PERFORMANCE EVALUATION OF CT SCAN IMAGE DENOISING AND SEGMENTATION TECHNIQUE FOR DETECTION OF LUNG CANCER

Dr. Shanti Mahesh[1], Karthikeyan A[2], Karunya S[3], Kulsum Hunny[4]

[1]Assistant Professor, Department of Information Science & Engineering, Atria Institute of Technology, Bangalore, India.
[2-4]Student, Department of Information Science & Engineering, Atria Institute of Technology, Bangalore, India.

Abstract - *Lung cancer is one of the frequently occurring cancers having very lowsurvival rate. Hence, earlier detection of lung cancer using CT scan images is crucial. The CT scan imaging is an advantage over the X-ray imaging since it is capable of taking a 360-degree image of internal organs. In order to detect the cancerous nodules in the CT scan images, it is necessary to first de-noise the CT scan images and then segment them. In this paper, we evaluate various de-noising and segmentation techniques in order to find using which one can result in accurate detection of cancerous nodules. The de- noising techniques discussed in this paper include Median Filtering, Average Filtering, Gaussian Filtering and Linear Filtering. After de-noising, we apply Fast Marching and Watershed methods to segment the CT scan images. By analyzing the various approaches, it was found that Median filtering technique wasthe most efficient de-noisingapproach while Fast Marching approach is best suited for segmentation.*

Key Words: **Gaussian Filtering technique, Average Filtering technique, Wiener technique and Median Filtering technique, PSNR, Fast Marching Technique.**

1. INTRODUCTION

Lung cancer is one of the frequently occurring cancers and it accounts for about 19 per cent of cancer related deaths around the world. A cancerous tumor is a new growth of abnormal tissue that is often uncontrolled and progressive. The tumors can spread into nearby tissues and also to other parts of the body. Lung cancer is one of the most dangerous type of cancers having very low survival rate. Earlier detection of cancer is crucial in order to improve the survival rate.

Lung Cancer is usually detected by doctors by looking into CT scan images of lungs. Manual detection is tedious and also involves risks of false detection. CT imaging is used to provide more information about the type and extent of disease.

The CT scan is a pioneering approach and it surpasses the X-ray technology since it is capable of taking a 360-degree image of internal organs. Also, the radiations during X-ray are more harmful as compared to CT scan, so CT scan of lungs is preferred. Hence, it is necessary to have a system to detect lung cancer efficiently in order to improve the survival rate as well as to avoid false detection. In order to detect the cancerous nodules, it is very important to first de-noise [7] the CT scan images and then segment them. Hence, we are evaluating various available techniques in order to find using which technique nodules can be detected efficiently.

The structure of the paper is as follows: Section II contains literaturesurvey onpapers published on Noise cancellation and Segmentation techniques. Section III illustrates our proposed study on noise removal and segmentation. Section IV shows result and discussion and Section V gives the conclusion.

2. LITERATURE SURVEY

In recent years, various noise removal algorithms like linear filtering, average filtering, Gaussian filtering, median filtering are used to de-noise the image. These noise removal algorithms are used to enhance the image. In [1], Nafis uddin Khan et al. presented a method for enhancement of the image by removing salt and pepper noise. It is done using partial unsharp masking and conservative smoothing using two linear filter algorithms. One algorithm helps in smoothing operation and other one is used for conservative smoothing operation. For noise reduction, the selected areas of the image are compared with the original image. Anna Fabijańska et al. [2] developed a new noise reduction algorithm called iterative noiseremoval. Theresults arefirst obtained using methods like median filtering and they are compared with results obtained from iterative noise removal algorithm. Proposed algorithm works iteratively. In [3], Po-Hsiung Lin et al. introduced the Median filtering technique which can be used for noise removal, especially in impulse noise removal techniques. This paper proposed an efficient method through which the image corrupted by high-density impulse noise can be corrected.

First, in order to identify the pixels which could have been contaminated by noise, adaptive median filter method is implemented [4]. Later, the images which are contaminated by noise are restored. This is done by applying a specialized regularization method to those candidates. In [5], a method is proposed for smoothing of image using fourth order PDE model. This helps in removal of noise without suppressing or destructing the important details of the image. A statistic approach for identifying the pixels in images which are corrupted by noise was introduced [6]. The statistical values obtained are then used to quantify the differences in the intensities of the pixels with their most similar neighbors. The result helps in restoring the image as well as obtain quantitative judgments for the quality of image. Two algorithms were presented by Antoni Buades et al. for image de-noising [7]. It helps to compare and evaluate the performance of various digital image de-noising methods. A strategy for de- noising of image [8] which is based on the enhanced sparse representation in the transform domain. Firstly, image fragments that are similar in 2-D are grouped together into data arrays in 3-D. Through this, sparsity enhancement can be achieved. In [9]

H. Hwang et al. proposed and algorithm which preserves the sharpness while removing the impulses.

The first method is called as RAMF (ranked order based adaptive median filter). In RAMF, a test has to be carried out to check if impulses are present in center pixel which is then followed by a test to check if residual impulses are present in the output of median filter. The second method is called SAMF (size based adaptive median filter). It is mainly based on finding the size of impulse noise. The images that are corrupted by impulse noise such as salt-pepper are restored using the methods PSM (progressive switching median) filter and median-based filter [10]. There are two main points in this algorithm: I) before filtering, an impulse detection algorithm is used, due to which, only a proportion of pixels are filtered rather than all the pixels. ii) Both the noise filtering and impulse detection procedures are applied progressively through multiple iterations.

A median filter based on switching with coalition of fuzzy-set theory, known as noise which is characterized by soft-switching median (NASM) filter, to accomplish much improved de-noising performance How-Lung Eng. et al. is proposed [11].In [17] the method of Hopfield Artificial Neural Network Classifier model to divide the cancerous lung regions from the CT images. The 2D Otsu algorithm defined on PSO (particle swarm optimization) is implemented in [13] to divide the image of lung in-order to find the cancerous nodules accurately. The first and fore most thing to detect the ailment related to the lungs such as tumor and carcinoma of the lungs, so this method helps to extract the pulmonary parenchyma from CT images. In many illness detection techniques, which are automized, segmenting the pulmonary lung image plays a significant role and result of image analysis are rely mainly on the effectiveness of segmentation. Many methods are comprehensively used to segment the CT images such as optimal iterative thresholding, region growing, 3-D connectivity labeling.

In [14], the entirely automatic process for cancerous lung image repairing and segmentation was proposed. The trouble of inefficient lung division techniques as in algorithms was proposed by scientists functioning in the area of analysis of medical image [15].The deficiencies of each algorithm have been explained post examining the algorithms in contrast to the collection of inputs. The combination of 'Watershed Technique' and 'Region growing' are implemented as the 'segmentation' strategy in [16].This mechanism is relying on the filters which are convenient in the 'Insight Segmentation and Registration Toolkit' (ITK). In or- der to segment lung regions from human chest Computer Tomography images, an enhanced technique is proposed [12]. A combination of bit-planes of each pixel are used to enhance edge detection of lung region lobes.

In [18] a completely automated and 3-D segmentation method was proposed, which involves the work of recognition of lung portion and any lung tissues using X-ray datasets. This method is used as pre-processing step in the CAD system for cancerous lung nodule detection. An implementation of a fast-marching segmentation method for lung nodule is done in [19], in order to overcome the boundary leakage issue in conventional fast marching technique. This technique begins by providing the training to a model about support vector machine (SVM) classification algorithm as a basic knowledge. Then it computes the decision parameter on each pixel in an image to force front end marching in fast marching method. A seed in a Fast-marching method is the source of the propagation. The selection of seed is very important thing to segment the image accurately. The center of mass of the cancer tumor segmentation is the seed in [20]. The inverted (minus) gradients map values were chosen in the propagation seed function. After de-noising the image, it needs to be segmented in order to detect the cancerous nodules. The various segmentation techniques include fast marching segmentation, watershed segmentation, K-means segmentation, Otsu segmentation and so on.

3. Proposed Work

Our work begins with collection of datasets which are CT scan images of lungs. With the given dataset, our motive is to segment the images in order to detect the cancerous nodules. Our proposed framework consists of two phases. The first phase enhances CT scan images and the second phase segments the CT scan images.

In first stage, we evaluate various de-noising methods and select the best method to enhance CT scan images. In second stage, we apply Fast Marching method to segment the CT scan images. Before segmentation it is necessary to de-noise the image. Accurate diagnosis of the disease requires sharp, clear and noise-free medical images. So we make use of Gaussian filtering, Wiener filtering, Average filtering and Median filtering techniques for de-noising. Further, we find the best technique among these by calculating PSNR values.

3.1 Enhancing CT scan image

Impulse noise is found to occur in CT scan images [1]. Factors that contribute to impulse noise include faulty pixels in the sensors of cameras, and image trans- mission over a noisy channel. Impulse noise is identified by substituting a set of random values in place of a portion of an image's pixel values, keeping the rest of the pixel values intact [2]. Another kind of image noise is the Gaussian noise. It is characterized by adding a value from a Gaussian distribution having mean zero to each image pixel [3].

Efficiency of segmentation requires good image quality. So removal of image noise is necessary. The most popular techniques for noise removal are the Gaussian filtering approach, the Average filtering approach, the Linear filtering approach and the Median filtering approach. The Gaussian noise removal methods elucidates the noise present in images as edges that need to be preserved. Therefore, Median filtering, a non- linear filtering technique, is used for impulse noise removal.

3.1.1 Gaussian Filtering Technique

A Gaussian filter [6] is a linear image filtering method. The Gaussian filter blurs the edges and reduces image contrast. Whenever an image is filtered using Gaussian filter, it results in reduction of image noise and image details. The Gaussian filter results in increased displacement of edge positions.

G(x,y)= $$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} exp(-\frac{x^2+y^2}{2\sigma^2})$$

A two-dimensional digital Gaussian filter can be expressed as:

G(x,y)= $$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} exp(-\frac{x^2}{2\sigma^2})$$

where x and y are the distance from origin in horizontal and vertical axis respectively and σ is standard deviation for Gaussian distribution.

3.1.2 Linear Filtering Technique

Linear filtering enhances both the edges as well as image components having high frequency through a procedure that subtracts an unsharped version of a given image from the actual image. The linear filtering technique [1] makes use of the Wiener effect to filter images. The Wiener effect reduces the overall mean square error in the entire process of filtering and noise removal. The key idea behind the Wiener filtering approach is to linearly estimate the original image. Usingthe orthogonality principle, in Fourier domain, Wiener filter can be ex- pressed as shown below:

W(f1,f2)= $$W(f_1,f_2) = \frac{H^*(f_1,f_2)S_{xx}(f_1,f_2)}{|H(f_1,f_2)|^2 S_{xx}(f_1,f_2) + S_{\eta\eta}(f_1,f_2)}$$

where $Sxx(f1, f2)$, $S\eta\eta(f1, f2)$)are respectively power spectra of the original image and the additive noise, and $H(f1, f2)$is the blurring filter.

3.1.3 Average Filtering Technique

Average filter is a low pass filter that smoothens signal images. The method- ology behind this approach is to find the average values of all the image pixels which are closer to the selected input pixel and initialize the output pixel to this average value. In order to calculate the corrupted image G's average value, we need to take a moving kernel window of size m x n which is centered at the pixel x. Then the corrupted pixel values are replaced by the average value. Sx,y be a set of coordinates in a moving kernel window.

F(x,y)= $$\hat{f}(x,y) = \frac{1}{mn}\sum_{(s,t)\in S_{xy}} G(s,t)$$

where (s, t) is a pixel in the moving kernel window, $\hat{f}(x,y)$ is the image filtered using average filter technique and $G(s, t)$ is the original gray scale image.

3.1.3 Median Filtering Technique

The Median filter [4] is a non-linear filter that is often used to reduce image noise. In median filtering, the output pixel value is determined by computing the median of the nearby pixels, rather than computing the mean of the pixels as in case of averaging filter. Median filtering is better able reduce noise in image without reducing image quality.

$$B(x,y,t) = median\{I(x,y,t-i)\}$$
$$\Downarrow$$
$$|I(x,y,t) - median\{I(x,y,t-i)\}| > Th \text{ where } i \in \{0,\ldots,n-1\}.$$

where x, y are the pixel values.

3.2 Segmentation using Fast Marching Technique

Segmentation [12] is a process of segregating a given image into regions of certain similar characteristics in order to simplify the image identification. Segmentation of CT scan images helps in easy identification of the nodules present in the lungs. It subdivides the objects present in the CT scan images and hence the presence of nodules can be easily spotted. Fast marching is one of the techniques used for segmentation. It performs a propagation spread from a starting point in all the possible directions.

Osher and Sethian introduced the Level-set and fast-marching methods [15]. These methods follow an interface (or front or contour) propagating under a speed function F. These methodologies have been broadly used in the medical imaging field. When applied to image segmentation, the boundary is considered as the desired final position of the propagating interface.

$$F_I(i,j,k) = \alpha F_{I,\mathrm{PDF}}(i,j,k) + \beta F_{I,\mathrm{grad}}(i,j,k),$$

where $Fl,PDF(i,j,k)$ and $Fl,grad(i,j,k)$ are the speed function components, at position (i, j, k) in the IVUS image volume I, respectively defined in terms of the PDF and intensity gradient; α and β are the weights of each component in the speed function Fl that should be in the interval [0, 1].

$$F_{I,\mathrm{PDF}}(i,j,k) = \frac{1}{N_v}\sum_{v s \in v} p_I(y_s),$$

$$F_{I,\mathrm{grad}}(i,j,k) = \frac{1}{1+|G_\sigma * g(y_s)|},$$

where ys is the gray level value of voxel s positioned at $I(i, j, k)$; v is the set of the Nv 3D neighbors of the voxel s; and $pl(ys)$ is the occurring probability of ys in region I.

4. Result and Discussion

The dataset comprises of CT scan images of lungs, obtained from Kaggle. The code for noise cancellation and segmentation are written and simulated using MATLAB R2017a. Each CT scan image is of size 512 x 512. All the images in the dataset are in gray scale. Each image is de-noised using Gaussian, Wiener, Average filtering techniques and further segmented using Fast Marching algorithm. The performance of de- noising and segmentation techniques has been evaluated by calculating PSNR values.

The PSNR (in dB) is calculated as:

PSNR= $$10.\log_{10}\frac{MAX_I^2}{MSE}$$

where M… ximum possible value of pixel of the in… E is the mean squared error which is calculated as:

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

where I is m x n monochrome image which is noise-free and K is its noise approximation.

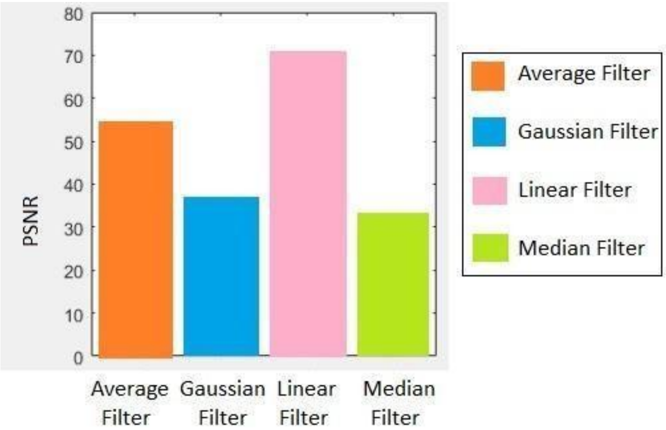


Fig. 1. PSNR graph of de-noising methods

4.1 Results of Image Enhancement

Noise removal techniques help in enhancing the quality of the image. It is very much essential in order to improve the efficiency of segmentation technique. The CT scan images in gray scale are de- noised to enhance the image quality. The methods used for noise cancellation are Gaussian, Linear, Average and Median Filtering techniques. As per our experiment, we have concluded that Median filtering is the best technique for noise removal. The figure 1, 2, 3, 4, 5 are original gray-scale image, Gaussian, linear, average and median filtered image.

In order to determine the optimal noise removal technique, we find the PSNR values for each of the filtering techniques. The PSNR for each of the de-noising approaches is as follows: 32.45 dB, 53.8752 dB, 34.4447 dB and 70.2113 dB for

Median, Averaging, Gaussian and Linear approaches respectively. These values are calculated for 256 images in the dataset. Lower the PSNR value, more efficient is the method. Thus, analyzing the obtained PSNR values it is evident that Median filtering technique has least PSNR value and hence, it is the best method for de-noising of image. Figure 6 shows the bar graph representing the PSNR values for the four noise cancellation methods.

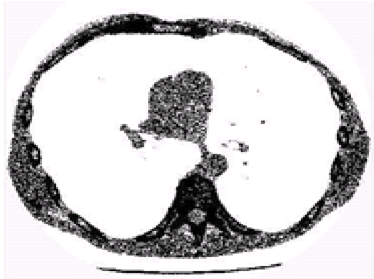
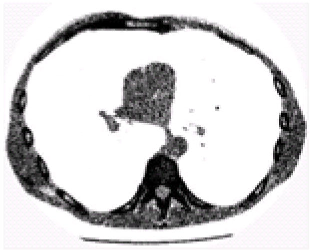


Fig.2 Original CT scan image in grey scale



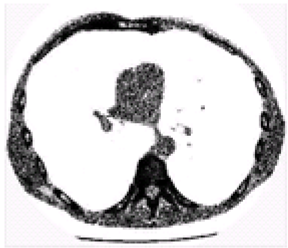


Fig.3 Gaussian filtered image Fig.4 Linear filtered image

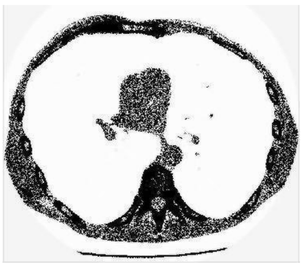


Fig.5 Average filtered image Fig.6 Median filtered image

4.2 Results of Segmentation

The CT scan images de-noised using Median filtering technique are further segmented using Fast Marching method. The result of Fast Marching method is compared with the watershed segmentation method [16]. Watershed algorithm which is used for image segmentation is a mathematics morphological method which is based on region processing. After that the PSNR values are calculated for both of these techniques in order to find best technique for segmentation. After calculating

PSNR, we found that Fast Marching method is more efficient to segment the CT scan images.

The figure 7, 8, 9 displays segmentation of CTscan images using Fast Marching and Watershed Segmentation. In order to evaluate the performance, we computed PSNR values for both segmentation approaches. Figure 10 depicts the PSNR values obtained for both the segmentation approaches. It is observed that PSNR value obtained using Fast Marching method is lower than that of Watershed method. Therefore, we conclude that Fast Marching method performs better when compared to Watershed segmentation method for CT scan images.

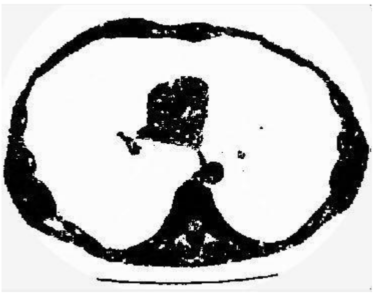


Fig.7 Median filtered image

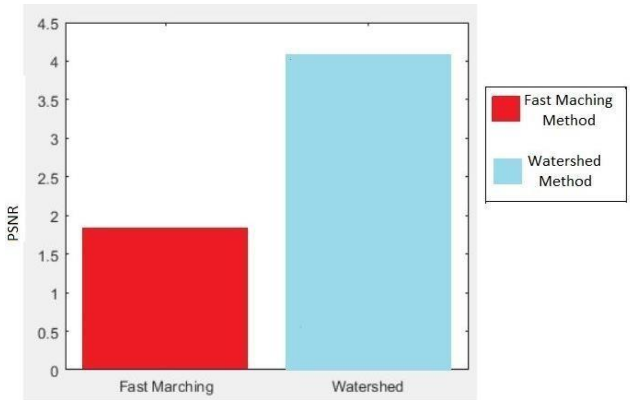


Fig. 10. PSNR graph for Segmentation approaches

5. CONCLUSIONS

Lung cancer is the leading cause of cancer deaths every year around the world. Manual detection of lung cancer using CT scan images is prone to errors thus increases the risk associated with diagnosis. In order to accurately detect the presence of nodules, the CT scan images are subject to de-noising and segmentation. In this paper, we have evaluated various de noising and segmentation techniques and have come to the conclusion that Median filtering and Fast Marching segmentation are the most efficient approaches for image de noising and segmentation respectively.

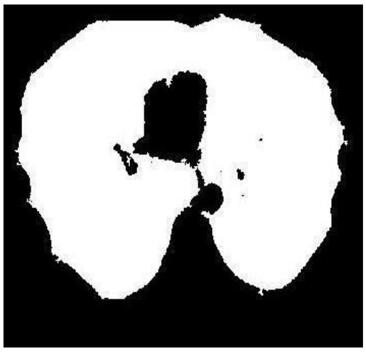


Fig.8 Fast Marching Segmented image

Fig.9 Watershed Segmented image

REFERENCES

[1] Uddin Khan, N., Arya, K. V., & Pattanaik, M. (2010, October). An efficient image noise removal and enhancement method. In 2010 IEEE International Conference on Systems, Man and Cybernetics (pp. 3735-3740). IEEEXiong Yaohua, Luo Wei, “The Smart Home System Based on ARM Platform”, IEEE 2018.

[2] Fabijanska, A., & Sankowski, D. (2007, February). Image noise removal-the new approach. In 2007 9th International Conference-The Experience of Designing and Applications of CAD Systems in Microelectronics (pp. 457-459). IEEE.

[3] Lin, P. H., Chen, B. H., Cheng, F. C., & Huang, S. C. (2016). A morphological mean filter for impulse noise removal. Journal of Display Technology, 12(4), 344- 350.

[4] Chan, R. H., Ho, C. W., & Nikolova, M. (2005). Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization. IEEE Transac- tions on image processing, 14(10), 1479-1485.

[5] Lysaker, M., Lundervold, A., & Tai, X. C. (2003). Noise removalusing fourth- order partial differential equation with applications to medical magnetic resonance images in space and time. IEEE Transactions on image processing, 12(12), 1579-1590.

[6] Garnett, R., Huegerich, T., Chui, C., & He, W. (2005). A universal noise removal al- gorithm with an impulse detector. IEEE Transactions on image processing, 14(11), 1747-1754.

[7] Buades, A., Coll, B., & Morel, J. M. (2005, June). A non- local algorithm for image denoising. In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) (Vol. 2, pp. 60-65).IEEE.

[8] Dabov, K., Foi, A., Katkovnik, V., & Egiazarian, K. (2007). Image denoising by sparse 3-D transform-domain collaborative filtering. Image Processing, IEEE Transactions on 16 (8), pp. 2080-2095.