



A STUDY ON IMAGE DENOISING FOR LUNG CT SCAN IMAGES

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Abstract: Medical imaging is the technique and process used to create images of the human body for clinical purposes and diagnosis. Medical imaging is often perceived to designate the set of techniques that non-invasively produce images of the internal aspect of the body. The x-ray computed tomographic (CT) scanner has made it possible to detect the presence of lesions of very low contrast. The noise in the reconstructed CT images is significantly reduced through the use of efficient x-ray detectors and electronic processing. The CT reconstruction technique almost completely eliminates the superposition of anatomic structures, leading to a reduction of "structural" noise. It is the random noise in a CT image that ultimately limits the ability of the radiologist to discriminate between two regions of different density. Because of its unpredictable nature, such noise cannot be completely eliminated from the image and will always lead to some uncertainty in the interpretation of the image. The noise present in the images may appear as additive or multiplicative components and the main purpose of denoising is to remove these noisy components while preserving the important signal as much as possible. In this paper we analyzed the denoising filters such as Mean, Median, Midpoint, Wiener filters and the three more modified filter approaches for the Lung CT scan images to remove the noise present in the images and compared by the quality parameters.

Keywords: Medical CT scan images; Noise removal; Statistical filters; Quality measures

I. Introduction

Medical image enhancement technologies have attracted much attention since advanced medical equipments were put into use in the medical field. Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise and other data acquisition devices, illumination conditions, etc. Our targets of medical image enhancement are mainly to solve problems of the high level noise of a medical image. The noise present in the images may appear as additive or multiplicative components and the main purpose of denoising is to remove these noisy components while preserving the important signal as much as possible[1]. The Medical Images normally have a problem of high level components of noises. There are different techniques for producing medical images such as Magnetic Resonance Imaging (MRI), X-ray, Computed Tomography and Ultrasound, during this process noise is added that decreases the image quality and image analysis. Image denoising is an important task in image processing.

II. Image Noise

There are several types of image "noise" that can interfere with the interpretation of an image. Although noise may infiltrate and corrupt the data at any point in the CT process, the ultimate source of noise is the random, statistical noise, arising from the detection of a finite number of x-ray quanta in the projection measurements.

Properties of CT Noise:

The consequences of statistical noise in CT reconstructions have been discussed by numerous authors [1][2][3]. Several of these authors have pointed out that the process of reconstruction leads to some peculiar characteristics of the noise in CT images. The properties of statistical (quantum) noise in CT reconstructions will be explored in this discussion. Although the precise random noise pattern of any image cannot be predicted a priori, it is possible to characterize the average behavior of the noise by a variety of methods. Some of these methods give a complete description of the noise characteristics, such as the noise power spectrum or the noise autocorrelation function, whereas others give only a partial description, such as rms noise. It will develop that the noise fluctuation in one pixel of a CT reconstruction is not independent of the noise fluctuations in other pixels. Rather, the fluctuations in two Separate pixels are, on the average, correlated.

Random Noise:

Image mottling, or fluctuations in the image density that change from one image to the next in an unpredictable and random manner, may be termed random noise. The Radiologist is familiar with random noise in the form of radiographic mottle found in standard radiographs taken with fast screen-film combinations [4].

Statistical Noise:

The energy in x-radiation is transmitted in the form of individual chunks of energy called quanta. Hence the response of an x-ray detector is actually the result of detecting a finite number of x-ray quanta. The number of

detected quanta will vary from one measurement to the next, not because of inadequacies in the detection apparatus, but because of statistical fluctuations that naturally arise in the "counting" process. As more quanta are detected in each measurement, the relative accuracy of each measurement improves. Statistical noise in x-ray images arises from the fluctuations inherent in the detection of a finite number of x-ray quanta. Statistical noise may also be called quantum noise and is often referred to as quantum mottle in film radiography. Statistical noise clearly represents a fundamental limitation in x-ray radiographic processes. The only way to reduce the effects of statistical noise is to increase the number of detected x-ray quanta. Normally this is achieved by increasing the number of transmitted x rays through an increase in dose.

Electronic Noise:

In processing electric signals, electronic circuits inevitably add some noise to the signals. Analog circuits, those which process continuously varying signals, are most susceptible to additional noise. The difficulty of noise suppression is compounded by the fact that for some types of x-ray detectors, the electronic signals are very small. Digital circuits, those which process discrete signals as in digital computers, are relatively impervious to electronic noise problems[5].

Structural Noise:

Density variations in the object being imaged that interfere with the diagnosis are sometimes referred to as structural "noise" or structural clutter. In standard radiography a large amount of structural clutter is produced by the superposition of various anatomic structures, for example, the image of rib bones overlaps that of the lung in a standard chest radiograph. The CT technique eliminates most of this superposition, but the radiologist should be aware that partial contributions may be introduced by structures that principally appear in adjacent CT slices. Some organs, such as the liver, may have density variations within them that have the appearance of random noise. Although the texture pattern of the organ may not be reproducible from one CT scan to the next because of patient motion, this type of structural variation is, of course, not random. Indeed, the classification of this density variation as a type of noise is ill-advised, since the variation is intrinsic to the object itself. The study of the tissue texture may be interesting for its potential diagnostic value [6].

Round-Off Errors:

Although digital computers are not subject to electronic noise, they do introduce noise in the reconstruction process through round-off errors. The errors arise from the limited number of bits used to represent numbers in the computer. For example, the product of two numbers must be rounded off to the least significant bit used in the computer's representation of the number. Round-off errors can normally be kept at an insignificant level either through choice of a computer with enough bits per word or through proper programming. It should be pointed out that in some CT scanners the final reconstruction is stored with the least significant bit equal to one CT number (0.1 % of the linear attenuation coefficient of water). This should not influence the accuracy significantly so long as the rms noise is greater than one CT number [7].

III. Denoising

Denoising plays a very important role in the field of the medical image pre-processing. It is often done before the image data is to be analyzed. Denoising is mainly used to remove the noise that is present and retains the significant information, regardless of the frequency contents of the signal. It is entirely different content and retains low frequency content. De-noising has to be performed to recover the useful information. In this process much attention is kept on, how well the edges are preserved and how much of the noise granularity has been removed [4-5] the main purpose of an image denoising algorithm is to eliminate the unwanted noise level while preserving the important features of an image.

Noise Removal based on filtering models:

Many image processing algorithms cannot work well in noisy environments. Specifically for the removal of noise from an input image there are several filters that can be considered as the state-of-art methods given their impressive performance [13]. There are many filters that are used to remove impulse noise from digital corrupted images. The following section describes the various filtering approaches considered in this work.

Mean filter:

This is the simplest of the mean filters. Let S_{xy} represent the set of coordinates in a rectangular subimage window of size $m \times n$, centered at point (x, y) . The arithmetic mean filter filtering process computes the average value of the corrupted image $g(x, y)$ in the area defined by S_{xy} . The value of the restored image f at any point (x, y) is simply the arithmetic mean computed using the pixels in the region defined by S_{xy} . In other words,

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

This operation can be implemented using a convolution mask in which all coefficients have value $1/mn$. An example of mean filtering of a single 3×3 window of values is shown below.

5	3	6
2	1	9
8	4	7

$$5+3+6+2+1+9+8+4+7=45/9=5$$

*	*	*
*	5	*
*	*	*

Mean filter simply smooth local variations in an image. Noise is reduced as a result of blurring. The mean filter is a simple sliding-window spatial filter that replaces the center value in the window with the average (mean) of all the pixel values in the window. The window, or kernel, is usually square but can be any shape[8][9].

Median filter:

The best known order-statistics filter is the *median filter*, which, as its name implies, replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel:

$$f(x, y) = \text{median}_{(s,t) \in S_{xy}} \{g(s, t)\}$$

The original value of the pixel is included in the computation of the median. An example of median filtering of a single 3x3 window of values is shown below.

6	2	0
3	97	4
15	3	10

0, 2, 3, 3, **4**, 6, 10, 15, 97

*	*	*
*	4	*
*	*	*

Center value (previously 97) is replaced by the median of all nine values (4). Median filters are quite popular because, for certain types of random noise, they provide excellent noise-reduction capabilities, with considerably less blurring than linear smoothing filters of similar size. Median filters are particularly effective in the presence of both bipolar and unipolar impulse noise. The median filter is also a sliding-window spatial filter, but it replaces the center value in the window with the median of all the pixel values in the window. As for the mean filter, the kernel is usually square but can be any shape.

Midpoint filter:

The Midpoint filter blurs the image by replacing each pixel with the average of the highest pixel and the lowest pixel (with respect to intensity) within the specified window size. For example, given the grayscale 3x3 pixel neighborhood;

22	77	48
150	77	158
0	77	219

The center pixel would be changed from 77 to 109 as it is the midpoint between the brightest pixel 219 and the darkest pixel 0 within the current window. The midpoint filter simply computes the midpoint between the maximum and minimum values in the area encompassed by the filter:

$$f(x, y) = \frac{1}{2} [\max\{g(s, t)\} + \min\{g(s, t)\}]$$

This filter combines order statistics and averaging. This filter work best for randomly distributed noise, like Gaussian or uniform noise.

Wiener Filter:

The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. Wiener filter estimates the local mean and variance around each pixel [8][9][10].

$$\mu = \frac{1}{NM} \sum_{n1, n2 \in \eta} a(n1, n2)$$

and

$$\sigma^2 = \frac{1}{NM} \sum_{n1, n2 \in \eta} a^2(n1, n2) - \mu^2$$

Where η is the N-by-M local neighborhood of each pixel in the image, then creates a pixel-wise wiener filter using these estimates,

$$b(n1, n2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2} (a(n1, n2) - \mu)$$

Where v^2 the noise variance is not given, then the average of all the local estimated variances.

IV. Proposed Filtering Methods

L-1(Leave-One) mean filter:

This is the modified version of the mean filters. Let S_{xy} represent the set of coordinates in a rectangular subimage window of size m X n, centered at point(x, y). This filter computes the average value of the corrupted image $g(x, y)$ in the area defined by S_{xy} with the interval of 1. The value of the restored image f at any point (x, y) is simply the arithmetic mean computed using the pixels in the region defined by S_{xy} . An example of mean filtering of a single 3x3 window of values is shown below.

5	3	6
2	4	9
8	4	7

5+6+4+8+7=30/5=6

*	*	*
*	6	*
*	*	*

L-1(Leave-One) median filter:

This is the modified version of the median filters. Let S_{xy} represent the set of coordinates in a rectangular subimage window of size m X n, centered at point(x, y). This filter computes the median value of the corrupted image $g(x, y)$ in the area defined by S_{xy} with the interval of 1. The value of the restored image f at any point (x, y) is simply the arithmetic mean computed using the pixels in the region defined by S_{xy} . An example of L-1 median filtering of a single 3x3 window of values is shown below.

5	3	6
2	4	9
8	4	7

4,5,6,7,8

*	*	*
*	6	*
*	*	*

L-1(Leave-One) midpoint filter: This is the modified version of the midpoint filters by replacing each pixel with the average of the highest pixel and the lowest pixel (with respect to intensity) within the specified window size with L1 property. For example, given the grayscale 3x3 pixel neighborhood;

5	3	6
2	4	9
8	4	7

Low=4,Max=8,Midpoint=6

*	*	*
*	6	*
*	*	*

Evaluation metrics:

The *Mean Square Error (MSE)* and the *Peak Signal to Noise Ratio (PSNR)* are the two error metrics used to compare image reconstruction quality. The higher value of PSNR and SNR denotes the better the quality of the reconstructed image [11].

$$PSNR = 10 \log_{10} \left(\frac{1}{MSE} \right) db$$

The MSE represents the cumulative squared error between the reconstructed and the original image, whereas PSNR represents a measure of the peak error.

$$MSE = \frac{\sum_{x=1}^M \sum_{y=1}^N f(x,y)' - f(x,y)}{MXN}$$

$$RMSE = \sqrt{MSE}$$

The lower the value of MSE and RMSE indicates the lower of the error.

V. Experimental Results and Analysis

Dataset:

The Lung Image Database Consortium image collection (LIDC-IDRI) consists of diagnostic and lung cancer screening thoracic CT scans with marked-up annotated lesions. It is a web-accessible international resource for development, training, and evaluation of computer-assisted diagnostic (CAD) methods for lung cancer detection and diagnosis. The LIDC-IDRI collection contained on The Cancer Imaging Archive (TCIA) is the complete dataset of all 1,010 patients which includes all 399 pilot CT cases plus the additional 611 patient CTs and all 290 corresponding chest x-rays. The lungs image data, nodule size list and annotated XML file documentations can be downloaded from the National Cancer Institute website [12].

For the experiment we taken 40 Non-Cancer Lung CT scan images and 50 Cancer Lung CT images from the LIDC dataset.

Figure 1: Different Filter Results on a Lung Cancer CT scan image

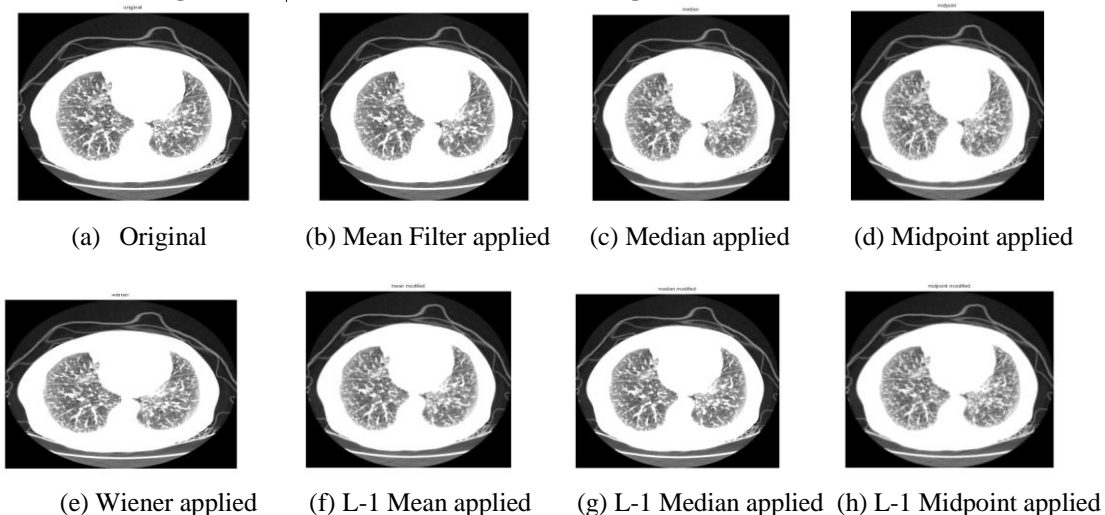
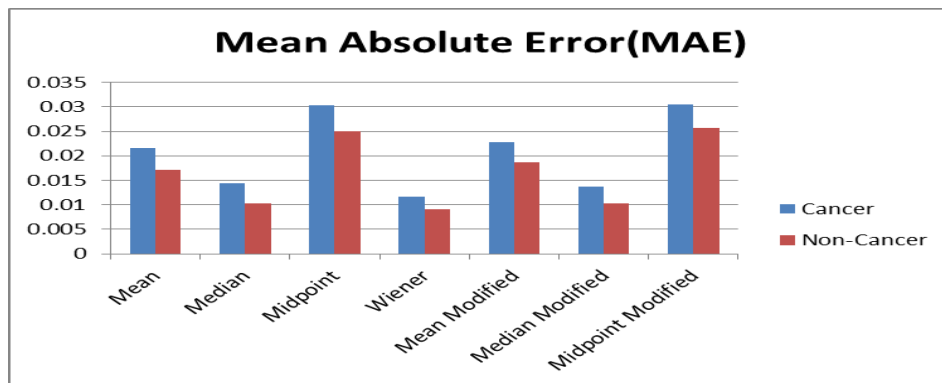


Table I: Comparison of different filters against the Lung CT scan images

Image Filter	Non-Cancer Image (average value of 40 images)				Cancer affected Image (average value of 50 images)			
	SNR	PSNR	MSE	RMSE	SNR	PSNR	MSE	RMSE
Mean	0.0410	76.2123	0.0016	0.0399	0.0611	75.6819	0.0029	0.0464
Median	0.0084	79.4146	0.0009	0.0286	0.0223	79.0497	0.0023	0.0348
Midpoint	0.0680	72.5220	0.0037	0.0607	0.0850	72.0057	0.0055	0.0680
Wiener	0.0128	83.2099	0.0004	0.0183	0.0242	82.6539	0.0007	0.0217
L-1 Mean	0.0449	75.5737	0.0019	0.0429	0.0636	75.0489	0.0032	0.0492
L-1 Median	0.0081	78.8604	0.0010	0.0305	0.0198	78.4121	0.0023	0.0365
L-1 Midpoint	0.0647	72.4172	0.0038	0.0615	0.0822	71.9250	0.0054	0.0682

From the Table-I, Wiener filter approach gives better result compare with other filters in the values of high PSNR and low RMSE value for both the cancer and non-cancer images. For the cancer and Non-cancer images both the basic midpoint filter and the proposed Leave-One (L-1) midpoint filter performs at the same level. In performance wise, the wiener filter gives best noise elimination compare with others.

Figure 2: Mean Absolute Error comparison of different filters



From the figure 2, the Mean Absolute Error also shows that the wiener filter performs superior than others. The proposed L-1Median modified filter performs more or less equal to wiener in both cases of the CT scan images.

VI. Conclusion

Image denoising is an essential task in medical image processing. Filters are very useful for removing noise from the images. In this paper we describe different filtering techniques and three more proposed filters. For the Lung CT scan images Wiener filter performs very well compare with other filters. The proposed L-1 filters are performing the same level of noise removal on both of the Cancer and Non-Cancer images compare with the basic filters, with less computational time.

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