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An Adaptive Preprocessing of Lung CT Images with Various Filters for Better Enhancement

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Abstract: In the present era Information Technology plays a crucial role in every fields of human survival. Especially, Digital Image Processing adopted a dominant place in such type of information processing systems. It is also integrated with the Medical Image Processing in the diagnosis of Lung Cancer and other diseases. Now a days Medical image processing has emerged in the diagnosis of various diseases especially for cancers. Elimination of noises in medical images is a challenging task in such kind of image processing. In order to overcome such issues preprocessing is a crucial task to eliminate the noises and for better image enhancement. In this paper, different preprocessing methods are compared with various filters. The performance is evaluated using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). Finally, Bilateral filter provides better PSNR and lower MSE values. Hence, we conclude that this filter is an efficient one for preprocessing medical images.

Key words: Medical Image Processing · Preprocessing · PSNR · MSE · Bilateral filter

INTRODUCTION

With the evolution of computers, the information processing is a primary task for all kind of automated systems. The representation of information through images is more powerful among the others. Images get more popular because an illiterate person can also be easily understand and recognize.

Computer Aided Detection/Diagnosis (CAD), are techniques in medical data set that assists radiologists to detect and diagnose the diseases, in the interpretation of medical images. CAD systems helps physician to highlight conspicuous areas like nodules. The success of the specific CAD system depends on the speed, automation and accuracy level. In addition, CAD may reduce the inter-and intra-observer variability in image interpretation. A number of studies [1-4] have demonstrated the usefulness of applying CAD to interpretation of thoracic Computed Tomography (CT) scans.

Lung cancer is one amongst the leading deadliest disease in the world. According to GLOBOCAN 2012 [5], the most commonly diagnosed cancers worldwide were those of Lung (1.8 million, 13. 0% of the total), Breast (1. 7 million, 11. 9%) and Colorectum (1. 4 million, 9. 7%). The most common causes of cancer deaths were cancers of the Lung (1. 6 million, 19. 4% of the total), Liver (0. 8 million, 9. 1%) and Stomach (0. 7 million, 8. 8%).

The survival of the patients' are closely correlated to the stage of lung cancer at the time of detection. Early prediction of lung cancer should play a vital role in the diagnosis process and for an effective preventive strategy [6, 7].

Preprocessing is a process which is used to increase the accuracy and interpretability. Image pre-processing is an important and challenging factor in the computer-aided diagnostic systems. In medical image processing tumour segmentation task is very important to preprocess the image so that segmentation and feature extraction algorithms work correctly. Accurate detection and segmentation of the tumour leads to exact extraction of features and classification of those tumours. The accurate tumour segmentation is possible if image is pre-processed as per image size and quality.

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Literature Survey: Image quality is determined by contrast, resolution and signal-to-noise ratio. Adaptive Neighbourhood Contrast Enhancement (ANCE) [8] method, computes the local contrast around each pixel using a variable neighbourhood. This technique provides the advantage of enhancing or preserving the image contrast while supressing noise. The main drawback of using ANCE is difficult to determine parameters used in the processing steps.

In [9], the lung CT images are initially preprocessed in order to remove noise. Then the preprocessed images are segmented by using Sobel edge detection method. After segmentation, the features such as Area of Interest, Shape and Size of nodule, can be obtained and diagnosis rule can be designed to exactly detect the lung nodules.

The abnormality nodules are situated within the lung parts of the CT scan image that is usually less than half of the area of the CT slice. If nodules have to search in the whole slice, it will take a long time. For time reduction, we have to search only those areas containing nodules. For this purpose, the authors in [10], have developed fully automatic method based on Genetic algorithms and Morphology based image processing techniques to segment that lung part. Thus, segmentation is used as a preprocessing step of a CAD.

The image data from CT/MRI devices usually needs preprocessing before visualization. Preprocessing can be done by using contrast enhancement, noise reduction and segmentation in [11]. For contrast enhancement the authors used, histogram equalization [12]. This strategy is convenient for images with backgrounds and foregrounds that are both bright and both dark. During digitization, noise can appear. Noises are eliminated by using average filters and different types of median filters. Before visualization, data's are divided into multiple segments.

In the paper [13], preprocessing method has two phases. In the first phase, noises and film artifacts can be removed by using median filter. In the second phase, erosion is applied to the structuring element three times; but every time decreases the size of the structuring element by one. Unwanted ribcage portion has been removed from the obtained result. This preprocessing also reduce the over segmentation problem, while retain the tumour.

In the work done by [14], single-view detection scheme is used to develop a multi-view scheme. Single –view detection consists of the stages like: segmentation and pre-processing, initial detection of suspected area, region segmentation and final single – view classification. Moreover, the authors specifically find out how multi-view analysis can be made more effective for improving case-based performance.

As an initial step pre-processing is done by using Gaussian filter in [15], to remove the speckle noise present in the Lung CT images. Image enhancement is done with the help of contrast stretching by uniformly redistributing the grey values.

A review of some of the popular algorithms for preprocessing/segmentation of color images are presented in [16]. The review suggests that the performance of these methods depend among various factors such as data distribution, operating parameters and the operating environment.

MATERIALS AND METHODS

Adaptive Median Filter: The Adaptive Median Filter [17] performs spatial processing to determine which pixels in an image have been affected by impulse noise. The Adaptive Median Filter classifies pixels as noise by comparing each pixel in the image to its surrounding neighbour pixels. The size of the neighbourhood is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbours, as well as being not structurally aligned with those pixels to which it is similar, is labelled as impulse noise. These noise pixels are then replaced by the median pixel value of the pixels in the neighbourhood that have passed the noise labelling test.

Adaptive median filter changes the size of Sxy (the size of the neighbourhood) during its processing.

Algorithm

```
Level A:  A1 = Zmed - Zmin
          A2 = Zmed - Zmax
          if A1 > 0 AND A2 < 0, go to level B
                else increase the window size
                if window size < Smax, repeat level A
           else output Zxy

Level B:  B1 = Zxy - Zmin
          B2 = Zxy - Zmax
          if B1 > 0 AND B2 < 0, output Zxy
          else output Zmed
```

Zmin= minimum gray level value in Sxy; Zmax = maximum gray level value in Sxy; Zmed = median of gray levels in Sxy; Zxy = gray level at coordinates (x, y); Smax = maximum allowed size of Sxy.

The main disadvantage of median filter is to undifferentiated noisy and fine detail pixels. Adaptive median filter, overcome this deficiency by performing spatial processing over pixels. A pixel mostly different from its neighbourhood pixels, as well as being not structurally aligned with those pixels to which it is similar is labelled as 'noise'. Those noisy pixels are then replaced by the median value of the pixels in the neighbourhood that has passed the noise labelling test.

Alpha-Trimmed Mean Filter: Alpha-trimmed mean filter [18] is a hybrid of mean and median filters. Place a mask (3x3, 5x5) on the structuring element. Then order the pixel elements. Discard the first and last pixel in the ordered list. Calculate the mean for the remaining ordered set. Here 'alpha' (α) represents the number of elements to be discarded. The minimum value for alpha parameter is zero and in this case alpha-trimmed mean filter degenerates into 'mean filter'. Maximum value for alpha is filter window size minus one and in this case the filter degenerated into 'median filter'.

Let $\{x(i), x(i-1), \ldots x(i-n+1)$ where n=2N+1, be a set of n sample signal values observed in a window W_i. The output of the Alpha-Trimmed Mean filter $y(i, \alpha)$ is:

$$y(i,\alpha) = \frac{1}{n-2[\alpha n]} \sum_{j=[\alpha n]+1}^{n-[\alpha n]} x_j(i) \qquad (1)$$

where [.] denotes the greatest integer part and $0 \le \alpha < 0.5$.

Gaussian Filter: Gaussian filter [19] gives more weight to the current pixel position and then tapers the weights as distance increases according to the Gaussian formula. This filter can better preserve the edges than the mean filter. This filter is applied to an image in a two phase approach. At first, the horizontal direction is filtered by taking each pixel in the image, centring the filter on that pixel (middle value) and then multiplying the pixel values by the weight at each filter location and then divides all to get the resulting new pixel value. This process is then repeated vertically on the horizontally processed image to create the final image.

The 2D Gaussian equation is represented as:

$$\frac{1}{2\pi\sigma^2} exp\left\{\frac{-x^2+y^2}{2\sigma^2}\right\} \qquad (2)$$

Gabor Filter: A Gabor filter [20] is obtained by modulating a sinusoid with a Gaussian. Let $g(x, y, \theta, \phi)$ be the function defining a Gabor filter centred at the origin with θ as the spatial frequency and ö as the orientation. We can view Gabor filter as:

$$g(x,y,\theta,\phi) = exp\left(\frac{-x^2+y^2}{\sigma^2}\right) exp(2\pi\theta i(xcos\phi + ysin\phi)) \qquad (3)$$

Gabor filters are extensively used in 'texture segmentation'.

High Pass Filter: A high-pass filter [21] might be utilized to make an image shown up clear. These filter stress fine parts, in the image. Unfortunately, while low-pass filtering smooths out noise, high-pass filtering does the exact inverse: it enhances *noise*. One can skip this, if the original image is not excessively noisy; generally the noise will overpower the image. We can high-pass filter only the brightest parts of the image, where the signal-to-noise ratio is most noteworthy.

High-pass filtering can additionally cause little, faint details to be greatly exaggerated. An over processed image will look grainy and unnatural and point sources will have dark donuts around them. While high-pass filtering can regularly enhance an image by sharpening detail, trying too hard can really debase the image quality fundamentally.

Let the input signal values be $x(0)$, $x(1)$,...$x(n)$. The constant α is calculated from:

$$\alpha = RC / (RC + dt) \qquad (4)$$

where dt is the time interval and RC is time constant.

The output of the High-pass filter is:

$$y[i] = \alpha * y[i-1] + \alpha * (x[i] - x[i-1]) \qquad (5)$$

Laplacian Filter: *A* Laplacian filter [22] could be utilized to underline the edges in an image. As such, this filter type is generally utilized within edge-detection provisions. The calculation works by convolving a kernel of weights with each pixel value and its neighbours in an image. The Laplacian is regularly connected to an image that has first been smoothed utilizing Gaussian smoothing filter within request to decrease its affectability to noise. The operator regularly takes a solitary gray level image as information and produces an alternate gray level image as yield. The Laplacian L(x, y) of an image with pixel intensity values I(x, y) is given by:

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \qquad (6)$$

Bilateral Filter: Bilateral filtering [23] smooths images while safeguarding edges, by method of a nonlinear synthesis of adjacent pixel values. The technique is non-iterative, simple and straightforward. It combines gray levels or colors dependent upon both their geometric closeness and their photometric comparability and inclines toward close values to inaccessible values in both domain and range. A bilateral filter smooth colors and safeguard edges in a manner that is tuned to human recognition. Additionally, bilateral filtering produces no phantom colors along edges in color images and reduces phantom colors where they show up in the original image. The output of the Bilater filter is obtained from:

$$BF[I]_p = \frac{1}{W_p} \sum_{qes} G_{\sigma_s}(\| p-q \|) G_{\sigma_r}(| I_p - I_q |).I_q \qquad (7)$$

Similarity Measure: For a long time, MSE & PSNR are used to measure the degree of image distortion, because they can represent the overall gray value error in the entire image.

Mean Square Error (MSE): Mean Square Error (MSE) can be estimated to quantify the difference between values implied by an estimate and the true quality being certificated. Given a noise free mxn monochrome image I and its noisy approximation K, MSE is defined as:

$$MSE = \frac{1}{m\,n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \qquad (8)$$

Peak Signal-to-Noise Ratio (PSNR): The Peak Signal to Noise Ratio (PSNR) is the difference between the maximum possible signal and the corrupting noise that affect the representation of an image. PSNR is usually expressed as decibel scale. High value of PSNR indicates the high quality of image.

$$PSNR = 20.\log_{10}(MSX_I) - 10.\ \mathrm{Log}_{10}\, MSE \qquad (9)$$

Here MAX_i is the maximum possible pixel value of the image. In both MSE and PSNR i, j represents the intensity of the image.

ALGORITHM

INPUT: Original image
OUTPUT: Preprocessed image
//Preprocessed Image//

Step 1: Start
Step 2: Select input image i from the image database.
Step 3: Process the image with the following filters:
a: Adaptive median filter
b: Alpha-trimmed mean filter
c: Gaussian filter
d: Gabor filter
e: High-pass filter
f: Laplacian filter
g: Bilateral filter

Step 4: Evaluate the PSNR and MSE values.

Step 5: Repeat Step2 through Step4 for all the images in the database.

Step 6: Select the filter which has higher PSNR and lower MSE values.

Step 7: Stop the process.

RESULTS AND DISCUSSION

The experimentation has been done with the CT images collected from various private hospitals with a set of 418 lung cancer images. The digitized images are stored in the JPEG format with a resolution of 8 bits per plane. All images are stored as 512x512x8 raw data.

Experiments were conducted using the original image with different types of filters in order to remove noise and other artifacts in the original image. The following Figures show the output of the various filtered images.

After pre-processing, the accuracy of the filtered image is measured by using the PSNR & MSE values. From the Table 1, we concluded that Bilateral Filter gives higher PSNR value and lower MSE when compared to other filters.

Table 1: PSNR & MSE values for different filters

Filters Name	PSNR Value	MSE Value
Adaptive Median Filter	39.4309	29.33109
Alpha Trimmed Mean Filter	71.86155	0.016638
Gaussian Filter	46.70281	17.08423
Gabor Filter	16.65061	5472.75
High Pass Filter	23.34334	3475.875
Laplacian Filter	21.34006	5573.9
Bilateral Filter	88.22711	0. 000379

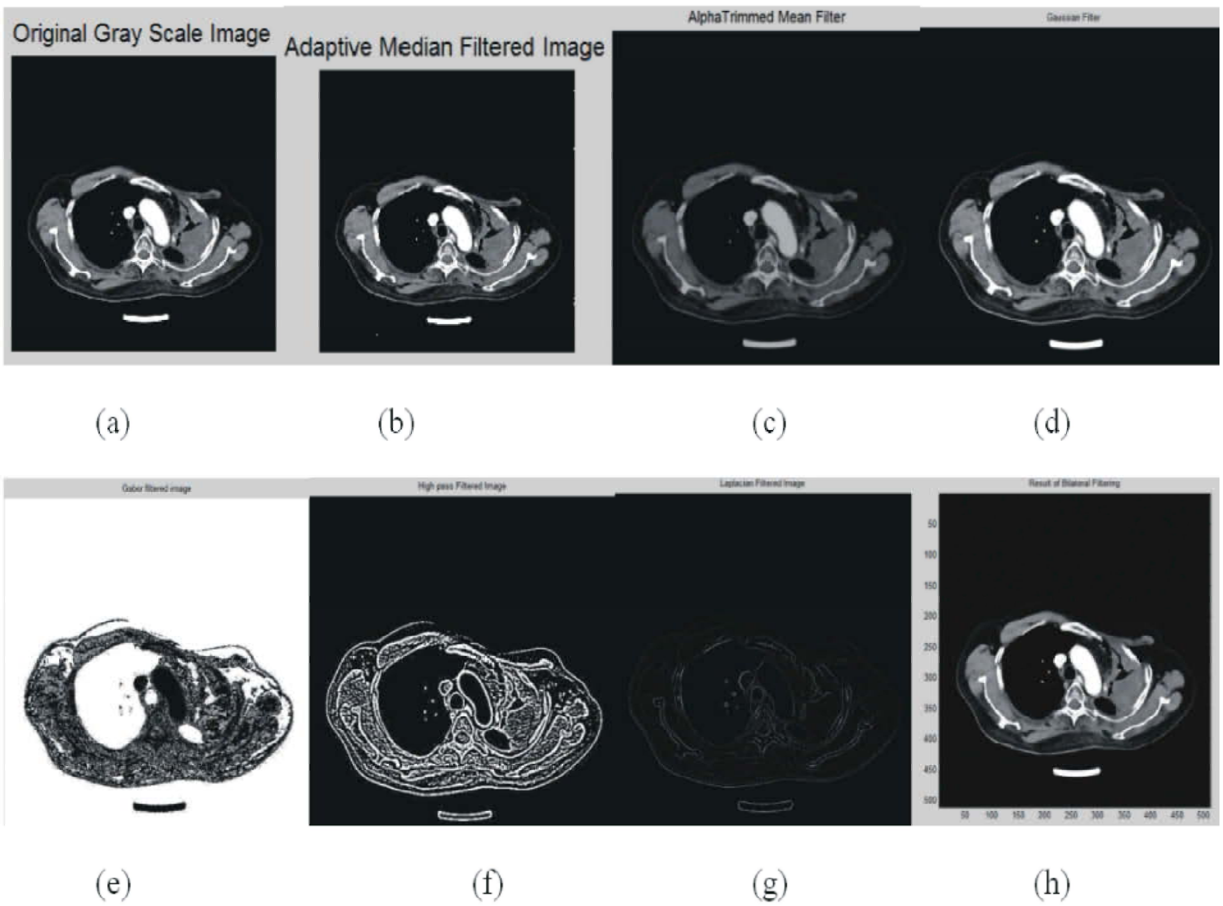

Fig. 1: Represents the Original Image & its Filtered Images. (a) Original Image (b) Adaptive Median Filtered Image. (c) Alpha Trimmed Mean Filtered Image. (d) Gaussian Filtered Image. (e) Gabor Filtered Image. (f) High Pass Filtered Image. (g) Laplacian Filtered Image. (h) Bilateral Filtered Image

CONCLUSION

In this paper various filters were analysed and experimented with the CT images collected from various hospitals. The main aim behind this preprocessing is to remove the noises and other artifacts from the medical images and to make better enhancement. In order to select the better filter the experimentation has been made with the various filters and the results are compared. The performance of this system is evaluated in terms of PSNR and MSE values. Finally, we conclude that Bilateral filter provides 88. 23PSNR and 0. 000379 MSE values, when compared with other filters.

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