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Robust Multiple Reblurred-Based CT Image Enhancement

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Abstract

In this paper, we present a new algorithm for solving the blind deconvolution problem. In our method, we reblur a given degraded CT image with R different, but known PSFs, and get R different degraded CT images. Then we blindly deblur using the R new degraded CT images. Also, we introduce Bilateral Total Variation regularization term. In computer simulations in Matlab, it is the most advantages of our proposed algorithm that it performs more effectively than M. Jiang's ENR method.

Keywords: Image enhancement, blind deconvolution, degraded image, reblurring.

1 Introduction

Degraded images occur in a variety of domains of applied science and engineering, such as medical diagnostics, atmospheric remote sensing and astronomy, etc. Many methods have been reported for restoring the degraded images under the assumption that the point spread function (PSF) is exactly known, and then there are some good experimental results. Moreover, the PSFs,

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especially for some degraded CT medical images, are not known in practice. The blind deconvolution problem is an inverse process that attempts to estimate the original image from the degraded image under the condition of an unknown PSF. It is an ill-posed problem, so there are many difficulties to restore the image and identify the unknown PSF [1-5,6-18].

In medical diagnostics, CT image is advantageous in visualizing and measuring bony structures [7-8]. As we known, CT scanners cannot resolve many important temporal bone details, and that, the PSF of the CT scanner has been often unavailable in practice. Fortunately, many researchers have been concerned the CT image restoration problem, such as, M. Jiang, G. Wang, M. Skinner, etc. However, the CT image restoration problem is a problem of blind deconvolution. In 1997, You and Chan used the anisotropic regularization methods and total variation model to restore some degraded images [2,15-16]. In 2002, Jiang proposed "expectation maximization (EM) algorithm" and "edge-to-noise (ENR) maximization principle" to deconvolution of spiral CT images [7-9]. According to the EM deblurring algorithm, it is firstly performed by a different Gaussian kernel; then the deblurring image is blurred by another Gaussian kernel. In this paper, we propose a fast and new blind deconvolution method to deblur some degraded CT images.

This paper is organized as follows. In section 2, we begin with proposing our robust multiple reblurred CT images restoration model. In section 3, we discuss detail the estimation of PSF support. In section 4, some simulation results are presented, and we compared them with those of M. Jiang's method [7,9]. Finally, we discuss the merit of our robust multiple reblurred model in section 5.

2 Robust Multiple Reblurred Model

2.1 Robust Data Fusion

On a single-slice scanner, it was validated that spiral CT can be modeled as a spatially invariant process with a Gaussian PSF [14]. Consequently, an arbitrary degraded CT image can be described as a two-dimensional Gaussian PSF and the actual cross section,

$$Z = h \otimes u + noise = H \otimes U + noise, \tag{1}$$

where Z is the observed CT section of interest, i.e., the blurred image, H represents the matrix form of the Gaussian point spread function h, with standard deviation parameter σ, U is the actual CT image, $\otimes$ is the convolution operator, and the noise of system is considered as white Gaussian noise.

In practice, the Gaussian PSF is not precisely known for an arbitrary degraded CT image. Hence, we need a blind deblurring approach to restore an actual image. As we known, the information obtained from a single observed CT section is always limited. Unfortunately, we cannot provide more than one blurred image at present. How will we provide our blind deconvolution model, and improve the image restoration? We know that our aim is to more clearly visualize many important temporal details, such as the bony structures, blood vessels, virus cells, etc, rather than restore completely the PSF and the actual CT image. Of course, we will be glad if we can achieve the above two terms. In Ref. [10-11], Li et al. show how multiple images can be used for blind deconvolution when the blur function differ from image to image. Using multiple images, the image restoration result of two blurred images is better than that of single image. In Ref. [4-5], Elad et al. recommend their fast and robust super resolution model using multi-frame images. Assuming that a single observed CT section is the initial frame, we can get the first, the second, and even the third frame using multiple reblurring the initial frame. Combining the convolution commutativity with associativity, we have the form as following,

$$\begin{aligned} Z_k &= H_K \otimes Z = H_k \otimes (H \otimes U) + noise \\ &= H \otimes (H_k \otimes U) + noise = (H \otimes H_k) \otimes U + noise \\ &= H_k \otimes H \otimes U + noise, \end{aligned} \tag{2}$$

where $H_k, k = 1, 2, \cdots, R$ is the PSF, but known. In general, we will choose some known PSF, such as motion blurred PSF, Gaussian PSF.

A popular family of estimator is the Maximum Likelihood Function Method (ML) estimator [6]. To find the ML estimate of the degraded images, many papers adopt a data fusion term and a regularization term while the system is the white Gaussian noise [1,2,10-11,15-16]. With this noise model, least-squares approach will result in the ML estimate. The least-squares formulation is achieved,

$$\left(\hat{U}, \hat{H}\right) = \underset{(U,H)}{ArgMin} \left[\sum_{k=1}^{R} \frac{1}{2} \left\| H_k \otimes H \otimes U - Z_k \right\|_2^2 \right]. \tag{3}$$

Certainly, for the special case such as salt and pepper noise, the least-squares estimation has the interpretation of being a nonrobust mean estimation.

2.2 Robust Regularization

A regularization term compensates the missing measurement information with some general prior information about the desirable restoration image, and is usually implemented as a penalty factor in the generalized minimization cost function,

$$\left(\hat{U}, \hat{H}\right) = \underset{(U,H)}{ArgMin} \left[\sum_{k=1}^{R} \frac{1}{2} \left\| H_k \otimes H \otimes U - Z_k \right\|_2^2 + \alpha \Upsilon(U) + \beta \Upsilon(H) \right], \tag{4}$$

where $\alpha, \beta,$ the regularization parameters, is a scalar for properly weighing the first term against the second term, the first term against the third term, respectively, and Υ is the regularization cost function.

One of the most widely referenced regularization cost functions is the Tikhonov cost function,

$$\Upsilon_T(f) = \left\| \Gamma f \right\|_2^2, \tag{5}$$

where Γ is usually a highpass operator such as derivative, Laplacian, or even identity matrix. As the noisy and edge pixels both contain high-frequency energy, they will be removed in the regularization process and the resulting denoised image will not contain sharp edge. In 1992, one of the most successful regularization methods for denoising and deblurring proposed by Chan is the total variation (TV) method. The TV criterion penalizes the total amount of change in the image as measured by the L_1 norm of the magnitude of the gradient and is defined as,

$$\Upsilon_{TV}(f) = \|\nabla f\|_1, \tag{6}$$

where ∇ is the gradient operator. The most useful property of TV criterion is that is tends to preserve edges in the restoration [1,11,15-16], as it does not severely penalize steep local gradients. In 1998, Tomasi introduced bilateral filtering for gray and color images [12]. Based on the spirit of TV criterion, and the bilateral filter technique, Elad et al. recommended their robust regularizer called bilateral TV, which is computationally cheap to implement, and preserves edges. The regularizing function looks like,

$$\Upsilon_{BTV}(f) = \sum_{l=-p}^{p}\sum_{m=-p}^{p} a^{|l|+|m|} \left\| f - S_x^l S_y^m f \right\|_1, \tag{7}$$

where operators S_x^l, and S_y^m shift X by l, and Y by m pixels in horizontal and vertical directions respectively, presenting several scales of derivatives. The scalar weight a, $0 < a < 1$, is applied to give a spatially decaying effect to the summation of the regularization term.

2.3 Robust Multiple Reblurred Implementation

In this subsection, based on the material that was developed in Sections 2-A and B, a solution for the robust blind deconvolution problem will be proposed. Combining the ideas presented thus far, we proposed the robust solution of the blind deconvolution of CT images as follows,

$$\left(\hat{U},\hat{H}\right) = \underset{(U,H)}{ArgMin}\left[\sum_{r=1}^{R}\frac{1}{2}\left\|H_r \otimes H \otimes Z - Z_r\right\|_2^2 + \alpha\sum_{i=-p}^{p}\sum_{j=-p}^{p} a^{|i|+|j|}\left\|U - S_x^i S_y^j U\right\|_1 + \beta\sum_{k=-p}^{p}\sum_{l=-p}^{p} b^{|k|+|l|}\left\|H - S_x^k S_y^l H\right\|_1\right]. \tag{8}$$

We use the steepest descent to find the solution to this minimization problem,

$$\hat{U}_{n+1} = \hat{U}_n - t_1 \cdot \left\{\sum_{r=1}^{R}\hat{H}_n^T H_r^T\left[H_r \otimes \left(\hat{H}_n \otimes \hat{U}_n\right) - Z_r\right] - \alpha\sum_{i=-p}^{p}\sum_{j=-p}^{p} a^{|i|+|j|}\left(I - S_x^{-i}S_y^{-j}\right)\cdot sign\left(\hat{U}_n - S_x^i S_y^j \hat{U}_n\right)\right\}, \tag{9}$$

$$\hat{H}_{n+1} = \hat{H}_n - t_2 \cdot \left\{\sum_{r=1}^{R}\hat{U}_{n+1}^T H_r^T\left[H_r \otimes \left(\hat{H}_n \otimes \hat{U}_{n+1}\right) - Z_r\right] - \beta\sum_{k=-p}^{p}\sum_{l=-p}^{p} b^{|k|+|l|}\left(I - S_x^{-k}S_y^{-l}\right)\cdot sign\left(\hat{H}_n - S_x^k S_y^l \hat{H}_n\right)\right\}, \tag{10}$$

where t_1 and t_2 are two scalars defining the step size in the direction of the gradient. $S_x^{-i}, S_x^{-k}, S_y^{-i}$ and S_y^{-l} define the transposes of matrices S_x^i, S_x^k, S_y^i and S_y^l, respectively, and have a shifting effect in the opposite directions as S_x^i, S_x^k, S_y^i and S_y^l.

3 Estimation of PSF Support and the Algorithm

In this section, we will give our initial estimated size of PSF h. You totally had information about original true size of PSF h, at least partially in their works [16]. Chan assumed their initial PSF

h_0 is the delta function in their work [2]. But larger the size of the initial estimated PSF is, more time and computer memory are spent.

We assume the size of the image be $M \times N$ pixels. In the most cases, the blurring level is not extra severity, so it is reasonable to assume that the size of the initial PSF h_0 is about ten percents of that of the observed image, and the h_0 is a disk with a diameter d, i.e. $d = \min\{M, N\}/10$. Here, we adopt an alternating minimization (AM) algorithm [2,16] for the above equations (9) and (10). The AM algorithm is run in order of (9) $\rightarrow$ (10) $\rightarrow$ (9) $\rightarrow$ (10) $\rightarrow \cdots$, see Table 1.

Table 1. Algorithm: Robust Multiple Reblurred Algorithm.

Algorithm: Robust Multiple Reblurred Algorithm
1: Given the observed CT image *Z*, and the initial blur kernel H is a disk;
2: Given several known PSFs $H_1, H_2, \cdots, H_R$;
3: **repeat**
4: Estimate U^{n+1} according to equation (9);
5: Estimate H^{n+1} according to equation (10), and set $n = n + 1$;
6: **until** $\left\Vert H^{n+1}U^{n+1} - Z \right\Vert^2$ is smaller than a given threshold or meets the maximum iterations;
7: **return** The restoration CT image $\hat{U} = U^{n+1}$.

4 Experimental Results

In this section, we present two numerical examples to test the proposed algorithm. The proposed algorithm is also compared with the algorithm of Ref. [7,9]. Since our main interest is to deblur sectional CT images of the temporal bone, especially the cochlea, we utilize the degraded CT images as shown in the first column image of Figs.1 and 2 [7,9].

For the blind deconvolution problem, we do not know the PSF form, except that a Gaussian blur kernel for spiral CT image. In order to avoid multiple blindly reblurring the actual CT image, and generating a lot of useless degraded CT image, we adopt three simple known kernels, that is, the first kernel is a horizontal motion blur operator, the second kernel is a vertical motion blur operator, the third kernel is a Gaussian blur operator. In this paper, we program in Matlab and use the Matlab function “fspecial ()” which produces the PSF. In our experiments, *p* is chosen 1 or 2, *R* = 3. In particular, the PSFs are as follows:

h_1 =fspecial (‘motion’, 5, 0);
h_2 =fspecial (‘motion’, 5, -90);
h_3 =fspecial (‘gaussian’, 5, 3);

In Fig. 1, we can see that CT image enhancement effect of our approach is indeed much better than that of the original. Comparing Fig. 1(a,c) with Fig. 1(b,d), we can achieve that some distinct region in Fig. 1(a,c) is still evident in Fig. 1(b,d), but parts of the obvious area in Fig.1(a,c) is significant enhancement in Fig. 1(b,d). However, there are unnatural for some parts of CT image enhancement in Fig.(d), which is distorted. Some parameters are as the following: $a = 0.4, b = 0.4$, iterations $n = 5$, $\alpha = 5 * 10^{-4}$, $\beta = 1.5 * 10^{-8}$.

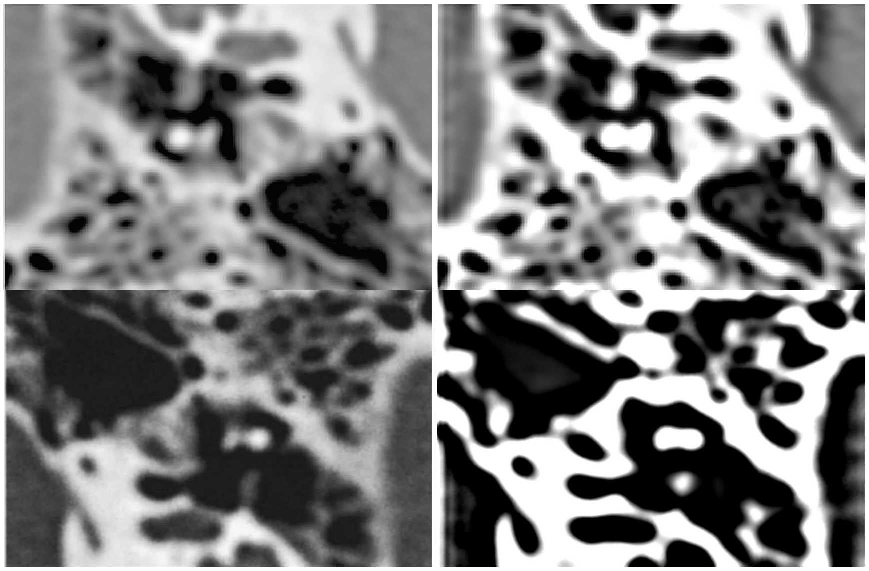

Fig. 1. Restoration images of our proposed method. The 1st column: Original blurred CT image. The 2nd column: Restoration image of our proposed method.

The blurred CT images shown in the first column of Fig. 2 [7-8] are in the region of the basal turn of the cochlea, and consist of 618×538, 474×318 pixels, respectively. The second column images in Fig. 2 are two blind deconvolution results using M. Jiang's ENR principle method [9]. The third column images in Fig. 2 are two blind deconvolution restoration of our proposed method. Comparison with the original blurred CT sections in the first column of Fig. 2, we can know that the CT image restoration effect of our proposed method enhances significantly. Comparing the second column restoration images in Fig. 2 with the third column restoration images in Fig. 2, we find that the enhancement effect of our proposed method is more evident than that of Jiang's ENR principle method. Some parameters are chosen as follows: $a=0.4, b=0.4$, iterations $n=5, \alpha=5*10^{-4}, \beta=1.5*10^{-8}$.

5 Discussion and Conclusion

In this paper, we propose an algorithm of multiple blurring the degraded CT images with our known PSF. In computer simulations run by Matlab, it is the most advantages of our proposed algorithm that it performs more effectively and spends less time than M. Jiang's ENR method. Because we use multiple degraded CT images, and the choice of simpler initial PSF is very important. Our numerical simulations demonstrate that our proposed blind deconvolution algorithm gives good estimates. Also, the algorithm has much higher efficiency.

Finally, we compare some numerical simulations of our algorithm with those of M. Jiang's ENR method. For the considered example, our model gives superior reconstructions.

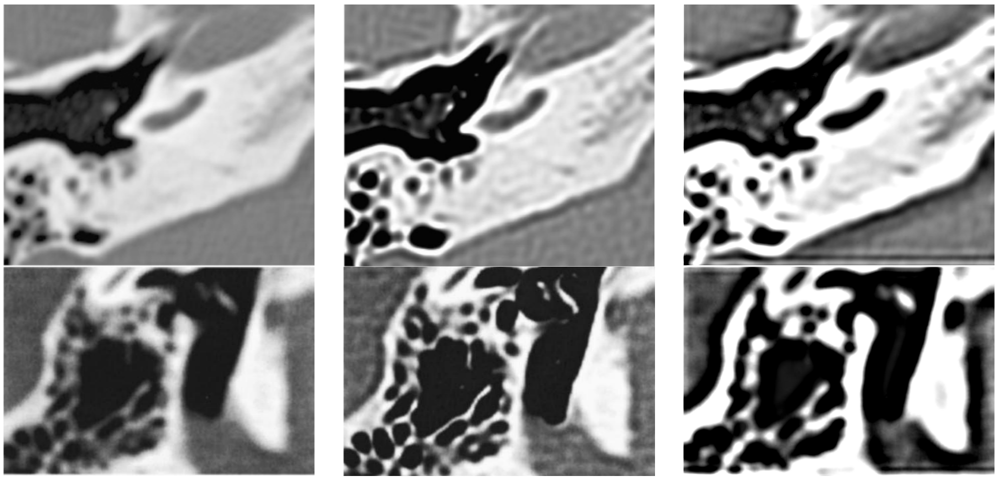

Fig. 2. Comparison of restoration image results. The 1st column: Original blurred CT sections; The 2nd column: Restoration images of Jiang's ENR method; The 3rd column: Restoration images of our proposed method.

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Competing Interests

Authors have declared that no competing interests exist.

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