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Low-dose CT restoration via stacked sparse denoising autoencoders

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ABSTRACT

To improve the imaging quality of low-dose computed tomography (CT) images, a deep learning based method for low-dose CT restoration is presented in this paper. Stacked sparse denoising autoencoders, which were designed originally for training noisy samples, are adopted to construct the architecture. Experimental results demonstrate that the proposed model outperforms several state-of-the-art methods, including total variation based projection on convex sets (TV-POCS), dictionary learning, block-matching 3D (BM3D), convolutional denoising autoencoders (CDA) and U-Net based residual convolutional neural network (KAIST-Net), both qualitatively and quantitatively. The proposed method is not only capable of suppressing noise but also recovering structural details. Furthermore, once the network is trained offline, the processing speed for target low-dose images is much faster than other methods.

1. Introduction

Because of the wide use of computed tomography (CT) in both clinical and industrial fields, the overall radiation dose of both patients and operators has drawn much public attention [1]. As a result, the famous ALARA (as low as reasonably achievable) principle is encouraged to refrain from causing excessive radiation doses in the medical community. Lowering the milliampere–seconds (mA s) parameter is a common way to reduce the radiation dose. However, this method will unavoidably increase the quantum noise in the projection data and the imaging quality of reconstructed CT images will be severely degraded. How to improve the quality of low-dose CT images has hence been a major topic in the CT field.

There are two approaches to lowering the radiation dose. The first one is to decrease the number of measurements. The second one is to reduce the amount of X-ray flux towards each detector element. Directly decreasing the number of measurements will produce insufficient projection data that suffers from too few views, limited angles, interior scans, or other problems. Reducing the X-ray flux can be implemented by modifying the operating current, potential, and exposure time of the X-ray tube, which will generate noisy projections. In practice, the second method is easier to implement clinically, so in this work, we focus on this kind of method.

Many methods have been proposed to improve the quality of low-dose CT images from noisy projections. These approaches can be categorized into three groups: Sinogram filtering, iterative reconstruction, and post-reconstruction restoration. Sinogram filtering directly smooths the raw data before filtered backprojection (FBP) is applied. Several typical methods including multiscale penalized weighted least-squares [2], maximum a posteriori [3], bilateral filtering [4], and structure adaptive sinogram filtering with ray contribution masks [5]. Iterative reconstruction optimizes a prior-regularized objective function iteratively. The key part of this kind of method is how to construct the image priors. Sparse representation is a powerful tool for completing this task with different sparse transforms [6]. The most common transform is the discrete gradient transform, which is also called total variation (TV) [7]. However, TV assumes that the signal is piecewise constant, and this defective assumption causes an undesired side effect called blocky effect. Many variants of TV were proposed in recent decades to overcome this problem [8–10]. In addition to TV-based methods, many other image priors have been presented, such as nonlocal means [11,12], dictionary learning (DL) [13,14], low rank [15,16], and adaptive Markov random fields [17]. Iterative reconstruction methods are not desirable because of their intensive computational burden. Despite the successes achieved by these two kinds of approaches for improving imaging quality, they are often limited in practice because of the difficulty of gaining well-formatted projection data from commercial CT scanners. The post-reconstruction restoration approaches, which do not rely on projection data, can be directly applied to low-dose CT images and easily integrated into current CT systems as post-processing software. This is a reasonable alternative for those institutes that cannot handle the expense of upgrading their current scanners to the latest model. Our target was to develop a restoration strategy that

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can be easily utilized in the CT community without considering machine-specific parameters. These requirements leads us to adopt post-reconstruction restoration techniques that are relatively simple to implement. Actually, the statistical property of low-dose CT images cannot be precisely determined in the image domain, so many methods proposed in image processing field are not suitable for low-dose CT images. Given this situation, many efforts have been made to handle this kind of special noise pattern. Chen et al. introduced dictionary learning to improve abdomen tumor low-dose CT images [18]. Nonlocal means is also a popular technique for suppressing the noise in low-dose CT images [19]. As the most efficient natural image denoising method, the block-matching 3D (BM3D) algorithm has also been applied [20,21].

In contrast, learning-based methods are immune to imaging models, because this kind of method is, to a large degree, optimized for training samples instead of the noise type. Recently, deep learning has attracted enormous attention in the field of computer vision tasks such as restoration, classification, and segmentation [22,23]. Deep learning simulates the information processing of humans and can efficiently learn high-level features from pixel-level data through a hierarchical multilayer framework. In the medical imaging community, the research has mainly focused on image analysis, including nuclei detection [24], organ segmentation, and classification [25–27]. Recently, Wang et al. proposed a compressive sensing based MRI (CS-MRI) model to accelerate reconstruction based on convolutional neural networks (CNNs) [28]. The mean square error (MSE) loss function of deep learning was imposed into the energy function as a regularization term. Kang et al. introduced a U-Net based CNN into low-dose CT restoration (KAIST-Net). The high frequency coefficients after wavelet decomposition were used as the inputs of this symetrical residual network [29]. A 5-layer convolutional denoising autoencoder (CDA) network with maxpooling layers was given by Gondara to decrease the number of parmaters and transfer the advantage of CNN for image processing [30]. Combining the idea of autoencoders and residual CNN, Chen et al. proposed a residual encoder–decoder convolutional network for low-dose CT and obtained promising results [31]. Meanwhile, the popular technique, generative adversarial network (GAN), was also introduced into this topic. With the help of an auxiliary adversarial discriminator CNN, Wolterink et al. achieved a better performance than CNN on task-driven evaluations [32]. Jin et al. [33] and Han et al. [34] separately presented sparse view CT restoration methods to remove streak artifacts with simialr network architecture as that in [29]. Würfl et al. mapped the FBP identically onto a deep neural network architecture. The weights of projections were learned by the training samples. This work is instructive for image reconstruction with deep learning [35]. Prliminary trials were given by two separate groups. Adler and Oktem proposed a learned primal-dual algorithm for tomographic reconstruction, which included the forward operator in a deep neural network inspired by unrolled proximal primal-dual optimization methods [36]. Chen et al. unfolded the general iterative reconstruction framwork into a CNN [37]. Both regularization terms and parameters can be learned from the training samples. Although limited studies have been published on this topic, it shows a large amount of future promise [38].

In this paper, we introduce stacked sparse denoising autoencoders (SSDAs) into low-dose CT imaging. Actually, there are several different architectures we can choose for dealing with low-dose CT, such as CNNs, multi-layer perceptrons (MLPs), restricted Boltzmann machines (RBMs), and SSDAs [22]. In this work, we chose SSDA, which is especially designed for noisy data and more suitable for our task [33]. In the next section, the network and training details are described. In the third section, qualitative and quantitative experimental results are given. In the last section, a discussion is presented and the conclusion is drawn.

2. Methods

2.1. Noise reduction model for low-dose CT images

Because of the encryption of the raw projection data, post-reconstruction restoration is a reasonable alternative. Once the target image has been created from the low-dose scans, the problem is transformed into denoising in the image domain. The only difference between low-dose CT and natural image restoration is that the statistical property of low-dose CT images, which cannot be precisely modeled in the image domain, has strong spatial correlations and variations. This property significantly impacts the performance of noise-dependent methods, such as the median filter, Gaussian filter, and TV, which are designed for a specific noise type. It is more difficult for such techniques to achieve an optimal banlance between retoration performance and detail preservation, or to obtain consistent performance across an entire volume. The quantum noise in the sinogram domain will transform into complicated noise and artifacts in image domain, which will make current denoising methods powerless. However, learning-based methods are immune to this problem because they are dependent on training samples, instead of noise type. We model the noise reduction problem in low-dose CT images with the following formulation.

Let $\mathbf{x} \in \mathbf{R}^{m\times n}$ be a low-dose CT image and $\mathbf{y} \in \mathbf{R}^{m\times n}$ be the corresponding normal-dose image. The following relationship can then be obtained [39]:

$$\mathbf{x} = \sigma(\mathbf{y}), \tag{1}$$

where $\sigma : \mathbf{R}^{m\times n} \to \mathbf{R}^{m\times n}$ represents the corruption of the quantum noise that contaminates the normal-dose CT image. The noise reduction problem can then be converted into the task of finding a function f such that

$$f = \arg\min_f ||f(\mathbf{x}) - \mathbf{y}||_2^2, \tag{2}$$

where f is treated as the best approximation of σ^{-1}.

2.2. SSDA for low-dose CT

A denoising autoencoder (DA) [39–41], which is a natural choice for image restoration tasks, is trained to reconstruct a clean output from a noisy input. Assuming $\mathbf{x}$ is a low-dose CT image and $\mathbf{y}$ is the corresponding normal-dose one, the feedforward functions of the DA can be defined as follows:

$$h(\mathbf{x}) = s(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{3}$$

and

$$z(\mathbf{x}) = s(\mathbf{W}'h(\mathbf{x}) + \mathbf{b}'), \tag{4}$$

where $\Theta = \{\mathbf{W}, \mathbf{b}, \mathbf{W}', \mathbf{b}'\}$ is the set of the weights and biases, $s(t) = (1 + \exp(-t))^{-1}$ is the sigmoid function, $h(\mathbf{x})$ is the hidden layer activation, and $z(\mathbf{x})$ is an approximation of $\mathbf{y}$.

Given low-dose CT image training data set $D = \{(x_i, y_i)\}$, where $i = 1, 2, \ldots, N$ and N denotes the total number of training samples, the sparse denoising autoencoder (SDA) is trained by a backpropagation algorithm to minimize the following sparsity regularized reconstruction loss function:

$$J(D;\Theta) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}||z(x^i) - y^i||_2^2 + \beta KL(\hat{\rho}\,||\rho) + \frac{\lambda}{2}(||W||_F^2 + ||W'||_F^2), \tag{5}$$

where β is the sparsity term parameter and λ is the weight decay term parameter. The sparsity term is the Kullback–Leibler