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A Deep De-noising Neural Network to Mitigate Noise in Computed Tomography Images

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ABSTRACT

Liver cancer is a cause of high mortality worldwide. Early detection can save lives and help the medical practitioners to plan the treatment. Blood tests, biopsy and imaging techniques like CT, MRI are widely used in the diagnosis of the liver cancer.Noise contaminated CT Image suffers with low resolution and often leads to wrong diagnosis which may lead to improper treatment.Deep denoising Neural Network is used to mitigate the effects of noise on CT images. Deep denoising neural network outperform other filtering methods like mean, median, wiener filters on CT images of liver from cancer imaging archive (TCIA)

Keywords: *Hepatocellular carcinoma; Weiner filter; Lucy-richardsonfilter; Deep denoising neural network.*

1.0 Introduction

Cancers are the main reason for deaths and severe health problems worldwide, and liver cancer is the most common cancer among them [1].The primary liver cancer starts in the liver, while the secondary starts in other organs of the body and spreads to the liver due to metastasis. Hepatocellular carcinoma, Cholangio carcinoma and Sarcoma are examples of primary tumors. Hepatitis-B, Hepatitis-C, alcohol drinking, cigarette and tobacco smoking, food contamination with aflatoxin, arsenic exposure, and dietary iron overload are the influencing factors responsible for liver cancers. Non-alcoholic fatty liver disease may progress to steato-hepatitis, cirrhosis, and hepatocellular carcinoma.The liver cancer can be diagnosed using blood tests, removing a sample of liver tissue (biopsy) and imaging tests like Computed Tomography (CT), Magnetic resonance Imaging (MRI) and ultrasound. Liver biopsy has a risk of bleeding and infection and therefore cannot be performed number of times to assess the progression of the disease.A CT scan is faster and cheaper mode of acquiring pictures of tissues, organs, skeletal structures, bone fractures, tumors, internal bleeding and in cancer monitoring. Early detection of cancer through imaging techniques is helpful for proper treatment planning.CT image acquire noise due to the high speed computation from multiple planar views, analog circuitry, bit error rate and inadequate photon count during image acquisition. This noise appears asadditive white Gaussian noise, impulse noise, speckle noise and Poisson noise. CT artifacts can severely degrade the image quality.

Streak artifact, partial volume effect, ring artifact are the few of them.Digital images are corrupted by noise due to acquisition, transmission and mathematical computation. Noise in the digital image appears in a random uncorrelated manner to degrade the visual quality of the images and also reduce the precision and accuracy of image interpretation and examination. Medical imaging suffers due to low light conditions and limited exposure types, leads to degradation of specimens by increasing the noise influence. Precise and accurate information extraction is of great importance for disease diagnosis and planning treatment.CT images suffer with different noises both internal and external and offer very low resolution.For improving resolution of the medical images more pixels are stored per unit area which makes it inherently more susceptible to noise. De-noising the images is necessary to improve diagnosis and treatment. Various types of noises influence the images are Gaussian Noise, Poisson Noise, Impulse Noise and Quantization noise.

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Additive White Gaussian Noise is added to the CT images during acquisition and transmission through analog circuitry. The impulse noise affects limited number of pixels in dark and white manner. Quantization noise, impulse noise, speckle noise and Poisson noise are mainly due to faulty manufacturing, bit error rate and inadequate photon count during image acquisition. Different denoising methods have been proposed in literature.This paper investigates the Deep Denoising Neural Network as a denoising mechanism to mitigate the effects of noise on CT images when compared to other popular filters like mean, median, wiener and lucy-richardson filters. Deep denoising neural network outperform other methods. Mean square error, Peak signal to noise ratio and Structural similarity Index are evaluated on test images of human liver from cancer imaging archive (TCIA) Dataset [2]. Section I describes motivation and introduction. Section II describes related work. Section III describes methodology. Section IV describes results and discussion. Section V describes conclusions and future scope.

2.0 Related Work

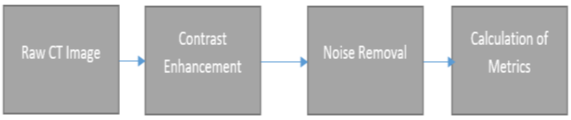
P Yugandhar et.al [3] has proposed improved DRLSE model to extract hepatic tumors from the noisy CT scan images. The noisy CT image is first filtered using median filter and segmented using Fuzzy C means clustering followed by level set to extract liver tumors. This approach is able to tackle the noisy medical images especially CT images efficiently.

Giraldo et al. [4] presented a comparative study of two noise reduction methods for computed tomography images: Bilateral filter and nonlocal means. They compared both techniques againstthose from a commercially available weighted filtered back-projection (WFBP) method. They tested their results over real CT images as well as simulated phantom images. It was observed from result analysis that both methods are providing better denoising by weighted filtered back-projection (WFBP) method

3.0 Methodology

The Cancer Imaging Archive (TCIA) [2], an open-source, open-access information resource to support research, development, and educational initiatives utilizing advanced medical imaging of cancer, consisting of several abdominalCT images in DICOM format. The Digital Imaging and Communications in Medicine (DICOM) Standard specifies a non-proprietary data interchange protocol, digital image format, and file structure for biomedical images and image-related information. Images of liver carcinoma are obtained from the dataset are used for denoising.

Figure 1: Block Diagram of the System



The acquisition CT images is affected by noise which often leads to false perception. Image (contrast) enhancement techniquesare essential to improve the visual quality of the CT image[7]. The intensity values in grayscale image are mapped to another grayscale image by saturating top and 1%-pixel values which improves the contrast of the image. The mean and standard deviation of the low contrast CT image is computed. The pixel values within one standard deviations from the mean are retained and rest of the pixels are saturated. Histogram equalization spreads out the most frequent intensity values, which increases the global contrast of image.

Contrast-limited adaptive histogram equalization operates on small regions in the image, and enhances the contrast of each small regions followed by bilinear interpolation to eliminate any induced boundaries. Fig 3.1 describes the steps carried out in denoising the CT Images viz contrast enhancement, Noise mitigation by various filters like mean, median, wiener and lucy- richardson filter followed by metrics calculation.

De-noising of image is performed using filtering which can be divided into spatial domain, frequency domain and wavelet domain. Spatial domain filters are classified as linear and nonlinear types.

Mean filter or average filter is windowed filter of linear class that smoothens the image. Every pixel in the image is replaced by average value across its neighbourhood. For Mean Filter, let the input image is Ix,y.

Table 1: Mean Filtering

Step 1: Choose a 2D window W of size 3x3.
Step 2: Calculate Wmean,the mean value of the pixel values I in window W
Step 3:I x,y is replaced with Wmean
Step 4: Repeat step 1 to step 3 up to total pixels in the image processed.

Median filter is a simple and powerful nonlinear filter, which is introduced by Tukeyet in 1977. Median filter is extensively used in image processing for smoothing and filtering the digital images [3]. It preserves edges[9] in an image while reducing impulse noise. The amount of noise reduction depends on the shape and size of the filter mask [4]. It reduces the intensity values between two points.

Table 2: Median Filtering

Step 1: choose a 2D window W of size 3x3.
Step 2: Calculate Wmed the median of the pixel values I in window W
Step 3:I x,y is replaced with Wmed
Step 4: Repeat step 1 to step 3 up to total pixels in the image processed.

Wiener filter calculatesa statistical estimation of an unknown signal.The Wiener filter can be used to filter out the noise components from the corrupted signal to produce an estimate of the underlying signal.The filter was proposed by Norbert Wiener during the 1940s and published in 1949.

The inverse filtering is a restoration technique for de-convolution. When an image is blurred by a known low-pass filter, inverse filtering works very well to remove the degradation but inverse filtering is very sensitive to additive noise. The Wiener filtering provides an optimal trade-off between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. Wiener filter is optimal in terms of the mean square error.

Richardson–Lucy algorithm, also known as Lucy–Richardson de-convolution [5-6], is an iterative procedure for recovering an image that has been blurred by a known point spread function. It was named after William Richardson and Leon Lucy. When an image is produced using an optical system and detected using photographic film or a charge-coupled device (CCD) it is blurred, with an ideal point source not appearing as a point but being spread out known as the point spread function[10]. Extended sources can be decomposed into the sum of many individual point sources, thus the observed image can be represented in terms of a transition matrix (p) operating on the image.

$$d_i = \sum_j p_{i,j} u_j$$

u_j is the intensity of image at pixel j

d_i is the detected intensity at pixel i

$P_{i,j}$ is the portion of light from source pixel j that is detected in pixel i.

A two dimensional detected image is a convolution of the image with a two dimensional point spread function P(Δx,Δy) with added detection noise.In order to estimate, given the observed $d_i$and a known P(Δix,Δjy) an iterative procedure is adopted as described in [3].

A neural network is a circuit of neurons. An artificial neural network, is an interconnection of artificial neurons . Predictive modelling, adaptive control are some of the application areas artificial neural networks. Self-learning resulting from experience can occur within networks, which can derive conclusions from a complex and seemingly unrelated set of information [wiki].

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analysing visual imagery. They are also known as shift invariant or spaceinvariant artificial neural networks (SIANN). Image and video recognition, recommender systems,image classification, medical image analysis, natural language processing,[4] and financial time series are few applications of these networks.

Convolutional neural networks can be used de noise an image. DnCNN is designed to predict the difference between noisy image and clean image. DnCNN removes the latent clean image with operations in the hidden layers. Unlike typical CNN, DnCNN may not contain pooling layers. A distinctive feature of DnCNN is not the output of the filtered image, but the prediction of the residual image, that is, the difference between noisy and clean image. Thus, DnCNN can be used to generate a correction signal which can be used obtain the de-noised image.

3.1 Quality metrics

3.1.1 Mean squared error (MSE)

In statistics, the mean squared error or mean squared deviation of an estimator measures the average of the squares of the errors i.e. the average squared difference between the estimated values and the actual values.

$$MSE = \frac{1}{MXN}\sum_{i,j=1}^{MXN}\left(\hat{I}(i,j) - I(i,j)\right)^2 \qquad \ldots(1)$$

3.1.2 Peak signal to noise ratio (PSNR)

$$PSNR = 10log_{10}\left(\frac{L^2}{MSE}\right) \qquad \ldots(2)$$

3.1.3 Structural similarity index (SSIM)

An image quality metric [8] that assesses the visual impact of three characteristics of an image: luminance, contrast and structure.

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma}$$

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

$$c(x,y) = \frac{2\mu_x\mu_y + C_2}{\mu_x^2 + \mu_y^2 + C_2}$$

$$s(x,y) = \frac{\sigma_{XY} + C_3}{\sigma_X\sigma_y + C_3}$$

μ_x,μ_y,σ_x,σ_y and $\sigma_{x,y}$ are local means, standard deviations, and cross-covariance for images x, y respectively.

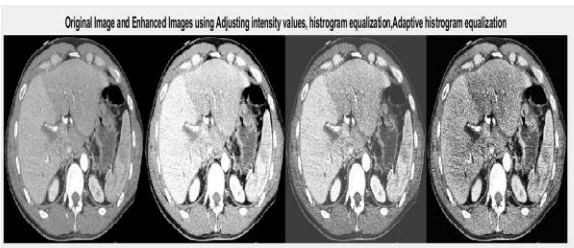
If α = β = γ = 1 and C3 = C2/2 then

$$\text{SSIM} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{XY} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad \ldots(3)$$

4.0 Results and Discussions

Two images obtained from TCIA dataset and they are fed to contrast enhancement module. Two common types of noise Gaussian Noise with mean=0 and variance=0.01, Salt and pepper noise with a noise density 0.02 are added to raw CT image.

Figure 2: Raw and Enhanced CT Images using Histogram Equalization



Different filters like Mean filter, median filter, Weiner filter, Lucy- Richardson filter and a deep denoising fully connected deep neural network are evaluated for different metrics like Mean square error, Peak signal to noise ratio and structural similarity index.

Figure 3: Histograms of Original and Enhanced CT Images

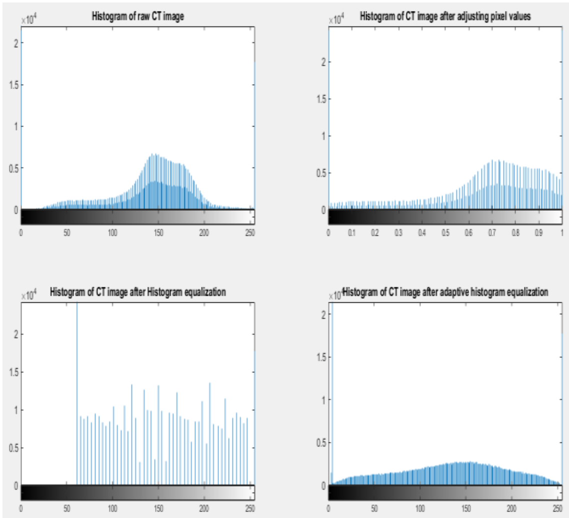


Figure 3: Original and Noisy (Gaussian) CT Image

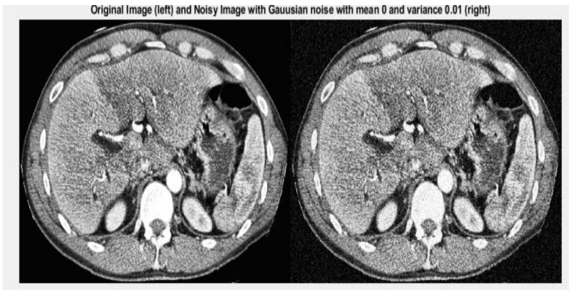


Figure 4: Original and Noisy (Salt & Pepper) CT Image

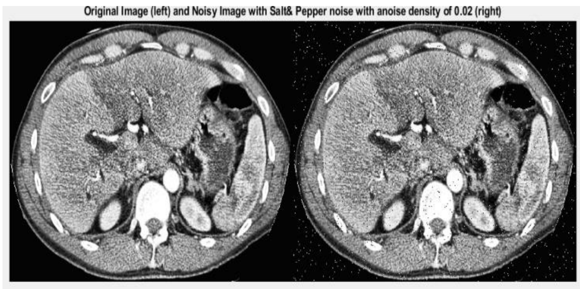


Figure 5: Response to Gaussian Noise with Mean Filter

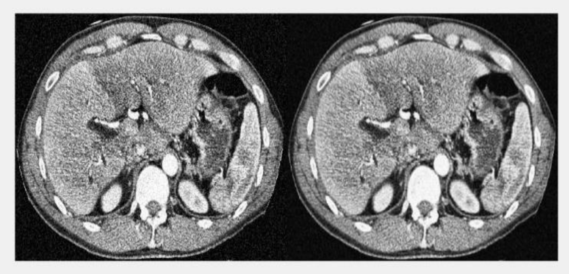


Figure 6: Response to Salt and Pepper Noise with Mean Filter

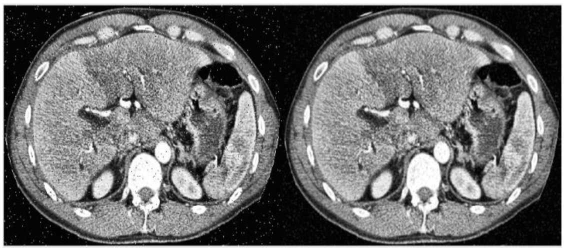


Figure 7: Response to Gaussian Noise with Median Filter

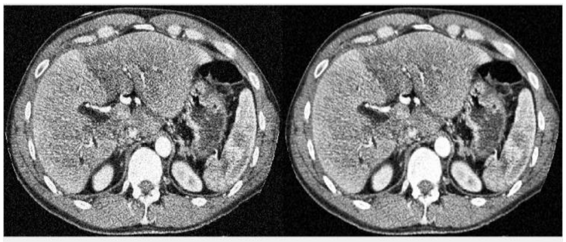


Figure 8: Response to Salt and Pepper Noise Median Filter

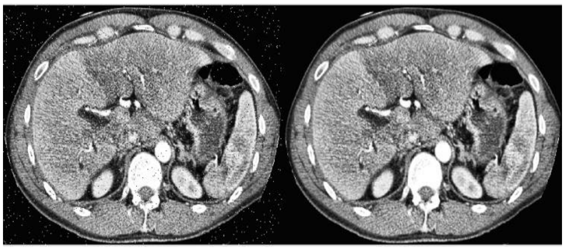


Figure 9: Response to Gaussian Noise Weiner with Filter

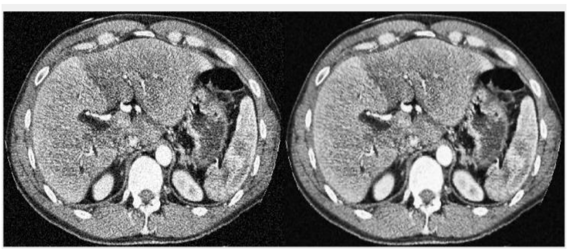


Figure 10: Response to Salt and Pepper Noise Weiner Filter

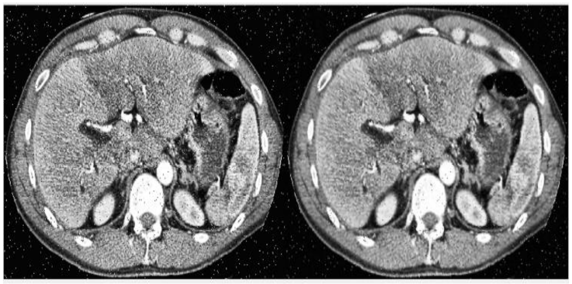


Figure 11: Response to Gaussian Noise with Lucy-Richardson Filter

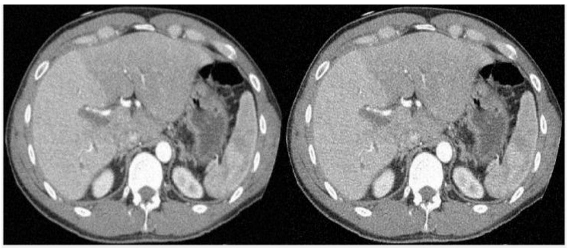


Figure 12: Response to Gaussian Noise and Motion Blur with Lucy Richardson Filter

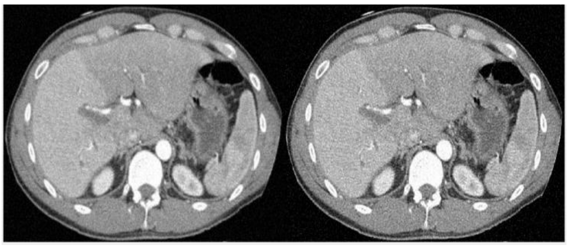


Figure 13: Original and De-noised CT Images using DnCNN with Gaussian Noise

Figure 14: Original and De-noised CT Images using DnCNN with Salt and Pepper Noise

Table 3: Performance Comparison of Filters for Noise Removal

Type of filter	MSE	PSNRdB	SSIM
Mean filter with Gaussian Noise	18209	0.0053	0.0076
Mean filter with salt and pepper noise	18209	0.0053	0.0373
Median filter with Gaussian noise	647.2104	0.1487	0.4938
Median filter Salt and Pepper noise	586.2178	0.1642	0.5889
Wiener filter with Gaussian noise	547.0748	0.1760	0.5271
Wiener filter with Salt and Pepper noise	585.6881	0.1644	0.5247
Lucy richardson filter with Gaussian noise	202.2652	0.4759	0.3837
Lucy- richardson filter with Gaussian noise and motion blur	366.4700	0.2627	0.1953
DnCNN with Gaussian noise	693.2171	0.1389	0.4876
DnCNN with Salt and Pepper noise	926.4914	0.1039	0.4519

5.0 Conclusions

Histogram equalization and adaptive histogram equalization are applied on raw CT Images. Adaptive histogram equalization enhances the contrast and outperforms other contrast enhancement techniques. Among the spatial filters median filter outperforms other methods. A deep denoising fully connected convolutional neural network removes Gaussian and salt and pepper noise. A deep denoising CNN for removal of other types noises in CT images has be to investigated further.

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