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A statistical iteration approach with energy minimization to sinogram noise reduction for low-dose X-ray CT

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ABSTRACT

Low-dose CT imaging has been particularly used in modern medical practice for its advantage on reducing the radiation dose to patients. However, excessive quantum noise is present in low dose X-ray imaging along with the decrease of the radiation dose; thus, there are obvious streak-like artifacts in reconstructed images. The statistical iterative reconstruction approach applied to the noisy sinogram before a filtered back-projection (FBP) is a resolution to deal with the noisy problem. In this paper, the statistical property of the noise sinogram was considered to achieve a satisfactory image reconstruction and a statistical iterative method with energy minimization was proposed to address the problem of streak-like artifacts. Simulations were performed and indicated that the proposed method could suppress noise and obviously decrease streak-like artifacts in reconstructed images.

1. Introduction

X-ray CT (computed tomography) has been widely applied to medicine field and shown effective actions in several types of tissue such as brain, bone and soft tissue. High-dose does harm to patients and leads to adverse health effects, at the same time, which is the reason why there is growing awareness of the significance of minimizing the radiation dose delivered to patients during X-ray CT [1]. Therefore, more and more scholars have applied themselves to the study of low-dose CT imaging. An issue needing attention is that X-ray reconstructed images will severely degrade because of the quantum noise which results from the low-dose scanning. Streak-like artifacts occur most frequently in the bony structures at the base of the skull and petrous bone region. This is because the very dense structures are only partially included in the slice, resulting in high contrast errors. Thus, how to suppress noise and remove streak-like artifacts in reconstructed images has recently become a hotspot.

Statistical iterative reconstruction, rather than the conventional FBP, is one effective way to deal with this problem. In the previous study of Elbakri and Fessler [2], the detected photon numbers were considered to follow a Poisson distribution plus a background Gaussian noise with zero mean. A penalized Poisson likelihood maximization algorithm was then proposed. Later, Whiting [3] proposed a compound Poisson distribution model, which takes both the characteristics of the energy-integrating sensors in the X-ray CT detector and the energy spectrum of X-ray beam into account. Li and coworkers [4–7] considered that the corrected and log-transformed projection data of low-dose CT approximately follow a Gaussian distribution and proposed a model in sinogram space that the data mean and variance relation has an analytical nonlinear relationship. And then the penalized weighted least-squares (PWLS) approach was applied to the noisy sinogram, thus, the optimal estimation of the projection data was obtained for FBP reconstruction. Recently, Ma et al. [8] designed a generalized Gibbs prior that exploited nonlocal information of the projection data for the noisy sinogram and used the FBP method to finish the final CT reconstruction. Chen et al. [9] studied the Bayesian statistical reconstruction for low-dose X-ray computed tomography using an adaptive-weighting nonlocal prior and got satisfactory effects.

In this paper, we proposed a statistical iteration approach with energy minimization for the sinogram space. This proposed method is base on the PWLS and combined with gradient energy as its penalty term. From experimental comparisons, it has been show that this proposed method can suppress noise and remove streak-like artifacts effectively while preserving edges without excess smoothing.

2. Materials and methods

2.1. Noise model

Wang in [5] expounded the noise modeling of the projection data. The projection data after system calibration and logarithm transformation are approximately Gaussian distributed in low-dose CT applications. And the proposed model described the

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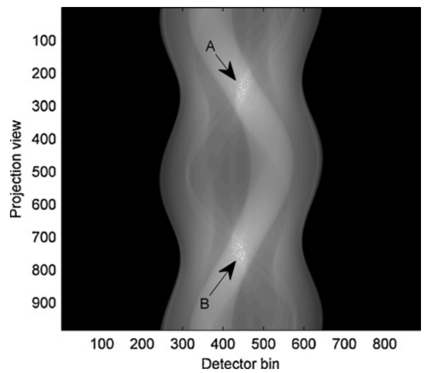

Fig. 1. Projection data.

relationship between the mean and the variance of the calibrated projection data as follows:

$$\sigma_{p_i}^2 = f_i \exp\left(\frac{\bar{p}_i}{\eta}\right) \quad (1)$$

where $\bar{p}_i$ denotes the expectation value of the projection in detector bin i and $\sigma_{p_i}^2$ denotes the corresponding variance. Notation η is a scaling parameter which is object-independent but completely determined by the system settings. And notation f_i is a parameter adaptive to different bins. It is obviously that the relationship between the data mean and the data variance is nonlinear.

To obtain a more accurate model Zhang et al. [10] studied the property of the projection data and found an important character that some isolated noise points may exist in some areas of the sinogram. In his study, the projection data approximately follows the non-stationary Gaussian distribution and these noise points should be removed before obtaining the optimal estimated projection data using the statistical method. Noisy sinogram in Fig. 1 and profiles in Fig. 2 illustrate this character. The noisy sinogram was obtained from the 2D Sheep-Logan head phantom in Fig. 3. It is obviously observed from Fig. 1 that there are two areas containing high noise which we have marked with "A" and "B". A profile along a projection view within area "A" is shown in Fig. 2(a), in which we can see that some data (seen as the isolated noise points) severely change within the range from 2.0×10^5 to 2.7×10^5. Therefore, projection data should be filtered before it was used to the Gaussian distribution model. For comparison, the same profile after a 3×3 window median filtering is shown in Fig. 2(b), it is seen that the isolated noise points are effectively removed and the filtered data approximately follow Gaussian distribution.

Characters of the low-dose CT projection data above were applied in our study, namely the noisy projection data were first dealt with a 3×3 window median filter before the statistical method.

2.2. Methods

Our strategy is to obtain a statistically optimal estimate of from the detected projection data and then to reconstruct the image by use of fanbeam filtered back projection (FFBP). The proposed method is based on the PWLS algorithm which is a useful solution for obtaining an optimal estimate of the projection data, the cost function in sinogram space can be described as follows:

$$\Phi(p) = (\hat{y} - p)\Sigma^{-1}(\hat{y} - p) + \beta I_\gamma(p) \quad (2)$$

The first term is the weighted least-squares method, where p is the vector of ideal projection data $\{p_i\}$, $\hat{y}$ is the vector of the system-calibrated and log-transformed projection measurements. Σ is a diagonal matrix with the ith element of $\sigma_{p_i}^2$, namely an estimate of the variance of the measured $\hat{y}$ at detector bin i which is calculated by Eq. (1). The second term is an energy function, where β is a smoothing parameter that controls the degree of agreement between the estimated and the measured data. Here the energy function $I_\gamma(p)$ can be described as follows:

$$I_\gamma(p) = \int_\Omega |\nabla p|^\gamma \, dx\, dy, \quad \gamma \geq 1 \quad (3)$$

where $\nabla p = (\partial p/\partial x, \ \partial p/\partial y)$ and $|\nabla p| = \sqrt{(\partial p/\partial x)^2 + (\partial p/\partial y)^2}$, x, y denotes the horizontal and vertical direction, respectively. Then the new penalized weighted least-squares estimation can be described as follows:

$$\hat{p} = \underset{p \geq 0}{argmin}\,\Phi(p) \quad (4)$$

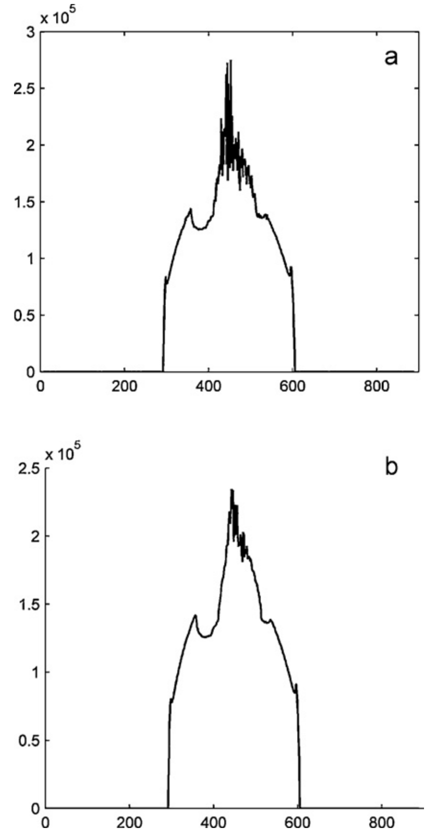

Fig. 2. A profile along a projection view within area "A": (a) profile along a projection view; (b) profile in (a) after being filtered.

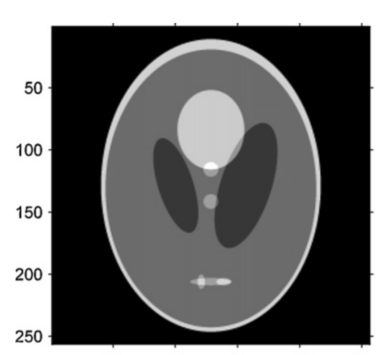

Fig. 3. Sheep-Logan head phantom.