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SR-NLM: A sinogram restoration induced non-local means image filtering for low-dose computed tomography



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ARTICLE INFO

Article history: Received 17 August 2012 Received in revised form 21 April 2013 Accepted 22 May 2013

Keywords: CT Low-dose Sinogram restoration Non-local means Image filtering

ABSTRACT

Radiation dose has raised significant concerns to patients and operators in modern X-ray computed tomography (CT) examinations. A simple and cost-effective means to perform a low-dose CT scan is to lower the milliampere-seconds (mAs) as low as reasonably achievable in data acquisition. However, the associated image quality with lower-mAs scans (or low-dose scans) will be unavoidably degraded due to the excessive data noise, if no adequate noise control is applied during image reconstruction. For image reconstruction with low-dose scans, sinogram restoration algorithms based on modeling the noise properties of measurement can produce an image with noise-induced artifact suppression, but they often suffer noticeable resolution loss. As an alternative technique, the noise-reduction algorithms via edge-preserving image filtering can yield an image without noticeable resolution loss, but they often do not completely eliminate the noise-induced artifacts. With above observations, in this paper, we present a sinogram restoration induced non-local means (SR-NLM) image filtering algorithm to retain the CT image quality by fully considering the advantages of the sinogram restoration and image filtering algorithms in low-dose image reconstruction. Extensive experimental results show that the present SR-NLM algorithm outperforms the existing methods in terms of cross profile, noise reduction, contrast-to-ratio measure, noise-resolution tradeoff and receiver operating characteristic (ROC) curves.

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1. Introduction

Radiation dose has raised significant concerns to patients and operators in modern X-ray computed tomography (CT) examinations and minimizing radiation dose is one of the major endeavors in CT fields [1,2]. A simple and cost-effective means to perform a low-dose CT scan is to lower the milliampere-seconds (mAs) as low as reasonably achievable in data acquisition. However, the associated image quality with lower-mAs scans (or low-dose scans) will be unavoidably degraded due to the excessive data noise, if no adequate noise control is applied during image reconstruction [3,4].

Up to now, for radiation dose reduction in CT examinations, various techniques including optimized scan protocols and auto-mAs control have been reported [5,6], and many image reconstruction algorithms with noise-induced artifact suppression have been explored [7,8]. Extensive studies have shown that for noisy data from low-dose scan, statistical iterative reconstruction (SIR)

* Corresponding author at: School of Biomedical Engineering, Southern Medical University, Guangdong, Guangzhou 510515, China. Tel.: +86 2061648285. *E-mail addresses*: jhma@smu.edu.cn, jhma75@gmail.com (J. Ma). methods, by modeling the noise properties of the measurements and imposing adequate regularization within image reconstruction, can achieve a performance superior to other existing methods in terms of noise reduction and noise-resolution tradeoff [9-13]. However, a critical problem in SIR is the high computational burden due to the multiple re-projection and back-projection operations during image iterative reconstruction. To overcome this, restoring the ideal sinogram data from acquired noisy one and reconstructing the CT image from the estimated ideal sinogram data is an interesting alternative strategy with computational efficiency and noise-induced artifact suppression [14-20]. One typical example is the penalized weighted least-squares (PWLS) algorithm [19,21,22], which can be derived from the Gaussian statistics of original sinogram data. However, the sinogram restoration algorithms often suffer noticeable resolution loss especially in the case of constant noise variance over all the sinogram data [21]. In an approach different from above mentioned SIR and sinogram restoration algorithms, many sophisticated linear/nonlinear noise-reduction algorithms via edge-preserving image filtering have also been investigated for low-dose CT image noise reduction without remarkable resolution loss [23-25]. Meanwhile, the noise in low-dose CT image is nonstationary and its distribution is usually unknown, which indicates that designing an edge-preserving

^{0895-6111/\$ -} see front matter © 2013 Elsevier Ltd. All rights reserved. http://dx.doi.org/10.1016/j.compmedimag.2013.05.004

image filter is a difficult task. Recently, a previous normal-dose scan induced non-local means (ndiNLM) image filter was proposed for addressing the problem of a conventional edge-preserving image filter by exploring the redundancy information from the reference image under the non-local means criteria [26].

In this study, inspired with the ndiNLM algorithm in low-dose CT image restoration [26], we present a sinogram restoration induced non-local means (SR-NLM) image filtering algorithm to retain the image quality by taking advantage of both the sinogram restoration and non-local means image filtering algorithms in low-dose CT image reconstruction. Specifically, for the present SR-NLM algorithm, the penalized-weighted least-squares (KL-PWLS) algorithm in the Karhunen–Loéve (KL) domain [19] was used for estimating the ideal sinogram from the low-dose noisy one and the non-local weights in weighted average operation were calculated according to the FBP image reconstructed from the KL-PWLS estimated sinogram. Qualitative and quantitative evaluations were carried out on the simulation and patient data in terms of cross profile, noise reduction, contrast-to-ratio measure, noise-resolution tradeoff and receiver operating characteristic (ROC) curves.

The remaining part of this paper is organized as follows. In Section 2, the KL-PWLS algorithm for CT sinogram restoration, nonlocal means (NLM) and ndiNLM algorithms for image filtering are presented, respectively, and then the proposed SR-NLM image filtering algorithm is described in details. In Section 3, experimental results are reported. Finally, the discussion and conclusion are given in Sections 4 and 5, respectively.

2. Materials and methods

2.1. Overview of the KL-PWLS algorithm for CT sinogram restoration

Wang, et al. proposed the KL-PWLS algorithm to de-correlate data signals along nearby projection views for CT sinogram restoration by employing the KL transform [19]. In this study, the adapted KL transform with dimension 3×3 was first applied to account for the correlative information of continuous data sampling along nearby views of the sinogram data. Let \hat{y} and y denote the KL transformed components and the corresponding original sinogram data in the spatial domain. Then, in the KL domain, the PWLS criterion can be used to estimate the *l*th KL component \hat{p}_l of ideal sinogram data by minimizing the following objective function [19]:

$$\Phi_l(\widehat{p}_l) = (\widehat{y}_l - \widehat{p}_l)' \widehat{\Sigma}_l^{-1} (\widehat{y}_l - \widehat{p}_l) + \left(\frac{\beta}{d_l}\right) \widehat{R}(\widehat{p}_l)$$
(1)

where $\hat{\Sigma}_l$ is the diagonal variance matrix and can be estimated from the variance $\sigma_{i,k}^2$ of the original sinogram data $y_{i,k}$ at detector bin *i* and view *k* [19]. The scalar β is a hyper-parameter, d_l is the eigenvalue of the *l*th KL basic vector, and $\hat{R}(\hat{p}_l)$ is the penalty term. Based on our previous analyses [27,28], the original sinogram data *y* has a unique property which can be expressed by a relationship between the sample mean and variance:

$$\sigma_{i,k}^2 = \frac{1}{I_{i0}} \exp(\bar{y}_{i,k}) \left(1 + \frac{\sigma_e^2 - 1.25}{I_{i0}} \exp(\bar{y}_{i,k}) \right)$$
(2)

where I_{i0} is the incident X-ray intensity along the projection path i, σ_e^2 is the variance of the electronic background noise, and $\bar{y}_{i,k}$ is the sample mean of $y_{i,k}$ estimated by neighborhood averaging with a 3 × 3 window in this study. In modern CT systems, the parameters I_{i0} and σ_e^2 can be measured as part of the standard routine

calibration operation [27]. In addition, the penalty term
$$\widehat{R}(\widehat{p}_l)$$
 can be defined as [19]

$$\widehat{R}(\widehat{p}_l) = \frac{1}{2} \sum_{i} \sum_{j \in S_l} \widehat{w}(i,j) (\widehat{p}_{l,i} - \widehat{p}_{l,j})^2$$
(3)

where S_i indicates the two nearest neighbors of the *i*th pixel in the KL domain along the 1-D bin direction. In this study, the parameter $\widehat{w}(i, j)$ is equal to 1 for the two neighbors.

For minimizing the PWLS objective function (1), a modified iterative Gauss–Seidel (GS) update algorithm can be used in the KL domain [19,29]. After all the projection views have been treated by the KL-PWLS strategy, the CT image can be reconstructed by using the FBP algorithm from the estimated sinogram data.

2.2. Overview of the non-local means algorithm

The non-local means (NLM) algorithm was originally proposed by Buades et al. [30] for image de-noising, which has been successfully applied to medical image restoration such as low-dose CT image restoration [26] and magnetic resonance image restoration [31]. Mathematically, the discrete version of their NLM algorithm can be expressed as follows: let *D* be a discrete grid of pixels and $\mu = \{\mu_i | i \in D\}$ be a noisy image. The restored intensity NLM(μ_i) at the pixel *i* by the NLM algorithm is the weighted average of all the pixel intensities in the image μ and can be expressed as follows:

$$\text{NLM}(\mu_i) = \sum_{j \in D} w(i, j) \mu_j \tag{4}$$

where μ_j is the original image intensity at the pixel j and w(ij) is the weight assigned to μ_j in the intensity restoration at the pixel i. The weight w(ij) depends on the similarity between the pixels i and j, and satisfies the conditions of $0 \le w(ij) \le 1$ and $\sum_{j \in D} w(i, j) = 1$, which can be expressed as follows:

$$w(i,j) = \frac{1}{Z(i)} \exp\left\{-\frac{\left\|\mu(V_i) - \mu(V_j)\right\|_{2,a}^2}{h^2}\right\}$$
(5)

where Z(i) is a normalizing factor, i.e., $Z(i) = \sum_{j \in D} \exp\{-||\mu(V_i) - \mu(V_j)||_{2,a}^2/h^2\}$. The terms V_i and V_j denote two local similarity neighborhoods (termed the patch-windows) centered at the pixels *i* and *j*, respectively. The term $\mu(V_i) := \{\mu(V_k, k \in V_i)\}$ denotes the vector of neighborhood image intensity restricted in the patch-window V_i . The notation $\|\cdot\|_{2,a}$ denotes a Gaussian-weighted Euclidean distance metric between two similarity patch-windows, where *a* represents the standard deviation of Gaussian function. The parameter *h* is a smoothing factor controlling the decay of the exponential function in Eq. (5). In the implementation, to reduce the computational burden, the search-window is often confined to an appropriate non-local neighborhood $N_i(<D)$ (termed the search-window) centered at the pixel *i* [26].

2.3. Overview of the ndiNLM algorithm

Since a normal-dose CT image scanned previously may be available in some clinical applications such as CT perfusion imaging and CT angiography, the previous normal-dose scan can provide a reference image to construct more reasonable non-local weights than those used in the original NLM algorithm for low-dose CT image restoration. With this observation, the ndiNLM algorithm was proposed recently by our group [26], which can be expressed as follows:

$$ndiNLM(\mu_{ld,i}) = \sum_{\tilde{j} \in \tilde{N}_i} \tilde{w}(i, \tilde{j}) \mu_{nd,\tilde{j}}^{reg}$$
(6)

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