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Low-dose CT statistical iterative reconstruction via modified MRF regularization

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ABSTRACT

It is desirable to reduce the excessive radiation exposure to patients in repeated medical CT applications. One of the most effective ways is to reduce the X-ray tube current (mAs) or tube voltage (kVp). However, it is difficult to achieve accurate reconstruction from the noisy measurements. Compared with the conventional filtered back-projection (FBP) algorithm leading to the excessive noise in the reconstructed images, the approaches using statistical iterative reconstruction (SIR) with low mAs show greater image quality. To eliminate the undesired artifacts and improve reconstruction quality, we proposed, in this work, an improved SIR algorithm for low-dose CT reconstruction, constrained by a modified Markov random field (MRF) regularization. Specifically, the edge-preserving total generalized variation (TGV), which is a generalization of total variation (TV) and can measure image characteristics up to a certain degree of differentiation, was introduced to modify the MRF regularization. In addition, a modified alternating iterative algorithm was utilized to optimize the cost function. Experimental results demonstrated that images reconstructed by the proposed method could not only generate high accuracy and resolution properties, but also ensure a higher peak signal-to-noise ratio (PSNR) in comparison with those using existing methods.

1. Introduction

X-ray computed tomography (CT) is used in a rapidly increasing host of imaging applications, especially for applications in image-guided intervention where repeated scans are required and the subsequent accumulated radiation dose could be substantial [1–3]. However, excessive X-ray radiation dose exposure to patients caused by repeated CT scans could result in significant risk to get genetic and cancerous diseases [4,5]. Therefore, it is highly desirable to study the low-dose CT imaging, which can be achieved through lowering the X-ray tube current (mAs) or tube voltage (kVp) and simultaneously reducing the total number of X-ray views per rotation around the body [6–9]. Generally, for a given set of noisy and sparse-view projection data, the associated image quality of results

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reconstructed by the conventional analytical reconstruction methods is degraded [10]. To reconstruct high-quality CT images from undesirable projection data, various reconstruction methods with varying degrees of success have been proposed in recent years [11–19]. Among these, SIR algorithms show superiority over the conventional FBP method due to the statistical modeling of projections and imaging geometry. Specifically, the cost function for SIR methods comprises two major parts. One part is the data-fidelity term which can be used to model the statistics of measurements. The other part is the regularization term which may be utilized to regularize the solution and reflect the prior information at the same time.

Many advanced SIR methods achieve satisfactory reconstructed images by introducing different regularizations, which mostly include smooth regularizations [20–23] and edge-preserving regularizations [24–28]. More broadly, the academic attention to regularizations covered the entropy prior, Gamma prior, MRF-based priors, TV-based regularizations, nonlocal-means (NLM)-based priors, dictionary learning (DL)-based regularizations, and patch-based roughness regularizations, etc. In general, the Gaussian and Gamma priors enable the pixel values to approach the mean value of the image. For this reason, the pixel values could be kept from "blowing up", but image smoothness cannot be well implemented [21,22]. By adjusting weighting coefficients, Wang et al. [23,24] proposed an improved MRF prior, which utilized the anisotropic weighting coefficients while retaining the quadratic-form potential function. Recently, many NLM-based SIR methods [25–28] were proposed and worked well. Inspired by the study on sparse and redundant representations over dictionary learning, Xu et al. [29] proposed to utilize the DL-based sparsification as the regularization for CT reconstruction. In addition, to improve the image quality of reconstructed results, Lu et al. [30] proposed a modified DL-based regularization which combine a transitional dictionary for atom matching and a global dictionary for image updating. Moreover, through training a multi-scale dictionary, Bai et al. [31] proposed a multi-scale DL-based regularization for SIR method which perform well on details extracting and resolution maintaining. For edge-preserving regularizations, a typical example is the TV-based regularization. Tian et al. [32] proposed to preserve the edges by the EPTV term which can preferentially perform smoothing only on the non-edge part of the image. Alternatively, Liu et al. [33] proposed the adaptive-weighted TV(AwTV) regularization for SIR methods which outperforms TV-based and EPTV-based methods due to the consideration of the anisotropic edge property. However, these methods often lead to "staircase effects" and the appearance of noticeable blocky or patchy artifacts in the reconstructed images. Other attempts have been carried out on the research of high-order TV [34], TV-strokes [35] and CT reconstruction methods via TGV [36,37], which aimed to reduce the staircase artifacts without sacrificing edge sharpness.

In this paper, a novel regularization scheme was proposed by modifying the conventional MRF regularization with the edge-preserving TGV, in order to eliminate the undesired artifacts and preserve the edges and details. Specifically, the TGV, which is a generalization of TV and capable to measure directional features and image high-order characteristics, was introduced into the novel MMRF regularization, aiming to incorporate smoothness up to a certain differential order, while still accounting for edges. Subsequently, a modified alternating iterative algorithm was adopted to optimize the associative objective function and to help design new algorithms. In summary, we proposed a modified-MRF (MMRF) regularization for the SIR algorithm via the penalized weighted least-squares (PWLS) criteria, which was defined as "SIR-MMRF", to suppress over-smoothing and eliminate the undesired patchy artifacts that appeared in low-dose CT reconstructed images. Experiments on different phantoms were designed to validate the validity of the approach.

2. Materials and methods

2.1. CT reconstruction model

Approximately, the process of low-dose CT measurement can be expressed as a discrete linear system

$$y = hf \tag{1}$$

where $\mathbf{y} = (y_1, y_2, \ldots, y_I)^T$ denotes the measurements from I detector bins, $\boldsymbol{h} = \{h_{ij}\}$ is the $I \times J$ system matrix, $\boldsymbol{f} = (f_1, \ldots, f_J)^T$ is a linear attenuation coefficients distribution of the object to be reconstructed. According to the Bayesian theory and the statistical measurement model Eq. (1) [16,22,26], the PWLS criterion with a regularization term $R(f)$ can be expressed as

$$\hat{f} = \arg\min_{f \geq 0} (y - hf)^T \sum^{-1} (y - hf) + \beta R(f) \tag{2}$$

where $\sum = \mathrm{diag}\{\sigma_{y_i}^2\}$ is a diagonal matrix with the ith element of $\sigma_{y_i}^2$, which denotes the corresponding variance of every y_i. Previous research [24] on CT measurements expounded that the projection data obey a Gaussian distribution after system calibration and logarithm transformation. The noise model can be described as

$$\sigma_{y_i}^2 = \varsigma_i \exp\left(\frac{\bar{y}_i}{\eta}\right) \tag{3}$$

where $\bar{y}_i$ is the expectation value of the projections measured by the ith bin, η is a object-independent parameter, and ς_i is determined by detector bin i.

2.2. Overview of the MMRF regularization

According to the classical MRF theory, $R(f)$ in Eq. (2) is a widely used quadratic-form regularization which can be described as

$$R(f) = \sum_j \sum_{k \in N_j} \vartheta_{jk} (f_j - f_k)^2 \tag{4}$$

where index j runs over all the pixels in the image domain, N_j denotes the search-window in the neighborhood of the jth pixel. As the weighting coefficient, ϑ_{jk} denotes the interaction degree between the central pixel j and its neighboring pixel k,