Computerized Medical Imaging and Graphics 37 (2013) 438–449

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

Low-dose computed tomography via spatially adaptive Monte–Carlo reconstruction

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ARTICLE INFO

Article history:
Received 14 November 2012
Received in revised form 1 May 2013
Accepted 29 May 2013

Keywords:
Low-dose computed tomography
Image processing
Biomedical imaging
Noise compensation
Image reconstruction

ABSTRACT

Low-dose computed tomography (CT) reduces radiation exposure but decreases signal-to-noise ratio (SNR) and diagnostic capabilities. Noise compensation can improve SNR so low-dose CT can provide valuable information for diagnosis without risking patient radiation exposure. In this study, a novel noise-compensated CT reconstruction method that uses spatially adaptive Monte–Carlo sampling to produce noise-compensated reconstructions is investigated. By adapting to local noise statistics, a non-parametric estimation of the noise-free image is computed that successfully handles non-stationary noise found in low-dose CT images. Using phantom and real low-dose CT images, effective noise suppression is shown to be accomplished while maintaining structures and details.

1. Introduction

Computed tomography (CT) is a commonly used diagnostic tool to visualize organs, bones and other tissues as cross-sectional images. Clinicians and radiologists use these images to detect and locate tumours and injuries to determine course of treatment and to guide in surgery or biopsies [1,2]. CT is a widely accepted technique that is becoming more commonly used in the medical field due to its speed, resolution and accuracy [2]. Between 2007 and 2009, the number of CT exams in North America increased from 331.3 to 353.3 scans per 1000 people [3]. The number of CT scanners in North America also went up from 47 in 2007 to 48.2 scanners per million population in 2009 [4]. With CT's increasing popularity, there has become a growing concern for its risks due to its use of X-rays for image generation [2,5]. CT has an increased dosage of radiation over conventional X-ray scans due to the series of cross-sectional images it takes to complete a full-body scan [6]. X-rays have been found, in high doses to be harmful to living tissue, causing cancer; making it important for clinicians and radiologists to keep track of patients' lifetime radiation exposure [2,7,8]. The use of low-dose CT scans and proper justification for this procedure are strategies being employed to decrease a patient's X-ray exposure [2,9]. However, the use of low-dose CT scans reduce the signal-to-noise ratio (SNR) and noise artifacts become more prevalent in images, making diagnosis and visualization more difficult [10,5]. To balance X-ray exposure and SNR, noise compensation techniques have been explored to improve low-dose CT scans.

Noise in low-dose CT images is caused by a number of factors such as quantum noise, sensor and hardware equipment phenomena, and logarithmic transformations of scaled measurements during reconstruction [11–13]. Most commonly, quantum noise is present, which results due to fluctuations of X-ray quanta reaching the detector [14,13]. CT noise has been found to change from a Poisson distribution in the projection data, to an unknown distribution following reconstruction. Typically, noise is considered stationary which infers that the noise statistics would be the same across the entire CT image volume. In real low-dose CT images however, the noise characteristics in the reconstructed image vary due to complex dependencies on scan parameters and spatial position, which result in unknown noise distributions and spatially changing noise statistics [15,13,14]. Due to this changing noise structure, the noise artifacts in low-dose CT images can be more appropriately considered as non-stationary [15,13]. Often, the noise appears as streaking artifacts that are caused by aliasing errors in the

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http://dx.doi.org/10.1016/j.compmedimag.2013.05.006

projection data. These errors can occur due to the number of views, the reconstruction grid, X-ray scatter and undersampling of the projections [15,16].

Due to the non-stationary nature of CT noise, noise reduction becomes more complicated and conventional spatially invariant low-pass or bilateral filtering strategies cannot be used to successfully compensate for such noise [11,13,9]. Therefore, other strategies for noise compensation in CT images have been devised and can be divided into three main strategies. The first strategy is to correct the projection data before reconstruction. This approach takes advantage of the known noise distribution (e.g. Poisson distribution) prior to reconstruction [17] and can also allow for real-time correction. The second strategy used is correction during CT reconstruction, which attempts to optimize the statistical objective function [14,12] or reconstruct the image iteratively to reduce noise [18,19]. The third strategy is to complete noise correction after initial CT reconstruction and suppress noise while attempting to preserve details and small structures [14]. The method introduced in this study falls into the third strategy, where noise compensation is performed on an initial CT reconstructed image and then reconstructed to create the noise-free image. State-of-the-art approaches that utilise this last strategy include non-local means approaches which use a weighted average of selective pixels with similar neighbourhoods [20–23]. This approach assumes that pixels with similar image structure have higher probability of being representative pixels for the same tissue types and attempts to exploit this redundant information. The disadvantage of this approach is that a fixed standard deviation is used to specify the weights. This requires testing to find an optimal value and the process of finding similar neighbourhoods can be time consuming. Another non-local approach is block matching and 3D filtering (BM3D) which groups similar two-dimensional blocks into three-dimensional data arrays that are subjected to collaborative filtering to determine preservable common details between blocks [24,25]. This approach shows difficulty in images with irregular structure and smooth surfaces. Another approach is using wavelets or multi-resolution approaches which use hard-thresholding or shrinking of wavelet coefficients to denoise after analyzing the noise at each wavelet scale [26–28]. The drawback of this method is that the transform cannot represent all the image details; for example, wavelets have difficulty representing textures and smooth transitions.

In this study, a new method is introduced that corrects non-stationary noise in low-dose CT using a spatially adaptive algorithm. The method develops a noise-free image reconstruction through non-parametric modeling based on a Monte–Carlo sampling approach that is spatially adaptive. The resulting noise-compensated image reconstruction can have significant benefits for improving segmentation accuracy and clinical diagnosis performance. For the remaining portion of this study, the method will be referred to as spatially adaptive Monte–Carlo reconstruction (SAMCR).

The rest of the study is organized as follows. First, the methodology of the proposed method is described in Section 2 with SAMCR's computational complexity analyzed in Section 3. Then the experimental setup is presented in Section 4 followed by the results in Section 5 where the proposed method will be compared with three other state-of-the-art methods. Finally, conclusions are drawn and future work is discussed in Section 6.

2. Methodology

In this section, the problem is formulated and the methodology of how the noise-compensated image reconstruction is obtained is discussed.

2.1. Problem formulation

Let the cumulative noise artifacts in low-dose CT images caused by various acquisition factors be characterized as non-stationary noise processes. As such, the relationship between the acquired low-dose CT image, $V(s)$, the noise-free CT image, $G(s)$, and the non-stationary noise process contaminating the image, $N(s)$, can be modeled as:

$$V(s) = G(s) + N(s), \tag{1}$$

where s denotes a pixel location. Based on the relationship expressed in Eq. (1), the problem of determining the noise-free CT image can be formulated as an inverse problem, where the goal is to derive $G(s)$ given only the acquired low-dose CT image, $V(s)$.

In this study, a statistical approach is employed where the problem of determining the noise-free image, $G(s)$, given the acquired low-dosage CT image, $V(s)$, is formulated as a Bayesian least-squares estimation problem, where the goal is to find an estimate of $G(s)$ (denoted as $\hat{G}(s)$) that minimizes the expected squared estimation error given the acquired low-dose CT image $V(s)$:

$$\hat{G}(s) = \arg\min_{\hat{G}(s)} E((G(s) - \hat{G}(s))^2 | V(s)) = \arg\min_{\hat{G}(s)} \left(\int (G(s) - \hat{G}(s))^2 p(G(s)|V(s)) dG(s) \right) \tag{2}$$

Taking the derivative of Eq. (2):

$$\frac{\partial}{\partial \hat{G}(s)} \int (G(s) - \hat{G}(s))^2 p(G(s)|V(s)) dG(s) = \int \{-2(G(s) - \hat{G}(s)) p(G(s)|V(s)) dG(s)\} \tag{3}$$

Then setting the derivative in Eq. (3) to zero:

$$\int G(s) p(G(s)|V(s)) dG(s) = \int \hat{G}(s) p(G(s)|V(s)) dG(s) = \hat{G}(s) \int p(G(s)|V(s)) dG(s) = \hat{G}(s) \tag{4}$$

Simplifying to:

$$\hat{G}(s) = \int G(s) p(G(s)|V(s)) dG(s) \tag{5}$$

where $p(G(s)|V(s))$ denotes the posterior distribution. The knowledge of the posterior distribution, $p(G(s)|V(s))$, however can be highly complicated and difficult to obtain analytically. Therefore, to estimate $p(G(s)|V(s))$ while accounting for the non-stationary nature of the underlying noise process, a non-parametric posterior estimation approach via a spatially adaptive importance-weighted Monte–Carlo sampling approach is employed.

2.2. Spatially adaptive Monte–Carlo posterior estimation

A spatially adaptive importance-weighted Monte–Carlo sampling approach was employed to estimate $p(G(s)|V(s))$. This approach is based on the importance-weighted Monte–Carlo sampling approach [29], but has been reformulated to accommodate for non-stationary noise processes. This is important, given the non-stationary noise characteristics exhibited in low-dose CT images. This approach establishes Ω, a set of samples and associated importance weights from a search space of pixels, n_s. The samples, s_k, are selected within a surrounding region of s_0, a pixel of interest. Then, a uniform instrumental distribution $Q(s_k|s_0)$ is used to randomly draw a subset of pixels from s_k in the search space n_s.

For each pixel s_k in the subset of randomly drawn pixels, an acceptance probability $\alpha(s_k|s_0)$ is calculated by determining the likelihood that the neighbourhood around the selected pixel s_k is a