled image. COC are expressed as values between +1 and -1. If the correlation coefficient is near to +1, then there exists stronger positive correlation between the original and despeckled image.

The Pearson correlation coefficient is defined as:

$$r = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}} \quad \text{------------(7)}$$

Where xi is the intensity of the ith pixel in image 1, yi is the intensity of the ith pixel in image 2, xm is the mean intensity of image 1, and ym is the mean intensity of image 2.

2.4.8 Structural Similarity Index:

The Structural Similarity Index (SSI) Measure is a method for measuring the similarity between two images. SSI is designed to improve on traditional methods like PSNR and MSE. The SSI metric is calculated on various windows of an image. SSI can better reflect the visual quality and structure similarity between the target image and the reference image. The measure between two windows and of common size N×N is:

$$SSI(x,y) = \frac{(2\mu_x\mu_y + C_1)a(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)a(\sigma_x^2 + \sigma_y^2 + C_2)} \quad \text{-----------(8)}$$

Where μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y. The maximum value of the Similarity index is 1 and Minimum Value is -1. If SI is 1, the estimated image is equal to the original image.

3. EXPERIMENTAL RESULTS AND DISCUSSION

Different kind of Tumor patient dataset were collected by a SIEMENS SOMATOM EMOTION SPIRAL CT scanner located at Multi Speciality Hospital, Coimbatore, Tamilnadu, India. The 3D image data consisted of DICOM (Digital Imaging and Communications in Medicine) consecutive slices, each slice being of size 512 by 512 and having 16-bit gray level resolution.

Experimentation is carried out on 100 number of different tumor patients contains 100 to 1000 slices of Computer Tomography images using different Filtering algorithm. The performance of the proposed hybrid filtering technique is compared with existing filtering techniques using all possible evaluation measures such as Mean Square Error (MSE), Mean Absolute Error (MAE), Signal-to-noise ratio (SNR), Peak signal-to-noise ratio (PSNR), Root mean square error (RMSE), Laplacian Mean Square Error (LMSE), Correlation Coefficient (COC), Structural Similarity Index (SSI). In this paper we demonstrate the performances of Wavelet transform filtering, curvelet transform filtering and Hybrid filtering techniques are listed below.

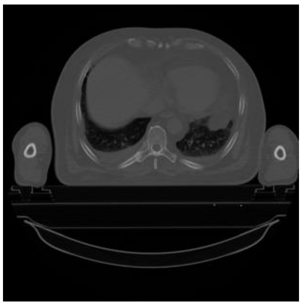

Figure 2: Input image

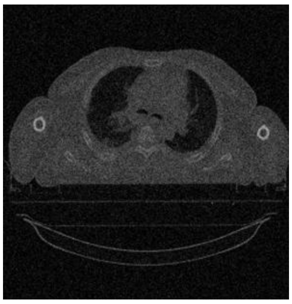

Figure 3 (a): Wavelet filter Gaussian noise

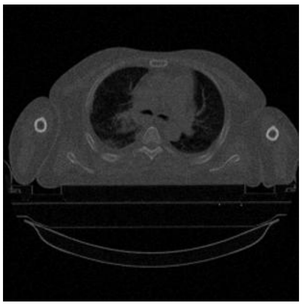

Figure 3 (b): Wavelet filter Poisson noise

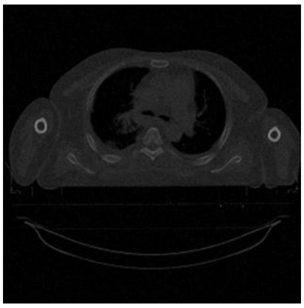

Figure 3 (c): Wavelet filter Quantum noise

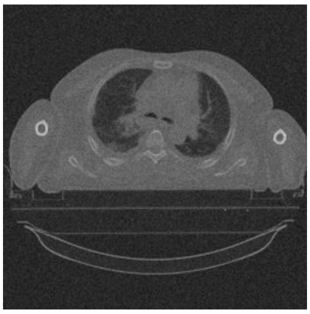

Figure 3 (d): Wavelet filter Uniform noise

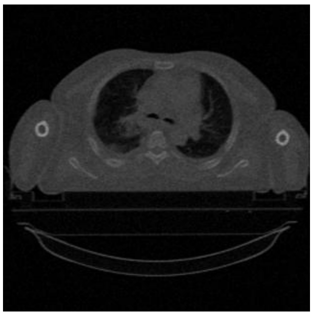

Figure 3 (e): Wavelet filter Streak artifacts

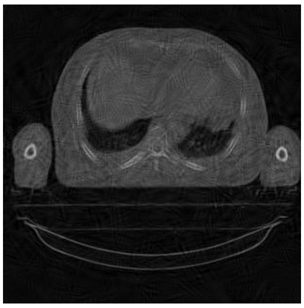

Figure 4 (a): Curvelet Filter Gaussian noise

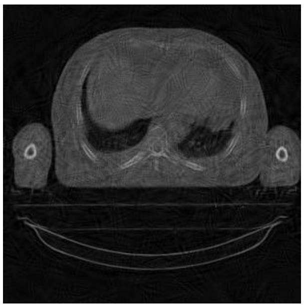

Figure 4 (b): Curvelet Filter Poisson noise

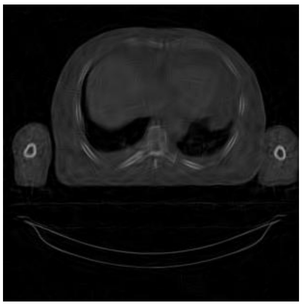

Figure 4 (c): Curvelet Filter Quantum noise

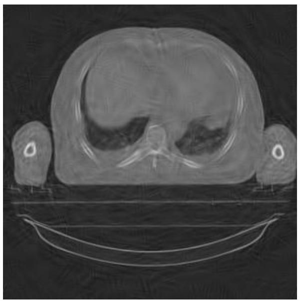

Figure 4 (d): Curvelet Filter Uniform noise

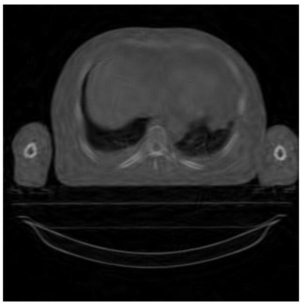

Figure 4 (e): Curvelet Filter Streak artifacts

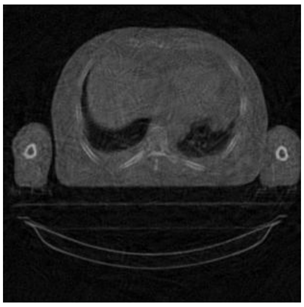

Figure 5 (a): Hybrid Filter Gaussian noise

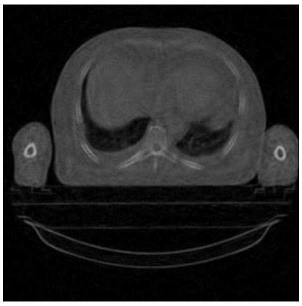

Figure 5 (b): Hybrid Filter Poisson noise

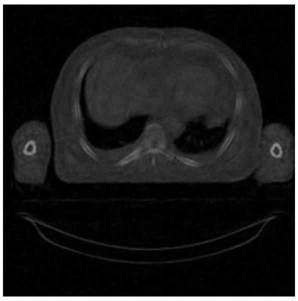

Figure 5 (c): Hybrid Filter Quantum noise

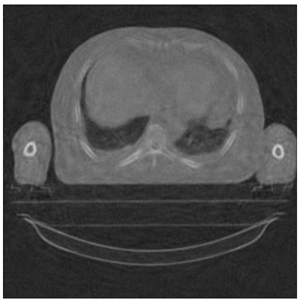

Figure 5 (d): Hybrid Filter Uniform noise

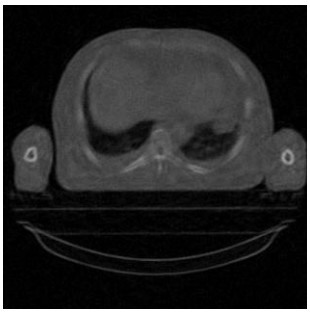

Figure 5 (e): Hybrid Filter Streak artifacts

Table 1: Performance Analysis of wavelet, curvelet and hybrid filters

Filtering Techniques	Quantitative Metrics	White Gaussian noise	Poisson noise	Quantum noise	Uniform noise	Streak Artifacts
Wavelet Transform	MSE	7.6633e+05	5.0826e+05	2.5315e+05	1.6840e+06	5.0247e+05
	MAE	40.2853	33.3877	25.5617	72.7741	33.2236
	SNR	24.7116	25.4200	25.0461	24.5751	25.1183
	PSNR	17.3036	18.1053	19.2127	14.7878	18.1160
	RMSE	932.6065	698.5075	601.4246	1.829e+03	773.8052
	LMSE	0.8856	0.8852	0.8848	0.8859	0.8850
	COC	0.8255	0.8647	0.8615	0.8550	0.8806
	SSI	0.0167	0.5137	0.5347	0.0012	0.4133
Curvelet Transform	MSE	5.2508e+04	6.3381e+04	4.0684e+04	6.1605e+04	6.3158e+04
	MAE	0.1562	1.0753	1.0956	0.0865	0.8112
	SNR	0.1305	0.1256	0.1100	0.1422	0.0567
	PSNR	23.1122	22.6602	23.5014	22.7421	22.6585
	RMSE	251.1166	270.8454	224.2856	256.6921	271.2287
	LMSE	0.1033	0.0236	0.0254	0.0239	0.0088
	COC	0.8334	0.8724	0.8713	0.8448	0.8823
	SSI	0.6118	0.7166	0.7139	0.6455	0.7317
Hybrid Filtering Technique	MSE	5.5353e+04	6.4099e+05	4.0387e+04	6.6078e+04	6.2674e+04
	MAE	0.1275	1.7432	1.6614	0.1732	1.5523
	SNR	0.3628	0.2103	0.2541	0.1628	0.1756
	PSNR	23.0764	22.6415	23.5033	22.5847	22.6812
	RMSE	255.6112	276.0334	226.6062	279.5377	273.5227
	LMSE	0.1396	0.0638	0.0652	0.0499	0.0209
	COC	0.8145	0.8531	0.8478	0.8367	0.8742
	SSI	0.5353	0.5438	0.5521	0.6086	0.5868

The above mentioned quantitative metrics have been considered to verify the performance of the proposed Hybrid filtering technique that is shown in Table.1. It shows that the value of MSE is low, SNR, PSNR is high, and SSI, COC, and QI gives between the ranges -1 to +1. Based on the experimental results indicates the proposed Hybrid filtering technique is good for noise removal. Experiments have been made with CT images of different patients and results are satisfactory. The proposed Hybrid filtering technique method suppresses the curves and also the filtered image is most suitable for segmentation.

4. CONCLUSION

In this paper, the quality of the denoised image been enhanced in terms of medical perspective. We have proposed an efficient Hybrid filtering technique has effectively removed noise from the CT images and improved the quality of the images. The discrete curvelet transform is highly redundant and produced more radial stripes this was overcome by the novel hybrid filtering technique and enhancing the quality of the denoised image and preserving important features and organ surfaces well. The implementation results show that the noise is removed efficiently and the particular information is well preserved; meanwhile, the whole visual quality is improved. It is also indicate that the proposed hybrid filtering technique performs significantly better than other existing techniques for CT images. The image quality has been decided by the most significant quantitative measures such as MSE, MAE, RMSE, LMSE, SNR, PSNR, SSI, COC, and QI. . It shows that the value of MSE is low, SNR, PSNR is high, and SSI, COC, and QI gives between the ranges 1 to 1. From the quantitative results in Table 1 it may be observed that the proposed method outperforms the wavelet and curvelet transform. The significant improvement in the quality metrics indicates the usefulness of the proposed method in terms of denoising. The results (Figure 3, 4, 5) show that the visual quality of the images has also been improved by the proposed method. The Proposed Hybrid filtering technique is an effective filtering technique for organ and tumor segmentation.

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