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Adaptive filtering with self-similarity for low-dose CT imaging

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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/and image domain to try to overcome this difficulty. In view of strong self-similarity contained in the special sinusoid-like strip data in the sinogram space, we propose an adaptive filtering with self-similarity, whose average weights are related to both the image FBP (filtered backprojection) reconstructed from the restored sinogram data and the image directly FBP reconstructed from the noisy sinogram data in a framework of weighted average processing. In order to filter sinogram data, a non-local means method is used with its smoothing adaptive to the variances of noisy data after an adaptive median filtering, which preserves important features and high accuracy of the data in sinogram domain. In simulation experiments, it is shown that our proposed method, with filtering in both image and projection domains, has a better performance in noise reduction and feature preservation in reconstructed images.

1. Introduction

Computed tomography (CT) has gained extensive applications in medical and industrial fields. However, high-dose radiation results in serious problems. In medical field, high-dose radiation probably increases the risk of cancer during the whole lifetime of patients and operators. Minimizing the X-ray exposure has been one of the major efforts in the medical CT field. In order to reduce the radiation exposure caused by CT scanning, low-dose CT has gained much interest in research as well as in medical applications. Now it is applied in some clinical aspects, such as annual screening for lung cancer high-risk groups. For screening purposes, the associate X-ray exposure dose must be reduced. To reduce the dose, there are mainly four types of methods: lowering the tube current [1–17], sparsity-based image restoration and reconstruction algorithms [18–24], iterative reconstruction algorithms [25–34], and other imaging methods or medical procedures [35–38].

Among the four methods mentioned above, the most simple and cost-effective way is to deliver fewer X-ray to the subject or directly lower the tube current (mAs) as low as achievable in current CT systems. However, the image quality with low-dose CT will be severely degraded due to the photon starvation [39]. Up to now, many noise-reduction algorithms have been developed to improve the image quality, which mainly include FBP reconstruction algorithms based on projection restoration [1–8,10,12,14–17], and direct image filtering algorithms in image domain [9,11].

As for the FBP reconstruction method based on projection restoration to improve image quality, recently, experts have done much research in this direction, among which there are mainly two types of algorithms, i.e. dealing with the raw projection data (raw projection domain) [12,14], and dealing with the calibrated and log-transformed projection data (sinogram domain) [1–8,10,16,17].

In raw projection domain, Huang et al. modeled the raw measurement with an approximative Poisson Model, and then used Anscombe transform and block-matching and 3D filtering (BM3D) method to deal with the measurement data [12]. Zhu et al. also modeled the raw measurement with a Poisson Model and used a modified ROF model estimation to denoise the raw projection data [14]. They all obtained inspiring results.

In sinogram domain, Lu et al. did an experimental study on the noise properties of X-ray CT sinogram data, and they found that the noise approximatively obeys a non-stationary Gaussian distribution [6]. There is a nonlinear relationship between the mean and the variance of the sinogram data [1,3,4]. Under this assumption, there are mainly three types of methods as follows. First, iterative reconstruction algorithms based on the statistical properties of sinogram data were developed in [2–5,10]. Second, there are anisotrophic

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diffusion methods based on nonlinear equations [16,17]. In [17], Cui et al. proposed a sinogram restoration method based on energy minimization, which is a modified anisotropic diffusion by an adaptive smoothness parameter, which makes the algorithm perform well in protecting the edges and reducing noise. Third, there are also some denoising methods with sparse representation [7,8]. In [7], a penalized weighted least-square method (PWLS) was proposed in wavelet domain. In [8], sparsity-based sinogram restoration algorithms for low-dose CT were proposed. The main idea of denoising methods in sinogram domain is to first filter the sinogram data according to their statistical properties in sinogram domain, and then to reconstruct CT images using the FBP reconstruction algorithm.

The non-local means filtering was proposed by Buades et al. [40] for image denoising, and then it has been applied to medical image filtering for low-dose CT [11,12,15]. In [15], a KL-PWLS sinogram restoration algorithm-induced non-local means image filtering was developed to enhance the CT image quality.

In view of strong self-similarity contained in the sinusoid-like strip data in the sinogram space, in this study, we develop a new adaptive filtering, in which smoothness parameters are adjusted adaptively to the variances of the noisy sinogram data. In image filtering, we design a special non-local means filtering, in which the smoothness parameter is adopted empirically, and the average weights are determined by images reconstructed from both noisy sinogram and non-local means restored sinogram by the FBP algorithm. It will be verified that, our proposed approach has a better performance in noise reduction and details preservation in reconstructed images in following experiments, as reported by our preliminary research [13].

We organize this paper as follows. In Section 2, an effective noise modeling and the non-local means algorithm are described, and our proposed adaptive filtering with self-similarity is presented in detail. Proper median filtering and estimations of real data are emphasized for a better restoration of sinogram data. In Section 3, simulated experiments are carried out to verify the effectiveness of the proposed algorithm. In Section 4, conclusions and next work are included to end this paper.

2. Our method

2.1. Noise model

In this paper, we call the calibrated and log-transformed projection data as sinogram. For noise reduction algorithms in sinogram domain, noise modeling is of great importance for improving the algorithm performance, especially for low-dose CT. The previous study [3,6] has 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. f_i is an adjustable factor adaptive to each detector bin i. In the previous work [10], it has been shown that there are also some isolated points in extremely noisy regions of sinogram data. Thus, we assume in such a model that the noisy sinogram data follow a non-stationary Gaussian distribution with a few interspersed isolated points.

2.2. Non-local means filtering

The non-local means (NLM) algorithm was first proposed by Buades et al. [40] for image denoising, which fully utilized high redundancy of natural images and has been successfully applied to low-dose CT image restoration [11,12,15]. The discrete expression of the NLM algorithm is as follows. Let Ω be a discrete grid of image pixels and $x = \left\{x_i, \quad i \in \Omega\right\}$ be a noisy image. The denoised intensity $\mathrm{NLM}(x_i)$ at the 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 an average weight which is determined by the similarity between the pixels i and j. The weight $w(i,j)$ can be 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. The term $x(N_i) := \{x_m, m \in N_i\}$ denotes image intensities restricted in the similarity window N_i. The notation $\|\cdot\|_{2,a}$ denotes the Gaussian weighted Euclidean distance between two similarity windows, where a is a standard deviation of the Gaussian function. The parameter h denotes a smoothing factor that controls the decay of the exponential function in Eq. 3). To reduce the computational burden and to improve the efficiency of the algorithm, 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. As Buades et al. pointed that natural images have properties of sparsity and self-similarity in [40], 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 features.

In the NLM algorithm, three parameters, 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 designing a better similarity metric among 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 sinogram domain and in image domain, respectively.

In the following, we denote by $p = \left\{p_k, k \in \Omega\right\}$ the low-dose CT sinogram data, $\widetilde{p} = \left\{\widetilde{p}_k, k \in \Omega\right\}$ the restored sinogram data by the NLM filtering, $I_{direct}^{\mathrm{FBP}} = \left\{I_{direct,k}^{\mathrm{FBP}}, k \in \Omega\right\}$ the image reconstructed from the noisy sinogram p, and $\widetilde{I}_{sinoNLM}^{\mathrm{FBP}} = \left\{I_{sinoNLM,k}^{\mathrm{FBP}}, k \in \Omega\right\}$ the image reconstructed from the NLM filtered sinogram data $\widetilde{p}$. Both $I_{direct}^{\mathrm{FBP}}$ and $\widetilde{I}_{sinoNLM}^{\mathrm{FBP}}$ are reconstructed by the FBP algorithm [38].

We discuss the two steps to adjust the smoothness parameter h. Firstly, in the sinogram domain we adapt $h = \left\{h_i, i \in \Omega\right\}$ to the