Evaluation of CT Scan image de-noising technique to estimate the best noise cancellation

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ABSTRACT

Lung cancer is one of the frequently occurring cancers having a very low survival 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. By analyzing the various approaches, it was found that Median filtering technique was the most efficient de-noising approach.

Keywords: Gaussian Filtering technique, Average Filtering technique, Wiener technique and Median Filtering technique, PSNR.

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 literature survey on papers published on Noise cancellation techniques. Section III illustrates our proposed study on noise removal. Section IV shows result and discussion and Section V gives the conclusion.

2. RELATED WORK

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 Fabijan´ska et al. [2] developed a new noise reduction algorithm called iterative noise removal. The results are first 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, sparcity 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].

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. 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 transmission 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].

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.

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

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

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

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. Using the orthogonality principle, in Fourier domain, Wiener filter can be expressed as shown below:

$$W(f_1,f_2) = \frac{H^*(f_1,f_2)S_{xx}(f_1,f_2)}{\mid H(f_1,f_2)^2 \mid S_{xx}(f_1,f_2) + S_{\eta\eta}(f_1,f_2)} \quad (3)$$

where $S_{xx}(f1,f2)$, $S_{\eta\eta}(f1,f2)$ 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 methodology 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. $S_{x,y}$ be a set of coordinates in a moving kernel window.

$$\hat{f}(x,y) = \frac{1}{mn} \sum_{(s,t)\in S_{xy}} G(s,t) \qquad (4)$$

3.1.4 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.

$$B(x,y,t) = median(I(x,y,t-i)) \qquad (5)$$

where x, y are the pixel values.

4. RESULT AND DISCUSSION

The dataset comprises of CT scan images of lungs, obtained from Kaggle. The code for noise cancellation is 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 and Median filtering techniques. The performance of de-noising techniques has been evaluated by calculating PSNR values.

The PSNR (in dB) is calculated as:

$$PSNR = 10.\log_{10} \frac{MAX_I^2}{MSE} \qquad (6)$$

Where MAX_i is the maximum possible value of pixel of the image and MSE is the mean squared error which is calculated as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \qquad (7)$$

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

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.

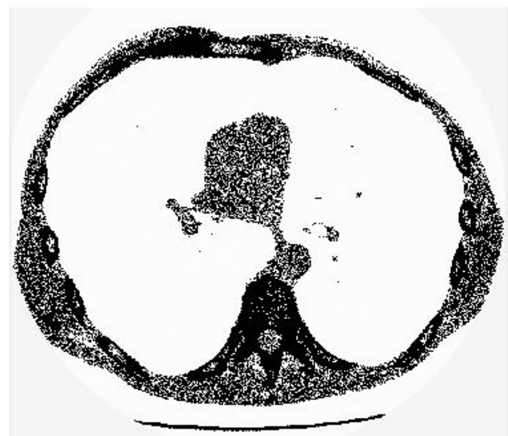

Figure 1: Original CT scan image in gray-scale

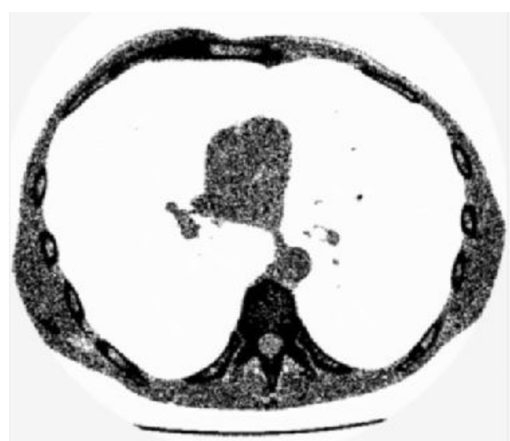

Figure 2: Gaussian filtered image

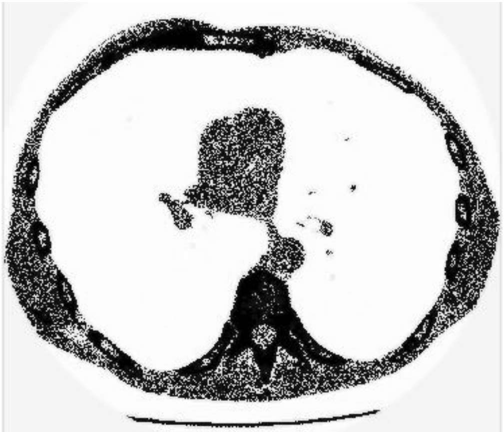

Figure 3: Linear filtered image

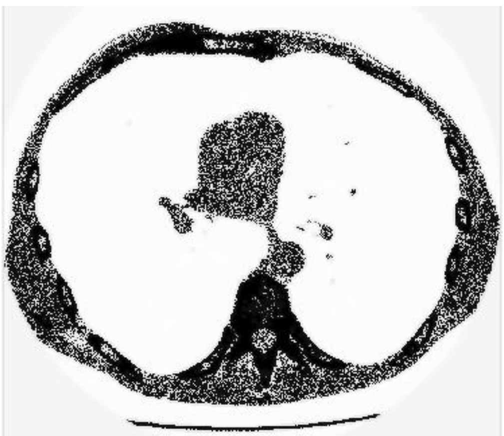

Figure 4: Average filtered image

Figure 5: Median filtered image

5. Conclusion

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 is subject to de-noising. In this paper, we have evaluated various de-noising techniques and have come to the conclusion that Median filtering is the most efficient approach for image de-noising.

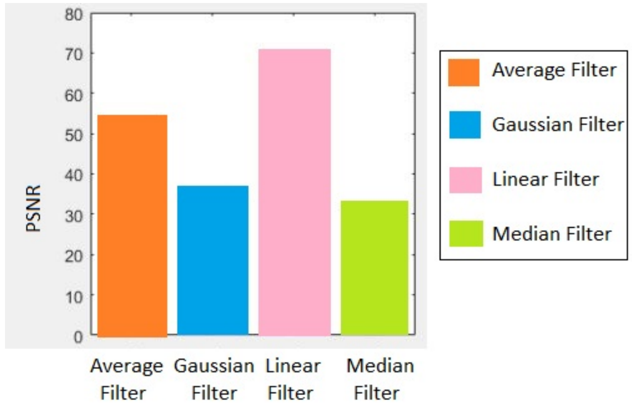

Figure 6: PSNR graph of de-noising methods

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). IEEE.

[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), 344350.

[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 Transactions on image processing, 14(10), 1479-1485.

[5] Lysaker, M., Lundervold, A., & Tai, X. C. (2003). Noise removal using fourthorder partial differential equation with applications to medical magnetic resonance images in space and time. IEEE Transactions on image processing, 12(12), 15791590.

[6] Garnett, R., Huegerich, T., Chui, C., & He, W. (2005). A universal noise removal algorithm 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.

[9] Hwang, H., & Haddad, R. A. (1995). Adaptive median filters: new algorithms and results. IEEE Transactions on image processing, 4(4), 499-502.

[10] Wang, Z., & Zhang, D. (1999). Progressive switching median filter for the removal of impulse noise from highly corrupted images. IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing, 46(1), 78-80.

[11] Eng, H. L., & Ma, K. K. (2001). Noise adaptive soft-switching median filter. IEEE Transactions on image processing, 10(2), 242-251.

[12] procedure that subtracts an unsharped version of a given image from the actual image. The linear filtering technique [1] makes use of domain collaborative filtering. Image Processing, IEEE Transactions on 16 (8), pp. 2080-2095.