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Image Enhancement Filtering Techniques to Enhancect Images of Lung Cancer

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Abstract: ***Medical images are susceptible to noise and poor contrast. Improving the quality of image using different image enhancement techniques is an important area of image research. In this paper, various image enhancement techniques are applied over lung cancer CT images. Identifying mechanisms to detect lung cancer is very important since men and women are found to be most affected by Lung cancer compared to other types of cancer. As per the report from the World Health Organization, 2.09 million cases of Lung cancer were reported in the year 2018. Early detection and treatment of Lung cancer improve the chances of survival. Thus, this paper aims at applying and reviewing different frequency based Image enhancement techniques like Butterworth filter, Gaussian filter, Gabor filter, fast Fourier transform, and Discrete wavelet transform and finding the best filtering technique used to detect Lung cancer from a sample of Computed Tomography (CT) images. Peak to signal noise ratio is calculated to find the best filter since it is similar to reconstruction quality in human's perception. The results from experiment analysis shows that Gabor filter has higher PSNR value and it's the best enhancement technique out of the filters taken under study.***

Keywords: ***Lung cancer, Image enhancement, Image pre-processing, filtering***

I. INTRODUCTION

Cancer arises from a multi-stage process that transforms healthy cells to tumor cells. Among different types of cancer, Lung cancer is found to be the deadliest type of cancer. World Health Organization reported 1.76 million deaths and 2.09 million cases affected by Lung cancer worldwide in the year 2018 [2]. Analysis and assessment of Lung nodule areessential to diagnose Lung cancer. There are four types of Lung nodules: well-circumscribed nodule, Juxtavascular nodule, Pleural-tail nodule, and Juxtapleural nodule. The first type of Lung nodule doesn't have any connection with other pulmonary structures whereas the second type of Lung nodule has uncertain connections to surrounding vessels. The third type of Lung nodule is characterized by the presence of a thin connection between the nodule and pleural. Between the nodule and the pleural large proportional connection is present in Juxtapleural nodule [3].

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The survival rate of patients can be improved from 14% to 49% if it is detected at an early stage [1]. Thus, early detection and diagnosis is an essential matter of concern, and many researches are being carried out to develop effective computer-aided systems.

The initial step of Image processing is image enhancement.Image enhancement is the process of applying specific techniques with respect to the nature of the image such that the visual appearance or features of the image are enhanced. The attributes of the image are modified in such a way that the resultant image ismore suitable for the application context. Broadly, Image enhancement techniques can be applied over two domains of an image – Spatial domain and Frequency domain. A transformation function is directly applied over the pixels of an image in spatial domain image enhancement techniques. The simplicity of this technique makes the analysis easy and understandable. But they lack enough robustness and imperceptibility requirements [4]. In the frequency domain, the filter function is multiplied with the Fourier transform of the image taken and converted to the spatial domain by taking the inverse transform. Spatial domain techniques are applied in the areas where the overall contrast of the image needs to be improved by altering gray level pixel values, whereas Frequency-domain techniques are applied when specific information of images like edges or other subtle information needs to be enhanced [5].

Motivation: Lung cancer is a deadly type of cancer. Detecting Lung cancer at an early stage is essential and image enhancement techniques are beneficial to achieve early detection. So, this paper aims at providing a comprehensive analysis of various filtering techniques for image enhancement and finding a suitable technique to detect Lung cancer from CT images.

Organization: The remaining section of this paper is structured as Section 2 gives an overview of related Literature review; Section 3 describes the implementation of various frequency-based image enhancement techniques, Section 4 and 5 provides experiment results and performance analysis respectively. And finally, in section 6 conclusions are drawn.

II. LITERATURE REVIEW

Finding and enhancing image enhancement techniques is an active area of research, and several authors have contributed to this field. Some of the related works are discussed in this section.Farag et al.suggested that the filtering approach plays a significant role in finding detailed structures and boundaries of the region of interest in an image [6,7]. This is done by sharpening the discontinuities and removing noise using wiener and anisotropic diffusion filters.Arun et al.

proposed a new method to overcome the disadvantages of conventional transform domain techniques by complementing it with techniques in the spatial domain [8]. Low contrast images are enhanced by combining alpha rooting algorithm with transformation techniques like power-law transform and logarithmic transform.

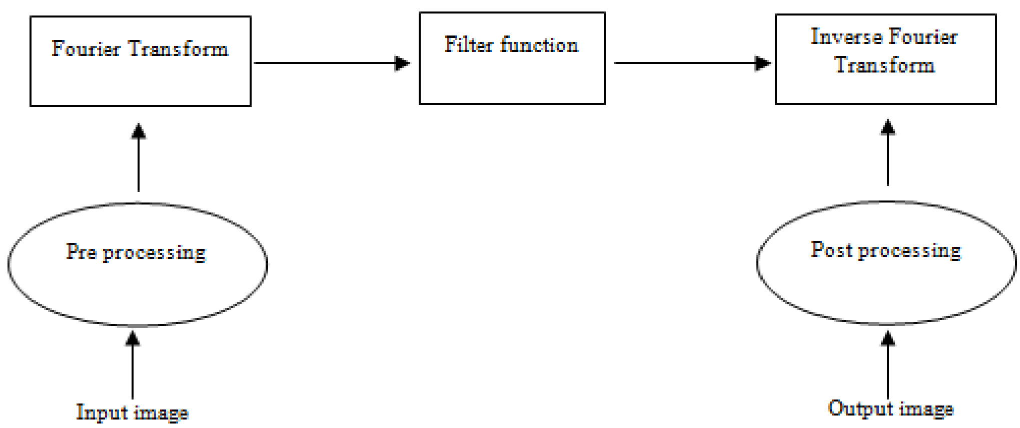
Sahiner etal. suggested two phases under the pre-processing stage in their research paper. In the first phase, the median filter is used to remove noise [9]. And in the second phase, the unwanted ribcage area is removed by applying erosion to the structuring element and reducing the size of the structuring element by one iteratively. Gajdhane and Deshpanderecommended a method to identify the stage of lung cancer by extracting features like area, eccentricity, and perimeter from CT images after applying Gabor filter and watershed segmentation techniques [10]. The results projected in this paper for lung cancer detection showed more chances of detecting it at the earlier stage.

Agaian etal.proposed the global histogram equalization method. This method tries to match an identical distribution by mapping and changing spatial image histogram [11]. The disadvantage of this method is it results in quality, intensity loss due to over enhancement of the image.Avinash etal. suggested that the Gabor filtering technique helps in the early detection of lung cancer compared to the discrete wavelet transform enhancement technique and auto enhancement algorithm- alpha trimmed filter technique [12]. This paper uses peak to signal noise ratio measure to identify the best technique out of the three filtering techniques under consideration. Ahamed and Rajamani proposed a hybrid filter by using the combination of fuzzy neuro network and spatial domain filtering to remove mixed noise in digital images [13]. The proposed method is effective in eliminating Gaussian and impulse noise and at the same time, helps in edge and line detection.Bedi and Khandelwal presented a review of various image enhancement techniques by citing their advantages and disadvantages [14].This paper also projects the scenarios under which an enhancement technique can be used. For example, to enhance the white region present over the dark region, the image negative technique is suggested. Thus, this paper presents an overall discussion on various image enhancement techniques falling under the spatial domain and frequency domain.

P.Janani etal.carried out an analysis of the performance of different filters like Mean, Median, Weiner, and Gaussian to de-noise different types of noise like Poisson, speckle, salt, and pepper, and Gaussian [15]. The experiment results concluded that the Weiner filter is apt for de-noising all kinds of noises. This paper also provided a detailed analysis of different spatial domain image enhancement techniques like histogram equalization, intensity transformation, etc.Rajput andSuralkarcompared and analyzed different spatial domain image enhancement techniques like histogram processing, edge adaptive hybrid filter, negative enhancement, adaptive weighted mean filter, contrast stretching, and edge adaptive sigma filter [16]. The results of performance measures like root mean square error, correlation coefficient, structural similarity and peak signal to noise ratio showed that edge adaptive sigma filter outperforms other filters in enhancing fingerprint images.Thus, various research works are being carried out in understanding and improvising the image enhancement techniques in spatial as well as frequency domain. This paper focuses on finding the best suitable filtering method to enhance CT images of lung cancer.

III. IMPLEMENTATION OF VARIOUS FREQUENCY-BASED IMAGE ENHANCEMENT TECHNIQUES

Frequency domain image enhancement techniques transform the image from the spatial domain to another abstract space by finding the Fourier transform of the image. Fourier transform is a type of integral function through which any signal can be represented as a weighted linear combination of harmonic (i.e., sine and cosine) functions having different periods of frequencies [17]. The process of image enhancement technique in the frequency domain is found the Fourier transform of an image, multiply the result by filter function and take the inverse Fourierto transform to get the enhanced image.



Filtering is the process of removing unwanted frequencies called noise from the image. Enhancement is achieved by multiplying every pixel of an image with a filter function. Broadly, there are three filter types – Low pass filter, High pass filter, Bandpass filter [5]. The choice of choosing the filter depends on the type of image outcome we expect.Low spatial frequencies help in building basic smooth shape, and high spatial frequencies are responsible for reproducing sharp transitions in an image. Low pass filter blocks high frequency, high pass filter blocks low frequency, and bandpass filter helps in retaining middle-frequency range.

Thus, the low pass filter helps to reduce noise and smooth the image while the high pass filter helps to sharpen the edges in an image whereas bandpass filter combines the properties of both low pass and high pass filter by allowing frequencies that are only within the band or range and helps in edge enhancement and noise reduction.

Various frequency-based techniques are chosen and implemented to find the most suitable enhancement technique for lung cancer detection. The focus of this paper is concentrated towardthe image enhancement stage only. A CT image of Lung cancer is given as an input image. This input image is processed using Fast Fourier Transform, Gaussian Filter, Gabor Filter, Butterworth filterand Discrete wavelet transform, and the results of each enhancement technique areanalyzed to find the best technique.

3.1. Fast Fourier Transform (FFT)

J.W. Cooley and J.W. Tukey developed the FFT algorithm to compute DFT and inverse DFT effectively. FFT works on the Fourier transform of an image.FFT algorithmsuccessively decomposes N-point DFT computation to smaller size DFTs, and inverse DFT is calculated for each block in an image and then combined. By this divide and conquer method, the computational complexity using FFT is reduced to $NLog_2N$ whereas DFT takes the order of N^2 for addition and multiplication operations. That is the reason why FFT is preferred compared to DFT.

a) Mathematical model

Discrete Fourier Transform contains samples that are essential to describe the image in the spatial domain. It's a form of sampled Fourier transform [18]. The mathematical equation of 2D DFT for representing a square image in the spatial domain with N rows and N columns to frequency domain or in Fourier space (H (k,l)) is given by:

$$H(k,l) = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} h(i,j)e^{-i2\pi(\frac{k}{N}+\frac{l}{N})} \quad (1)$$

Similarly, the inverse Fourier transform to represent the image back to the spatial domain is given by:

$$h(a,b) = \left(\frac{1}{N}\right)\sum_{k=0}^{N-1}\sum_{l=0}^{N-1} H(k,l)e^{i2\pi(\frac{k}{N}+\frac{l}{N})} \quad (2)$$

A number of multiplications involved in evaluating DFT is N^2.

If the waveform is periodic and input data points are finite, DFT (H[n]) is given by:

$$H[n] = \sum_{k=0}^{N-1} h[k]e^{-j\frac{2n}{N}} \quad (3)$$

Since the computational complexity is high, the Fast Fourier transform was introduced. Corresponding, Mathematical equations of FFT (H(x)) and inverse FFT (h(n)) is given by the following equations:

$$H(x) = \sum_{k=0}^{N-1} h(n)e^{-j2\pi(x\frac{n}{N})} \quad (4)$$

$$h(n) = \left(\frac{1}{N}\right)\sum_{k=0}^{N-1} H(x)e^{j2\pi(x\frac{n}{N})} \quad (5)$$

The filter function of two-dimensional ideal low pass filter is –

$$H(u,v) = \begin{cases} 1, \text{if}(d(u,v) \le do \\ 0, \text{else} \end{cases} \quad (6)$$

And the filter function of two-dimensional ideal high pass filter is –

$$H(u,v) = \begin{cases} 0, \text{if}(d(u,v) \le do \\ 1, \text{else} \end{cases} \quad (7)$$

Where cut off frequency is measured as do and from the origin, Euclidean distance is calculated in d(u, v).

b) Algorithm:

Step1: Feed the input image.
Step2: Convert the input image to array
Step3: Apply FFT on the resultant array and shift the fourier frequency.
Step4: Define convolution function fortwo dimensional low pass filter using the mathematical equation (6).
Step5: Perform convolution of convolution function defined in step 4 with the array obtained in step 3.
Step6: Calculate magnitude using inverse FFT.
Step7: Convert the resultant array to image.
Step8: Similarly, repeat all the steps for two dimensional high pass filter. Mathematical equation(7) is used instead of the mathematical equation (6) to define convolution function for two dimensional high pass filter.
Step9: Estimate PSNR value

3.2. Gaussian Filter

Gaussian filter is one of the many linear filter types used for image smoothing and was proposed by Marr and Hildreth in the 1980s [21]. Neurons in the human visual perception system work like the Gaussian filter to understand the visual images.Gaussian filter estimates the weighted mean of pixel intensities at adjacent positions. The weights decrease with respect to spatial distance to the centre. As a result, the image is blurred, and the noise is removed.

a) Mathematical model of Gaussian filter:

Impulse response I(x) and frequency response (I(f)) of 1D Gaussian filter

$$I(x) = \sqrt{\frac{a}{\pi}}.e^{-a.x^2} \text{ and } \quad I(f) = e^{-(\pi^2 f^2)/a} \quad (8,9)$$

With standard deviation as the parameter, the above equations are represented as:

$$I(x) = \left(\frac{1}{\sqrt{2\pi}\sigma}\right).e^{-x^2/2\sigma^2} \text{ and } \quad I(f) = e^{-(f^2)/2\sigma_f^2} \quad (10,11)$$

In the two-dimensional plane, the Gaussian equation is the product of two Gaussian functions with x measured from the origin of the horizontal axis and y measured from the origin of the vertical axis

$$I(x,y) = \left(\frac{1}{2\pi\sigma^2}\right).e^{-((x^2+y^2)/2\sigma^2)} \quad (12)$$

The frequency coefficients in Gaussian filtering don't cut abruptly and follow a smooth transition. The frequency components attenuate farther away from the centre (M/2, N/2) in case of Gaussian low pass filter and it is given by the equation-

$$I(x,y) = e^{-(((\frac{M}{2}-u)^2+(\frac{N}{2}-v)^2)/2\sigma^2)} \quad (13)$$

Whereas in Gaussian high pass filter, the frequency components near to center attenuate and the convolution function is given as –

$$I(x,y) = 1 - e^{-(((\frac{M}{2}-u)^2+(\frac{N}{2}-v)^2)/2\sigma^2)} \quad (14)$$

b) Algorithm:

Step1: Feed the input image.
Step2: Convert the input image to array
Step3: Apply FFT on the resultant array and shift the fourier frequency.
Step4: Define convolution function for Gaussian low pass filter using the mathematical equation (13).
Step5: Perform convolution of convolution function defined in step 4 with the array obtained in step 3.
Step6: Calculate magnitude using inverse FFT.
Step7: Convert the resultant array to image.
Step8: Similarly, repeat all the steps for Gaussian high pass filter. Mathematical equation(14) is used instead of the mathematical equation (13) to define convolution function for Gaussian high pass filter
Step9: Estimate PSNR value

3.3. Gabor Filter

One of the best band-pass filters is the Gabor filter. Dennis Gabor introduced a Gabor filter for texture analysis. It is a type of linear filter which analyses specific frequency content around the localized region under analysis. Optimum localization is achieved using Gabor function since it produces excellent local and multiscale decomposition. Gaussian kernel function modulated by sinusoidal plane waveforms the two-dimensional Gabor filter in the spatial domain [1].

a) Mathematical model for Gabor filter

The filter function of the Gabor filter defined as the convolution of the Fourier transform of the harmonic function and the Fourier transform of Gaussian function is represented as-

$$h(k,l) = m(k,l)n(k,l) \quad (15)$$

Where complex sinusoid f (c, d) and two-dimensional gaussian envelope g (c, d) is –

$$m(k,l) = e^{-j2\pi(p_o k+q_o l)+h} \quad (16)$$

$$n(k,l) = (\frac{1}{\sqrt{2\pi\sigma}})e^{-(\frac{1}{2})\left(\frac{k^2}{\sigma_k^2}\right)-(\frac{1}{2})(\frac{l^2}{\sigma_l^2})} \quad (17)$$

Here, h is the stage of the sinusoid, and (po,qo) is the spatial frequency.

The real and imaginary part of the sinusoid is –

$$real\left(m(k,l)\right) = \cos\left(2\pi(p_o k + q_o l) + h\right) \quad (18)$$

$$imaginary\left(m(k,l)\right) = \cos\left(2\pi(p_o k + q_o l) + h\right) \quad (19)$$

In polar coordinates, the spatial frequency with magnitude Lo and path Zois defined as –

$$F_o = \sqrt{(p_o^2 + q_o^2)} and z_o = \tan^{-1}(\frac{q_o}{p_o}) \quad (20)$$

$$p_o = F_o \cos z_o \quad and \quad q_o = F_o \sin z_o \quad (21)$$

On substituting the above values in f (c, d), the complex sinusoid function becomes-

$$m(c,d) = e^{-j2\pi L_o(k\cos z_o+l\sin z_o)+h} \quad (22)$$

The Gaussian envelope Zr(k, l) is defined as –

$$Z_r(k,l) = k \exp\left(-\pi(i^2(c-c_o)_r^2 + j^2(d-d_o)_r^2)\right) \quad (23)$$

and $(c-c_o)_r = (c-c_o)\cos\theta + (d-d_o)\sin\theta$ (24)

$$(d-d_o)_r = -(c-c_o)\sin\theta + (d-d_o)\cos\theta \quad (25)$$

Where (co, do) is the peak of function, i and j are scaling constraints, and r denotes rotation operation.

b) Algorithm:

Step1: Feed the input image.
Step2: Use bilinear transformation to decimate the image.
Step3: In steps of 45^o by varying theta from 0^o to 360^o, apply Gabor filter and add the magnitude of resultant images.
Step4: Use bilinear transformation to manipulate the sum image.
Step5: Estimate PSNR value.

3.4. Butterworth Filter

Discrete approximation to Gaussian filter results in the Butterworth filter. Stephen Butterworth, in the 1930s,designed and described the Butterworth filter as a filter that has a maximum flat frequency response in the passband[23].Order of filter that controls the sharpness of an image and critical frequency are the essential parameters that define this filter. The point from which the frequency starts to roll-off toward zero is called cut-off frequency. In Butterworth Low Pass Filter (BLPF), the frequency transition gets steeper from passband to stopband with the increase in the order of the filter. An increase in the order of filter leads to a ringing effect. BLPF keeps the frequencies specified within the cut off frequency and discardsthe values outside it by introducing a gradual transition from 1 to 0 is applied. An increase in cut-off frequency results in a smooth transition in blurring and no ringing effect is observed [22]. Whereas in Butterworth High Pass Filter (BHPF), the values inside the cut-off frequency are discarded, and transition from 0 to 1 is introduced for the values outside to diminish the ringing effects. BHPF has less distortion and is smoother than the ideal high pass filter when the order of the filter is small and cut-off frequency increases. Because of the gradual transition in Butterworth filter, noise is smoothed, and at the same time image resolution is preserved.

a) Mathematical formulation:

BLPF has the convolution function, H (u, v) as

$$H(u,v) = 1/(1 + \left(\frac{d(u,v)}{d_o}\right)^{2m}) \quad (26)$$

Whereas the convolution function of BHPF is represented as

$$H(u,v) = 1/(1 + \left(\frac{d_o}{d(u,v)}\right)^{2m}) \quad (27)$$

Here, m is the order of the filter, d(u, v) is the distance measured from the origin and d_o is the cut-off frequency.

b) Algorithm:

Step1: Feed the input image.
Step2: Convert the input image to array
Step3: Apply FFT on the resultant array and shift the fourier frequency.
Step4: Define convolution function for BLPF using the mathematical equation (26).
Step5: Perform convolution of convolution function defined in step 4 with the array obtained in step 3.
Step6: Calculate magnitude using inverse FFT.
Step7: Convert the resultant array to image.
Step8: Similarly, repeat all the steps for BHPF. Mathematical equation (27) is used instead of the mathematical equation (26) to define convolution function for BHPF.
Step9: Estimate PSNR value

3.5. Discrete Wavelet Transform

Alfred Haar invented the first DWT. IngridDaubechies formulated the most frequently used DWT based on recurrence relations [24].

The transformation of image pixels to wavelets to perform wavelet-based compression and coding is called Discrete Wavelet Transform (DWT) [20]. Wavelets are small waves having varying frequency, and finite duration and wavelet transform give both time and frequency components together.

DWT transforms the image from spatial to the frequency domain by decomposing the input image to four different sub-bands which are a mutually orthogonal set of wavelets [18].

The frequency of four sub-bands called Low-Low Decomposition (LLD), Low-High Decomposition (LHD), High-Low Decomposition (HLD), and High-High Decomposition (HHD), cover the entire frequency spectrum of the original image.

This is achieved by applying on the rows of one-dimensional image DWT and decomposing the results along the columns to the 2dimensional wavelet decomposition of an image.

Thus, sub-band images of high frequency and low-resolution images are interpolated using a filter function as shown in Fig and combined using inverse DWT to yield an image with enhanced resolution. In this way, the noisy signal can be denoised easily. Fig shows the entire workflow of DWT to enhance an image [19].

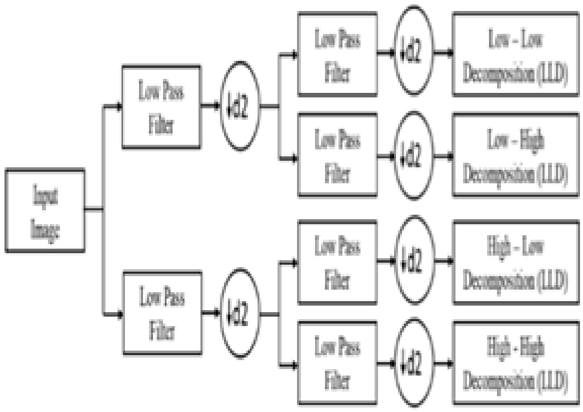


Figure 1Filter functions in DWT

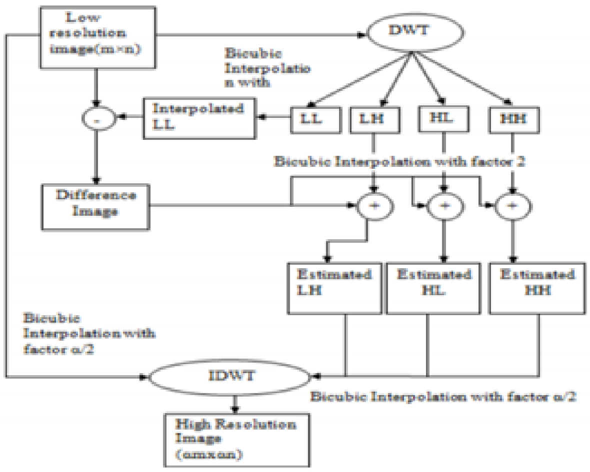


Figure 2DWT workflow in image enhancement

a) Mathematical formulation of DWT [20]:

Different sub bands in two-dimensional Discrete wavelet transform is given as:

$$LL = \emptyset(x,y) = \emptyset(x)\emptyset(y) \quad (28)$$

$$LH = \varphi^{H}(x,y) = \varphi(x)\emptyset(y) \quad (29)$$

$$HL = \varphi^{V}(x,y) = \emptyset(x)\varphi(y) \quad (30)$$

$$HH = \varphi^{D}(x,y) = \varphi(x)\varphi(y) \quad (31)$$

Where the superscripts H,V, and D represents horizontal, vertical and diagonal decomposition direction.
Wavelet and scaling functions are represented by-

$$\varphi^{i}_{j,m,n}(x,y) = 2^{j/2}\varphi^{i}(2^{j}x - m, 2^{j}y - n) \quad (32)$$

$$\emptyset_{j,m,n}(x,y) = 2^{j/2}\emptyset(2^{j}x - m, 2^{j}y - n) \quad (33)$$

Where I is a set of H, V, D.
The discrete wavelet transform function f(x,y) with M rows and N columns is given below:
Scaling function $W_{\phi}(j_o, m, n)$ is

$W_{\emptyset}(j_o, m, n) = \left(\frac{1}{\sqrt{MN}}\right) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\emptyset_{jo,m,n}(x, y)$ (34)

Horizontal sub-band ($W_{\varphi}^{H}(j, m, n)$), Vertical sub-band ($W_{\varphi}^{V}(j, m, n)$) and Diagonal sub-band ($W_{\varphi}^{D}(j, m, n)$) is represented as

$W_{\varphi}^{H}(j, m, n) = \left(\frac{1}{\sqrt{MN}}\right) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\varphi_{j,m,n}^{H}(x, y)$ (35)

$W_{\varphi}^{V}(j, m, n) = \left(\frac{1}{\sqrt{MN}}\right) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\varphi_{j,m,n}^{V}(x, y)$ (36)

$W_{\varphi}^{D}(j, m, n) = \left(\frac{1}{\sqrt{MN}}\right) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\varphi_{j,m,n}^{D}(x, y)$ (37)

And the inverse DWT is found using the formula,

$f(x, y) = \left(\frac{1}{\sqrt{MN}}\right) \sum_m \sum_n W_{\emptyset}(j_o, m, n)\emptyset_{jo,m,n}(x, y) +$

(1MN)i=H, V, Dj=jo∞mnWφij,m,nφj, m, ni(x,y) (38)

b) Algorithm for DWT:

Step1:Read the input image
Step2: Decompose the input image to four sub-bands called Low-Low Decomposition (LLD), Low-High Decomposition (LHD), High-Low Decomposition (HLD), and High-High Decomposition (HHD) using the mathematical equations –(28),(29),(30),(31) respectively.
Step3: Calculate the difference by subtracting LLD image from original image
Step4: Individually sum the difference with LHD, HLD, HHD and form composite image
Step5: Find inverse DWT using the resultant images and input image
Step6: Repeat the process on all the input images
Step7: Estimate PSNR value

IV. EXPERIMENT RESULTS

In this paper, the CT images of Lung cancer available at the ELCAP Public Lung Image Database is used for analyzing different filtering techniques [25]. The results of various filtering techniques for an input image is given below:

a. Enhancement with FFT enhancement technique

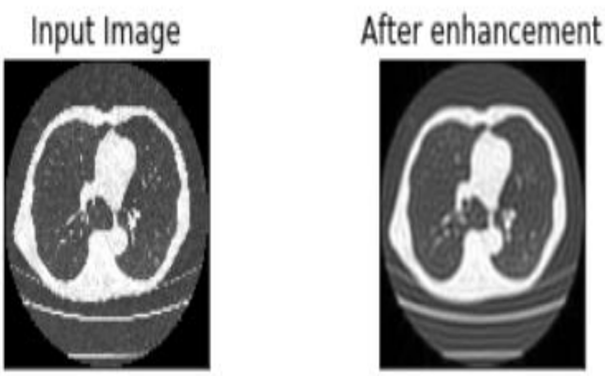


Figure 3Comparison of input and FFT enhanced the image

b. Enhancement with Gaussian filtering technique

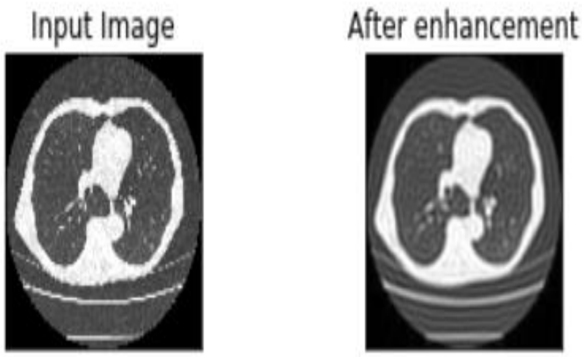


Figure 4Comparison of input and Gaussian filtered image

c. Enhancement with Butterworth filtering technique

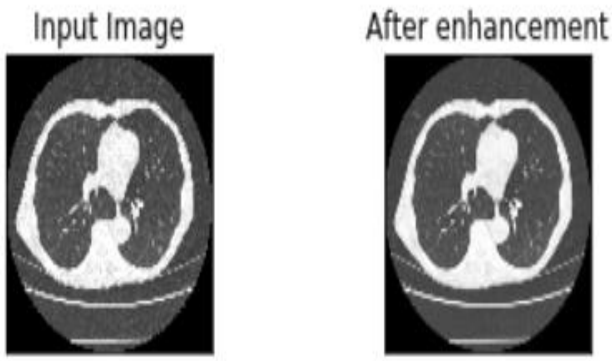


Figure 5Comparison of the input image and Butterworth filtered image

d. Enhancement with Gabor filtering technique

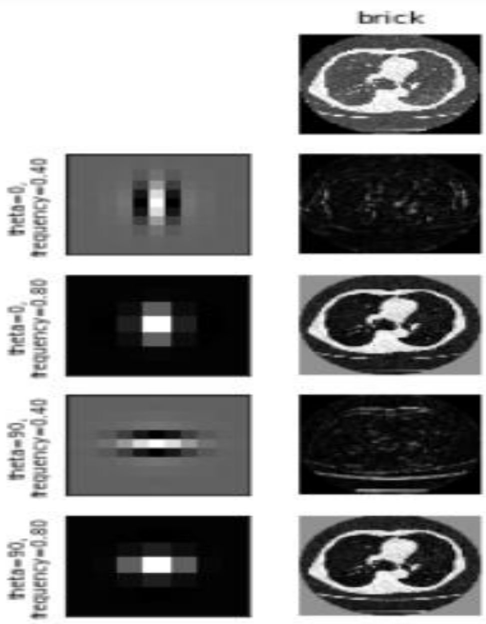


Figure 6Results of the enhanced image on applying Gabor filter for varying theta and frequency values

e. Enhancement with Discrete wavelet transformtechnique

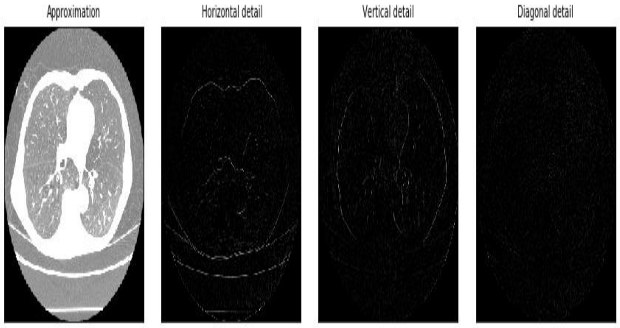


Figure 7Approximate, horizontal, vertical and diagonal details of the image on applying DWT

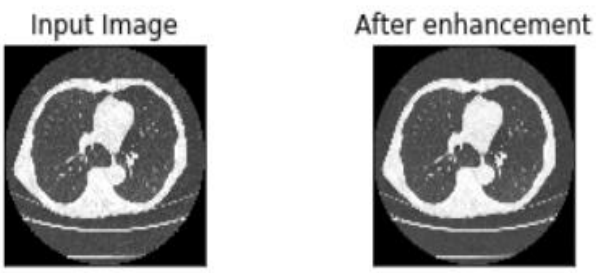


Figure 8Comparison of input and DWT enhanced the image

V. PERFORMANCE ANALYSIS

The reconstruction quality of the output image after applying filtering methods due to lossy compression is measured using the statistical measures like the peak to signal noise ratio (PSNR) and mean square error (MSE) [15]. The human perception of reconstruction quality is similar to the result of PSNR values. The higher the value of PSNR value, higher is the reconstruction quality.

$$\text{PSNR} = \frac{\text{maximum possible power of a signal}}{\text{power of corrupting noise that affects the fidelity of its representation}}$$

And the mathematical formula of PSNR is given by:

$$\text{PSNR} = 10.\log_{10}\left(\frac{\text{Max}_I^2}{\text{MSE}}\right)$$

where for (m x n) monochrome image, with I and its noisy approximation K, MSE is defined as

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

The best filter is chosen depending on the high value of PSNR.In this paper, different filtering methods like FFT, Butterworth filter, Gaussian filter, Gabor filter,and discrete wavelet transform are applied over the lung cancer CT images, and the performance of each filter is evaluated by estimating PSNR values as shown in Table 1.

Table 1PSNR values on applying different filters on an image

Subject	FFT	Butterworth filer	Gaussian filter	Gabor filter	Discrete wavelet transform
Sub1	14.54	30.84	21.19	34.82	30.54
Sub2	13.12	29.74	21.25	35.14	31.36
Sub3	16.48	26.28	20.34	35.97	31.95
Sub4	11.79	22.94	17.97	34.75	30.95
Sub5	15.22	28.18	21.20	35.69	31.73
Sub6	15.24	32.44	22.86	36.42	32.28
Sub7	11.64	28.25	22.24	37.53	33.66
Sub8	13.70	26.83	20.27	35.28	31.75
Sub9	14.46	25.01	19.41	35.53	32.98
Sub10	16.44	29.75	21.93	36.15	31.71
Mean	14.26	28.03	20.86	35.72	31.89

From the above table, it is observed that the images that are better enhanced are the ones havinghigh PSNR value.

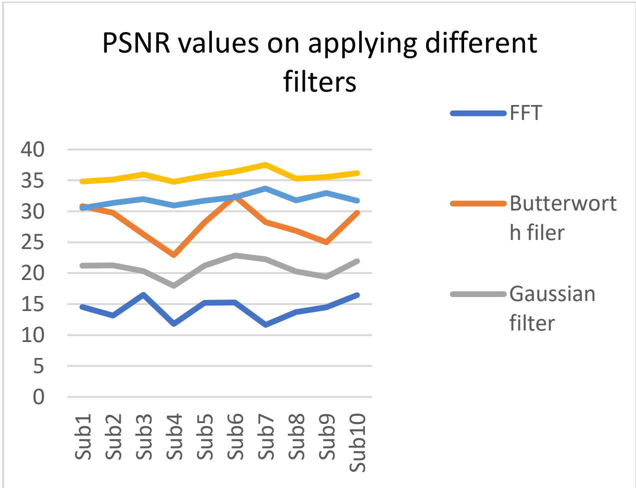


Figure 9PSNR values on applying different filters

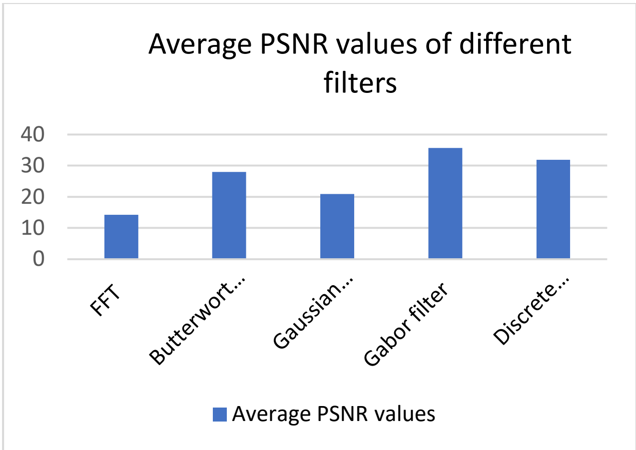


Figure 10Average PSNR values of different filters on Lung cancer image

The average PSNR value for FFT is 14.26, whereas, for the Gabor filter, it is 35.72. Thus, the enhancement of image on applying FFT is very less, and better-enhanced images are obtained on applying the Gabor filter.

VI. CONCLUSION

Image enhancement is an important step in analysing the medical images via computer-aided diagnosis system. The output from the image enhancement process is used as input for further process involved in identifying lung cancer.

Thus, identifying a suitable filter to enhance the quality of lung cancer CT images is an important step. In this paper, image enhancement techniques for detecting Lung cancerare analysed since lung cancer is one of the many cancer types that worldwide men and women are prone to. And dentifying it at an early stage helps in the diagnosis and improvement of the patient's survival rate. In this paper, different frequency basedfiltering techniques like Fast Fourier Transform, Gaussian Filter, Gabor Filter, Butterworth Filter, and Discrete Wavelet Transform are applied over a sample of 10 different lung cancer CT images and the experimental results are analysed and reviewed in detail.

The performance of different filters are estimated in terms of PSNR values. The PSNR value for FFT is found to be the lowest and Gabor filter has the highest PSNR value which implies more meaningful features from CT image can be extracted using Gabor filter and very less using FFT. Thus, from the experimental results and analysis, it can be concluded that the Gabor filter is best suitable compared to other techniques in enhancing Lung cancer CT images.

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