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REDUCING THE GAUSSIAN BLUR ARTIFACT FROM CT MEDICAL IMAGES BY EMPLOYING A COMBINATION OF SHARPENING FILTERS AND ITERATIVE DEBLURRING ALGORITHMS

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ABSTRACT

Obtained images through imaging systems are considered as degraded versions of the original view. Computed Tomography (CT) images have different types of degradations such as noise, blur and contrast imperfections. This paper handles the issue of deblurring CT medical images affected by Gaussian blur. Image deblurring is the procedure of decreasing the blur amount and grant the filtered image with an overall sharpened form. In this paper, the authors considered the Laplacian sharpening filter and the iterative Richardson – Lucy algorithm, and implemented a mixture of these two techniques to process the CT medical images. The suggested technique is applied to medical images that are synthetically and naturally degraded by blur. Moreover, an evaluation between the proposed combination and each employed technique is provided, along with the accuracy calculation using the universal image quality index (UIQI).

Keywords: *Image Deblurring, Gaussian Blur, Computed Tomography (CT), Medical Image Processing, CT Degradations, Point Spread Function (PSF), Iterative Richardson – Lucy, Laplacian Sharpening Filter, Universal Image Quality Index (UIQI).*

1. INTRODUCTION

Medical image processing is the fastest growing field of imaging science nowadays [16]. Miscellaneous kinds of medical images such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasonography (USG), Magnetic Resonance Angiography (MRA), Position Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT) and functional MRI (fMRI) [17] utilize the image processing techniques because of various types of degradations. This paper focuses on CT medical images. This type of medical images owns lots of degradations such as noise [18] blur [20] and contrast imperfection [19] that spoils the image quality and hampers the process of acquiring precise medical information. This paper handles the matter of deblurring CT medical images only.

When the blur affects the CT images, it decreases the visualization and visibility of the small components in the image [20]. Therefore, Image deblurring techniques are extensively employed to recover back the undegraded form of the image from its corrupted version and grant the image a sharper appearance because acquired images are considered as the degraded version of that view [9]. The type of blur that spoil the CT medical images is proven to be a Gaussian blur [10].

Many reasons led to have blurry CT images for instance, the finite size of the X-ray source focal spot and the detector element within the CT array [11], the imaging system owns an imperfect resolution [12], and Image data lost throughout the image acquisition [13]. The purpose of writing this paper is to deliver an improved procedure in deblurring images that are degraded by Gaussian blur particularly CT medical images. As a final point, Enhancements in imaging technology and algorithms have obviously increased the clarity of medical images, and contributed to a better diagnosis [21]. Because of the blurring artifact in the CT medical images, the need to decrease the amount of blur and enhance the overall image quality is also increased since CT images are vital instruments for the diagnosis of serious diseases.

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2. DEBLURRING PROCEDURE

The deblurring procedure begins by employing a sharpening filter such as the Laplacian filter as an initial mode of deblurring. After that, an iterative deblurring algorithm such as Richardson - Lucy algorithm is utilized to decrease the residue of the blur and grant the image a better sharpened look. Before applying the iterative algorithm, the point spread function (PSF) must be calculated to be used within the deblurring algorithm. The proposed scheme is explained as the subsequent:

2.1 *Point Spread Function (PSF) Calculation*

The PSF is the degree of spreading (blurring) a point of light (pixels) caused by imaging systems or techniques [14]. Prior to the initiation of the deblurring process, the PSF must be computed [15]. When using iterative deblurring algorithms such as Richardson – Lucy to process an image, the PSF must be computed since it will be utilized within the deblurring algorithm [6]. The type of PSF used in this paper is the Gaussian PSF. Thus, the blur parameter (σ) must be determined along with the size of the PSF matrix, the PSF equation is [5]:

$$h_g(m,n) = e^{\frac{-(m^2+n^2)}{2\sigma^2}}$$

$$h(m,n) = \frac{h_g(m,n)}{\sum_m \sum_n h_g}$$

In this paper, the PSF size is a 3×3 and sigma (σ) is equal to (1). The PSF is extremely essential in the deblurring techniques since the quality of the image depends on it.

2.2 *Laplacian Sharpening Filter*

Sharpening images using a Laplacian filter is commonly performed to grant the processed image with better visual details and highlight fine features. Laplacian kernels are a 3×3 matrix that is convolved to the image. The outcome of the convolution is considered as a mask that will be subtracted from the degraded image to procedure the sharpened image. There exist various Laplacian kernels sorts. In this experiment, the sort of kernel used is shown in Figure 1 [4].

0	1	0
1	-4	1
0	1	0

Figure 1: The Laplacian Kernel

The Laplacian sharpening equation can be designed as:

$$R = I - [I \otimes K]$$

Where, (R) is the resulted sharpened image, (I) is the blurry image, (K) is Laplacian kernel, and (⊗) is the convolution operation.

2.3 *Iterative Richardson-Lucy Algorithm*

When it comes to image deblurring, there exist different algorithms that recover corrupted images. The Richardson-Lucy algorithm is one of the most famous algorithms in this field, and it has been used to restore the images that are degraded by a known PSF [14]. This algorithm owns some positive properties such as it can function well in the event of noise existence, prior information about the original image is not required and the repetition (Iterative) feature [1] [2]. The formula of the Richardson-Lucy algorithm can be described as [3]:

$$f^{n+1} = f^{n} H^{*} \left(\frac{g}{Hf^{n}}\right)$$

Where f^{n+1} is the new approximation from the prior image f^{n}, (g) is the blurry image, (n) is the iteration number, (H) is the blur filter (PSF), (H^*) is the Adjoint of (H), and (f^{n}) = g in the first iteration.

3. DETERMINING THE ACCURACY

Universal image quality index (UIQI) is one of the most famous metrics in measuring the accuracy between two images because it employs various aspects in its measurements such as luminance, contrast, and structural comparisons. The UIQI outcome is a value in the interval of [-1 to 1]. The finest quality images are the images that own a value that is near to (1). The formula of UIQI is as the following [7]:

$$\text{UIQI} = \frac{4\,\mu_x \mu_y\, \sigma_{xy}}{(\mu_x^2 + \mu_y^2)(\sigma_x^2 + \sigma_y^2)}$$

Where, (σ_x^2) is the variance of (μ_x), (σ_{xy}) is the covariance of (μ_x, μ_y), (μ_x) = {$x_1 \dots x_n$} [8].

4. EXPERIMENTAL RESULTS

The experiment contains two parts. The first part is to apply the suggested method on synthetically degraded CT images by Gaussian blur to and compare the results accuracy of the Laplacian filter, Richardson-Lucy, and the proposed technique to determine which method gives the highest accuracy. The second part is to apply the proposed technique to images degraded naturally by the CT imaging systems. In this experiment, two

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synthetically degraded CT images have been used, both of them are degraded by Gaussian blur, but the amount is different. Figure 2 shows the original and the degraded images. Figure 3 and 4 demonstrates the results of the experiment, and Table 1 displays the experiment accuracy measurement values.

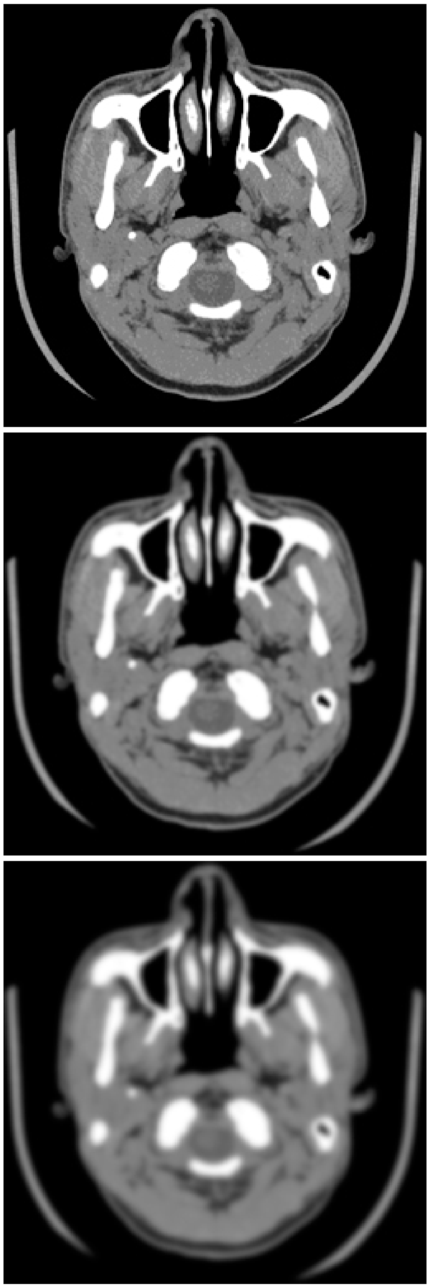

Figure 2: Images From Top To Bottom: Original CT Image, Degraded By Gaussian Blur (Radius =1), Degraded By Gaussian Blur (Radius =2).

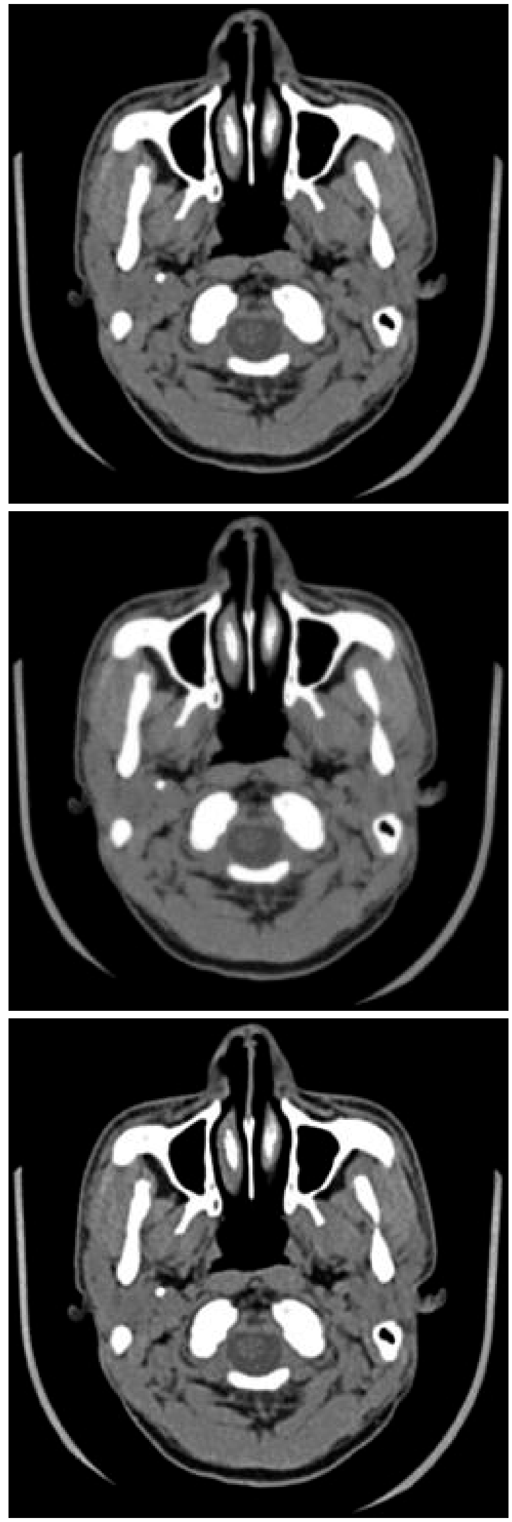

Figure 3: CT Image Degraded By Gaussian Blur (Radius =1) Restoration From Top To Bottom: Restored By Laplacian Filter, Restored By Richardson-Lucy Algorithm, Restored By The Suggested Procedure.

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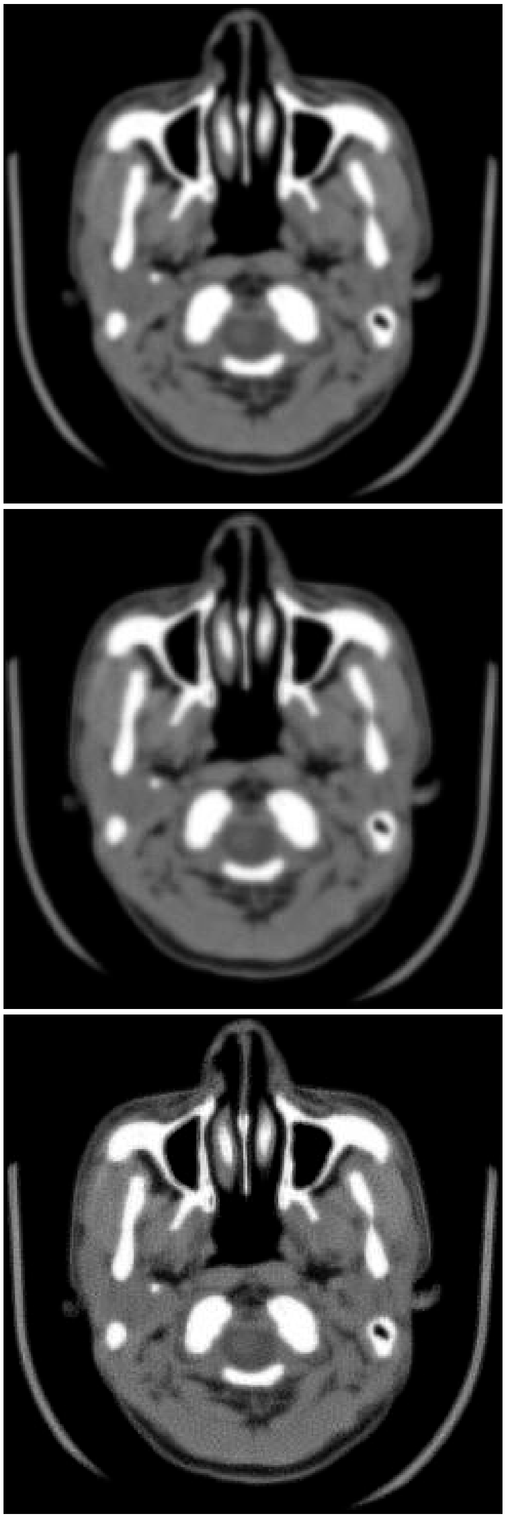

Figure 3: Ct Image Degraded By Gaussian Blur (Radius =2) Restoration From Top To Bottom: Restored By Laplacian Filter, Restored By Richardson-Lucy Algorithm, Restored By The Suggested Procedure.

Table 1: The Accuracy Measurement Values Of The Previous Experiment.

Methods	*UIQI 1*	*UIQI 2*
Degraded Image	0.7854	0.6464
Laplacian Filter	0.8227	0.6922
Richardson-Lucy	0.8348	0.7022
Suggested Technique	**0.8562**	**0.7502**

Where, UIQI1 represents the image degraded by Gaussian blur (Radius =1) and its restored versions. UIQI2 represents the image degraded by Gaussian blur (Radius =2) and its restored versions. From the table above, the proposed procedure gave the highest accuracy value when measuring with UIQI. The second part of the experiment is to apply the suggested method to images that are naturally degraded by the CT scans imaging devices. Figure 5, 6 shows the CT images and their restored versions.

Figure 5: Images From Top To Bottom: Naturally Degraded CT Image With Gaussian Blur, Its Restored Version With The Proposed Technique.

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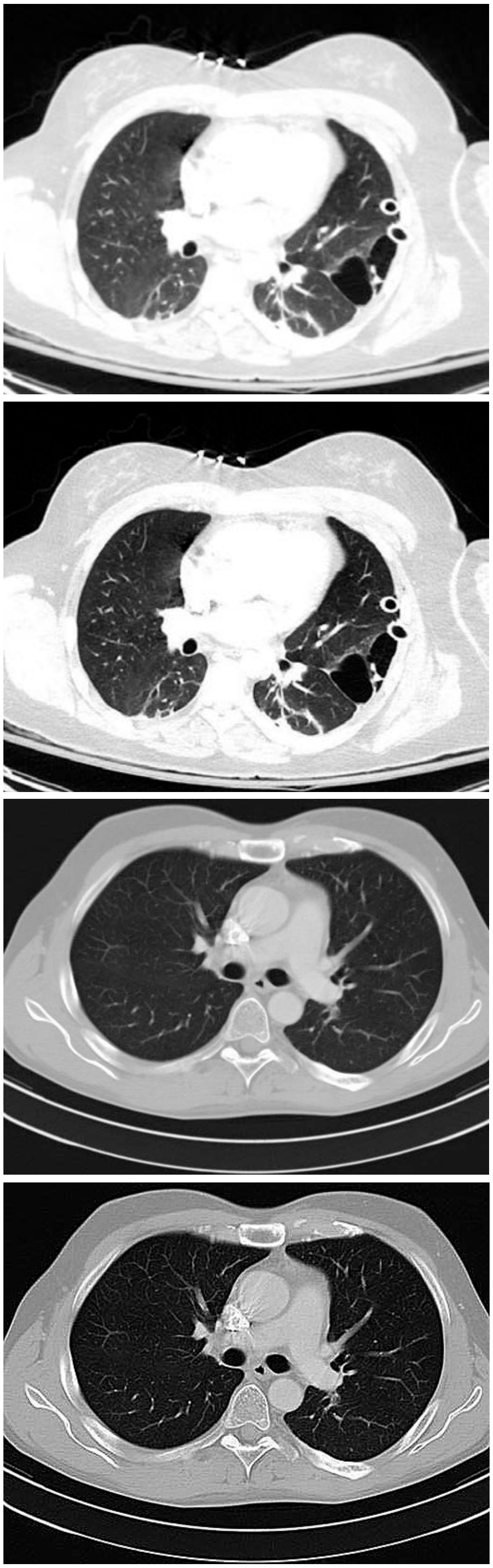

Figure 6: Images From Top To Bottom: Naturally Degraded CT Images With Gaussian Blur And Their Restored Version With The Proposed Technique.

5. CONCLUSION

This paper introduces a novel technique to deblur images spoiled by Gaussian blur, especially CT medial images. The proposed procedure involves combining a sharpening filter such as a Laplacian filter with an iterative deblurring algorithm such as the Richardson-Lucy Algorithm to deblur the degraded image. The reason of this combination is that, the Laplacian filters perform fast and well with the Gaussian blur, but the problem is the amount of needed sharpness cannot be tuned when using these filters. Likewise, the iterative deblurring algorithms such as Richardson-Lucy require time to deblur images due to the iterative process, and many mathematical operations involved in each algorithm. The mix of these two techniques allows better tuning for sharpening amount and less iteration involve in the deblurring process, causing faster, more efficient and more accurate results. The proposed method has been compared with the Laplacian filter, the Richardson-Lucy algorithm, and the suggested technique where it gave the highest score using the UIQI metric.

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