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An adaptive nonlocal filtering for low-dose CT in both image and projection domains

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Abstract

An important problem in low-dose CT is the image quality degradation caused by photon starvation. There are a lot of algorithms in sinogram domain or image domain to solve this problem. In view of strong self-similarity contained in the special sinusoid-like strip data in the sinogram space, we propose a novel non-local filtering, whose average weights are related to both the image FBP (filtered backprojection) reconstructed from restored sinogram data and the image directly FBP reconstructed from noisy sinogram data. In the process of sinogram restoration, we apply a non-local method with smoothness parameters adjusted adaptively to the variance of noisy sinogram data, which makes the method much effective for noise reduction in sinogram domain. Simulation experiments show that our proposed method by filtering in both image and projection domains has a better performance in noise reduction and details preservation in reconstructed images.

Keywords: Low-dose CT; Noise reduction; Sinogram restoration; Non-local filtering; Weighted average

1. Introduction

Computed tomography (CT) has gained extensive applications in medical and industrial fields. However, high-dose radiation increases the risk of cancer during the whole lifetime of patients and operators. In order to reduce radiation exposure caused by CT scanning, a simplest and most cost-effective way is to deliver fewer X-ray to an object or directly lower the tube current (mAs) as low as achievable in current CT systems. Consequently, the image quality with low-dose CT imaging will be severely degraded due to the photon starvation [1,2].

To get satisfactory reconstructed images for medical applications, the filtered backprojection (FBP) reconstruction algorithms based on projection restoration have been reported in previous researches [3–10]. There are also some direct image filtering algorithms in image domain [4,11,8], and mixed filtering methods in both domains [12].

Lu et al. did an experimental study on noise properties of X-ray CT sinogram data, and they found that the noise approximatively obeys a non-stationary Gaussian distribution [5]. Under this assumption, Cui et al. proposed a sinogram restoration method based on energy minimization in [10], which is a modified anisotropic diffusion with an adaptive smoothness parameter, where the algorithm performs well in both reducing noise and protecting the edge. However, there is still some obvious artifacts in the reconstructed images, and this is an iterative algorithm with low computational efficiency.

Although there have been lots of algorithms to deal with images with Gaussian noise in previous studies, fewer have not been used in CT images and sinogram data of low-dose CT simultaneously. Recently, the non-local means filtering was applied to medical image filtering for low-dose CT [7,11,12] since it was first proposed by Buades et al. [13] for natural image denoising.

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Inspired by the idea of algorithms based on sinogram restoration such as the SR-NLM filtering [12], in order to deal with stripe artifacts in reconstructed image for low-dose CT, we develop a new adaptive nonlocal filtering for low-dose CT in both image and projection domains. In projection domain, its smoothness parameter is adjusted adaptively to the variance of noisy sinogram data; while in image domain, the smoothness parameter is adopted empirically, and the average weights are determined by the image FBP reconstructed from both the noisy sinogram and the non-local means restored sinogram. In following experiments it will be verified that our proposed approach has a better performance in noise reduction and details preservation in reconstructed images.

We organize the remaining part of this paper as follows. In Section 2, noise modeling and the main idea of the non-local means algorithm are presented, respectively, and then our proposed non-local means filtering based on sinogram restoration is described in detail. In Section 3, simulated experiments are implemented to verify the effectiveness and the feasibility of our proposed algorithm. In Section 4, we give the conclusion of this study.

2. Methods

2.1. Noise model

In this study, the calibrated and log-transformed projection data are called sinogram. The previous studies [3,5] have shown that low-dose sinogram data follow a non-stationary Gaussian distribution, with a non-linear relationship between the mean and the variance of the sinogram data, which is described by

$$\sigma_i^2 = f_i * \exp(p_i/\eta), \tag{1}$$

where p_i and σ_i denote the mean and standard deviation at detector bin i, respectively, while f_i and η are object-independent parameters that are specified by different CT systems. At the same time, it is shown that there are also some isolated points in extremely noisy regions of the sinogram data in [6].

2.2. Non-local means filtering

The non-local means (NLM) algorithm was first proposed by Buades et al. [13] for image denoising, which fully utilized the large redundancy of natural images and has been successfully applied to low-dose CT imaging [7,11,12]. Let Ω be a discrete grid of image pixels and $x = \{x_i | i \in \Omega\}$ be a noisy image, the denoised intensity $\mathrm{NLM}(x_i)$ at pixel i can be expressed by

$$\mathrm{NLM}(x_i) = \frac{\sum_{j \in \Omega} w(i,j) x_j}{\sum_{j \in \Omega} w(i,j)}, \tag{2}$$

where $w(i,j)$ is the average weight determined by the similarity between the pixels i and j, which is adopted as

$$w(i,j) = \exp\left\{ -\frac{\| x(N_i) - x(N_j) \|_{2,a}^2}{h^2} \right\}, \tag{3}$$

where N_i and N_j are similarity windows centered at pixels i and j, respectively; $\| \cdot \|_{2,a}$ denotes the Gaussian distance between two similarity windows with a standard deviation a; h denotes a smoothing factor that controls the decay of the exponential function in Eq. (3). To reduce the computational burden and improve the efficiency, the search window is always restricted to a proper local neighborhood S_i in Ω. The denominator of (2) is a normalizing factor.

2.3. Our method

The projection of a single point in any object forms a sinusoidal curve in the sinogram space. Because any object can be approximated by a collection of points located in space, its projection (sinogram) is obviously formed with a set of overlapped sine curves in the sinogram space [2]. As Buades et al. pointed that natural images have properties of sparsity and self-similarity in [13,14], sinogram data in low-dose CT are composed of special sinusoid-like strip data with same stronger self-similarity among these strip data (for example, see Fig. 2); FBP reconstructed images also have these properties, while noise does not have these special properties. So we can make use of this point to restore data contaminated seriously by noise. At the same time, we also find that we can match similar points more exactly by using the reconstructed image after sinogram restoration, which facilitates the aim of removing noise and preserving important details.

In the NLM algorithm, three parameters, i.e. search window, similarity window and smoothness parameter h, play an important role, among which h is especially critical. A larger h could cause too much smoothness in the data, while a smaller h would leave the restored data with excessive noise. In order to get a better weight in the NLM filtering, we develop our algorithm along two directions, including modifying the smoothness parameter h and the image intensity difference in similar neighborhoods. In this study, in order to find an appropriate h to smooth the data properly, ensuring the noise largely removed and the details preserved at the same time, we take two steps to adjust it both in the sinogram domain and in the image domain, respectively. In the following, we denote $p = \{p_k, k \in \Omega\}$ the low-dose CT sinogram data, $\tilde{p} = \{\tilde{p}_k, k \in \Omega\}$ the restored sinogram data by the NLM filtering, $I_{direct}^{FBP} = \{I_{direct,k}^{FBP}, k \in \Omega\}$ the image reconstructed from the noisy sinogram p, and $\tilde{I}_{sinoNLM}^{FBP} = \{I_{sinoNLM,k}^{FBP}, k \in \Omega\}$ the image reconstructed from the NLM filtered sinogram data $\tilde{p}$. Both I_{direct}^{FBP} and $\tilde{I}_{sinoNLM}^{FBP}$ are reconstructed by the FBP algorithm. As for the two steps to adjust the smoothness parameter h, firstly, in the sinogram domain we adjust $h = \{h_i, i \in \Omega\}$ to the standard deviation of the sinogram to control the smoothness of the NLM filtering

$$h_i = k_0 * \sigma_i, \tag{4}$$

where k_0 is a constant, σ_i is the standard deviation of the sinogram. The weight $w_{sino}(i,j)$ is then adopted as

$$w_{sino}(i,j) = \exp\left\{ -\frac{\| p(N_i) - p(N_j) \|_{2,a}^2}{h_i^2} \right\}, \tag{5}$$