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Few-view CT reconstruction via a novel non-local means algorithm

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ABSTRACT

Purpose: Non-local means (NLM) based reconstruction method is a promising algorithm for few-view computed tomography (CT) reconstruction, but often suffers from over-smoothed image edges. To address this problem, an adaptive NLM reconstruction method based on rotational invariance (ART-RIANLM) is proposed.

Methods: The method consists of four steps: 1) Initializing parameters; 2) ART reconstruction using raw data; 3) Positivity constraint of the reconstructed image; 4) Image updating by RIANLM filtering. In RIANLM, two kinds of rotational invariance measures which are average gradient (AG) and region homogeneity (RH) are proposed to calculate the distance between two patches and a novel NLM filter is developed to avoid over-smoothed image. Moreover, the parameter h in RIANLM which controls the decay of the weights is adaptive to avoid over-smoothness, while it is constant in NLM during the whole reconstruction process. The proposed method is validated on two digital phantoms and real projection data.

Results: In our experiments, the searching neighborhood size is set as 15×15 and the similarity window is set as 3×3. For the simulated case of Shepp-Logan phantom, ART-RIANLM produces higher SNR (36.23 dB > 24.00 dB) and lower MAE (0.0006 < 0.0024) reconstructed images than ART-NLM. The visual inspection demonstrated that the proposed method could suppress artifacts or noises more effectively and recover image edges better. The result of real data case is also consistent with the simulation result.

Conclusions: A RIANLM based reconstruction method for few-view CT is presented. Compared to the traditional ART-NLM method, SNR and MAE from ART-RIANLM increases 51% and decreases 75%, respectively.

1. Introduction

Computed tomography (CT) has been widely used in clinical examinations since its advent in the 1970s. However, it is reported that excessive radiation exposure to patients may potentially increase the risk of cancer [1–4]. Therefore, low dose high-quality CT image reconstruction has been a great concern in the recent years [5–7].

Decreasing the number of projections is an effective strategy to reduce radiation dose delivered to patients [8]. Since few-view projections does not satisfy the Nyquist sampling rule theoretically, conventional filtered back-projection (FBP) method inevitably leads to severe streak artifacts in a reconstructed image [9]. Recently, iterative reconstruction methods have been proven to have potential to reconstruct acceptable images from few-view projections [10], and adding some prior knowledge or reasonable regularization constraints into the process of iterative reconstruction can further improve the image quality [11]. In the past decade, compressed sensing (CS) theory proposed by Candes has demonstrated that total variation (TV) minimization can recover signal accurately from a small number of measurement data [12,13]. Subsequently, the TV regularization has been introduced to CT image reconstruction by Sidky, and generates satisfactory images reconstructed from few-projection data [14,15].

Non-local means (NLM) filter, a more effective image denoising method [16,17] than TV, was firstly used in few-view CT image reconstruction by Huang, and produced better results than TV regularization [18]. We name Huang's method as ART-NLM in this paper. Due to its promising capability, more reconstruction methods based on NLM have been studied in different imaging field [19–23]. However, the traditional NLM based reconstruction methods tend to cause the effect of over-smoothed edges. In ART-NLM, the distance parameter d which reflected the similarity between patches was only dependent on the pixel intensity without considering rotational invariance. Any patch with similar structure but different orientations to the reference patch would have a small

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weight. That is why ART-NLM often leads to a sub-optimal reconstructed image. On top of this, the parameter h in ART-NLM is changeless during the whole iteration process. For few-view CT reconstruction issue, the reconstructed image often contains noises and artifacts. Thus large h is chosen for suppressing the noises and artifacts, but this results in over-smoothed edges. If the edges are expected to remain sharp in the image, then small h is chosen. However, small h in the NLM method cannot remove noises and artifacts efficiently. To deal with the problem caused by ART-NLM, we propose an adaptive NLM (ANLM) reconstruction algorithm based on rotational invariance (RI) and term the proposed method as ART-RIANLM in this study. In ART-RIANLM, a novel similarity metric that is rotational invariance is proposed to calculate the distance between two patches. In this way, any patch with similar structure but different orientation to the reference patch would win a relatively large weight to preserve edges effectively. Additionally, the filter parameter h in RIANLM of this paper is adaptive in the iteration calculation and determined by the current iteration number and the pixel gradient value of the reconstructed image. The proposed method compares with FBP, ART and ART-NLM in this paper.

The rest of the paper is organized as follows. In Section 2, CT imaging model, conventional ART-NLM and proposed ART-RIANLM are introduced, respectively. Section 3 shows the qualitative and quantitative experimental results. Section 4 provides a discussion of the study of this paper. Section 5 has a conclusion in the paper.

2. Materials and methods

2.1. CT imaging model

The mathematical model of CT imaging can be expressed as a discrete linear system:

$$g = A\mu \tag{1}$$

where g denotes the measured projection data, A is the system matrix which accounts for the system geometry, and μ represents the reconstructed image. The goal of CT image reconstruction is to estimate the unknown image μ from the set of projection data g and system matrix A. Mathematically, Eq. (1) is known as an ill-posed inverse problem for few-view CT image reconstruction. As stated in Section 1, iterative algorithms can reconstruct acceptable images in this case. Adding prior knowledge or useful regularizations into the iterative process can be essential for improving the image quality.

2.2. ART-NLM algorithm

The non-local means (NLM) filter, which was originally proposed by Buades et al., has become an effective denoising method by taking advantage of the structural self-similarity property of an image [16,17]. The NLM filter estimates the pixel value by using a weighted average of pixels' intensity in an image. The mathematical formula can be denoted as follows:

$$\begin{aligned} \mu(i) &= \frac{\sum_{j\in\Omega} w(i,j)\mu(j)}{\sum_{j\in\Omega} w(i,j)} \\ w(i,j) &= \exp\left(-d/h^2\right) \\ d &= \|N_i - N_j\|_2^2 \end{aligned} \tag{2}$$

where Ω represents the searching neighborhood, $\mu(j)$ denotes the intensity of pixel j, the weight $w(i,j)$ is the similarity index between two patches N_i and N_j centered around pixels i and j, d is the distance between patches and h is a parameter controlling the strength of the filter and often related to the level of the noises in the image.

Inspired by NLM in image denoising, Huang et al. firstly introduced it to few-view CT image reconstruction and proposed ART-NLM algorithm [18]. The ART-NLM algorithm uses ART reconstruction and NLM filtering as two-phase reconstruction strategy. The implementation steps can be summarized as follows:

(1) Reconstructed image and parameters Initialization.
(2) ART reconstruction and positivity constraint.
(3) NLM filtering.
(4) Return to Step 2 until the stopping criterion is satisfied.

The ART-NLM algorithm can improve the quality of image significantly. However, it can't be ignored that ART-NLM algorithm identifies the similarity between two patches only depending on pixel intensity without considering rotational invariance, thus leading to the image edges blurring. Moreover, the parameter h in ART-NLM is constant in the whole image, which ignores local information property. In this case, in order to remove the noises and artifacts effectively, the reconstructed image tends to be over-smoothed.

3. Adaptive NLM filter based on rotational invariance (RIANLM)

To solve the problems from traditional NLM applied to CT reconstruction, we propose a novel NLM filter in this work. Firstly, two kinds of rotational invariance measures which are average gradient (AG) and region homogeneity (RH) are used to develop a new filter. Also, an adaptive filter parameter h is designed.

3.1. Average gradient (AG)

Two patches (similarity windows) with the same structures but different orientations would have a higher similarity in the gradient domain, compared to traditional NLM similarity measurement in the image domain. These patches with gradient similarity would contribute to edge preserving after filtering. To achieve this goal, Perona et al. approximated the norm of the gradient as the absolute intensity difference in a particular direction [24]. Then Yu et al. discretized the $\|\nabla\|^2$ as the average of the eight squared directional differences [25]. Citing Yu's idea, we define the average gradient (AG) as follow:

$$AG(i) = \left[\frac{1}{|\xi_i|}\sum_{j\in\xi_i}\|\mu(i)-\mu(j)\|^2\right]^{\frac{1}{2}} \tag{3}$$

where $\mu(i)$ and $\mu(j)$ are pixel values for pixel i and j in image μ. ξ_i denotes a cross-like window (a central pixel with four neighborhood pixels in horizontally and vertically), and $|\xi_i|$ represents the number of pixels in ξ_i.

3.2. Region homogeneity (RH) measure

In addition to AG defined above, the similarity between two patches can be measured by region homogeneity (RH) [26]. RH measure defines the gradient operator as the average gray gradient which includes all the pixels in the neighborhood. Let N_i be a circle in which the center is pixel i, and the semi-diameter is r. The angle between x-axis and r is θ. Diameter L divides N_i into two parts: $s_1(\theta)$ and $s_2(\theta)$. The region homogeneity measure can be expressed as:

$$RH(i) = \max_{\theta\in[0,\pi]}\left(\frac{1}{|s_1(\theta)|}\left|\sum_{j\in s_1(\theta)}\mu(j) - \sum_{j\in s_2(\theta)}\mu(k)\right|\right) \tag{4}$$