ARTICLE IN PRESS
Journal of King Saud University – Computer and Information Sciences (2016) xxx, xxx–xxx

King Saud University
Journal of King Saud University – Computer and Information Sciences
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CT image denoising using locally adaptive shrinkage rule in tetrolet domain

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Received 11 December 2015; revised 24 February 2016; accepted 17 March 2016

KEYWORDS
Image denoising;
Wavelet transform;
Tetrolet transform;
Shrinkage rule

Abstract In Computed Tomography (CT), image degradation such as noise and detail blurring is one of the universal problems due to hardware restrictions. The problem of noise in CT images can be solved by image denoising. The main aim of image denoising is to reduce the noise as well as preserve the important features such as edges, corners, textures and sharp structures. Due to the large capability of noise suppression in noisy signals according to neighborhood pixels or coefficients, this paper presents a new technique to denoise CT images with edge preservation in tetrolet domain (Haar-type wavelet transform) where a locally adaptive shrinkage rule is performed on high frequency tetrolet coefficients in such a way that noise can be reduced more effectively. The experimental results of the proposed scheme are excellent in terms of noise suppression and structure preservation. The proposed scheme is compared with some standard existing methods where it is observed that performance of the proposed scheme is superior to the existing methods in terms of visual quality, MSE, PSNR and Image Quality Index (IQI).

1. Introduction

CT examination is widely used in medical science for detection of diseases such as lung cancer. Higher radiation dose used for clinical CT scanning may increase the risk of cancer in the patients (Zhoubo et al., 2014). However, it is mentioned in the guidelines of CT scanning that the use of radiation should be as low as reasonably required. But many times, we have to compromise with these guidelines to achieve good quality CT images. On the other-side, low-dose CT imaging may produce a noisy image which degrade the diagnostic performance. Thus, there is a need to develop the techniques which can control the noise in low dose CT scan images.

Various techniques have been investigated for controlling noise in CT scan imaging. Broadly, these techniques can be categorized in three major parts : projection based denoising, iterative reconstruction (IR) based denoising and post processing based image denoising.

Projection based techniques such as projection space denoising with bilateral filtering and CT noise modeling for dose reduction in CT imaging (Manduca et al., 2009) work on raw data or sinogram, where noise filtering is applied on

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Peer review under responsibility of King Saud University.

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http://dx.doi.org/10.1016/j.jksuci.2016.03.003
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Please cite this article in press as: Kumar, M., Diwakar, M. CT image denoising using locally adaptive shrinkage rule in tetrolet domain. Journal of King Saud University – Computer and Information Sciences (2016), http://dx.doi.org/10.1016/j.jksuci.2016.03.003

raw data or sinogram and reconstructed image comes in the form of denoised image. Many iterative reconstruction approaches for noise suppression in CT have also been investigated, for example, ordered subset reconstruction for X-ray CT scan (Beekman and Kamphuis, 2001) that optimizes statistical objective functions. Iterative reconstruction techniques have an advantage of using noise statistics directly in the projections during the reconstruction process, the disadvantage, however, is the high computational cost. Post processing based methods can denoise directly to the reconstructed CT images by applying linear or nonlinear filters (Motwani et al., 2004). Several linear or nonlinear filtering methods for noise reduction in the projection data have been proposed. Linear filters such as Wiener filter (Li and Zhang, 2010; Naimi et al., 2015) in the wavelet domain gives optimal results when the signal distortion is estimated by Gaussian approximation and the accuracy is measured by calculating Mean Square Error (MSE). Most of the techniques like bilateral filtering (Durand and Dorsey, 2002; Manduca et al., 2009), total variation denoising (Chambolle, 2004; Goldstein and Osher, 2009), nonlocal means (NLM) denoising (Buades et al., 2005), local linear SURE based edge-preserving image filtering (LLSURE) (Qiu et al., 2013) and K-singular value decomposition (K-SVD) algorithm (Aharon et al., 2006) take an advantage of statistical properties of objects in image space and preserve clinical structures such as sharp edges, similarities between neighboring pixels, etc. In transform-domain denoising techniques, the input data are decomposed into its scale-space representation (Mallat, 1989). Various thresholding techniques for noise reduction have been introduced with wavelet such as efficient image denoising method based on a new adaptive wavelet packet thresholding function (Fathi and Naghsh-Nilchi, 1989), ideal spatial adaptation via wavelet shrinkage (Chang et al., 2000), SURE-LET approach for image denoising (Thierry and Florian, 2007), etc. For CT image denoising, selection of a threshold value is a cumbersome task for edge preservation and noise suppression. By selecting a small threshold value, the resultant image may left noisy while large threshold value may produce blurring on the edges of resultant image. To deal with this situation, an appropriate algorithm is to be selected to estimate a threshold value. Three major algorithms to estimate threshold value are VISUShrink, SUREShrink and BayesShrink. VISUShrink (Donoho and Johnstone, 1994) is non-adaptive universal threshold, which depends only on the number of samples and known for finding smoothed images. Its threshold choice can be large due to its dependence on the number of pixels in the images. From literature, it can be observed that threshold estimation of VISUShrink tends to over-smooth the signal while SUREShrink (Donoho, 2010) uses a hybrid of the universal and the SURE [Stein's Unbiased Risk Estimator] thresholds, and performs better than VISUShrink. BayesShrink (Abramovitch et al., 1998) minimizes the Bayes' risk estimator function assuming generalized Gaussian approximation and thus finds adaptive threshold value. In most of the cases, BayesShrink provides better outcomes in comparison to both VISUShrink and SUREShrink. Thresholding is one of the strategies to clean the pixels or images. In wavelet based thresholding, small wavelet coefficients in high frequency bands are removed and large wavelet coefficients are preserved. Hard and soft thresholding are very popular methods for thresholding. In hard thresholding (Donoho, 2010), each coefficient value is compared with estimated threshold value and values less than threshold are replaced by zero. In soft thresholding (Prakash and Khare, 2014), the replacement process is same as in hard thresholding, additionally rest of coefficients are modified by subtracting threshold value from those coefficients. Comparing the two, Soft thresholding gives better performance for visual appearance of images. Due to hard thresholding, image artifacts may be generated near the edges on denoised CT images. Soft thresholding has a limitation with large coefficient values which may not be good for more sophisticated CT images. Other thresholding schemes have also been proposed, which take the advantages of both soft and hard thresholding. Some well-known shrinkage rules are hyperbola function (Vidakovic, 1998), firm thresholding (Gao and Bruce, 1997), garrote thresholding (Gao, 1998) and SCAD thresholding (Antoniadis and Fan, 2001).

Recently, some researchers extended the idea of shrinkage with geometric wavelets methods (Krommweh, 2010) such as ridgelet, curvelets, contourlets, directionlet and tetrolet. CT image denoising is a challenging task because of finding correct noise variation, relationship between coefficients and achieving an optimal tradeoff between denoising and blurring or artifacts. To overcome these challenges, we propose a method for CT image denoising based on the variation of neighborhood pixels or coefficients.

This paper is organized as follows. In Section 2, a brief introduction of tetrolet transform is described. In Section 3, we describe the proposed methodology for CT image denoising where a locally adaptive shrinkage rule is performed in tetrolet transform. In Section 4, we describe the experimental results and compare with some existing denoising methods. Finally, conclusions are drawn in Section 5.

2. Tetrolet transform

The idea of tetrolet transform comes from a famous computer game 'Tetris', where five geometric patterns (as shown in Fig. 1 (a)) are used with rotation and reflection properties (Krommweh, 2010). These geometric patterns are known as tetrominoes. Tetrolet transform is a powerful tool for signal and image processing tasks because of local enhancement through tetrominoes, multi-resolution analysis, sub-banding and localization in both frequency and time domain. All the tetrominoes are connected with a four equal sized squares. In tetrolet transform, an image $X[i,j]_{i,j=1}^{N}$ with $N = 2^P,\ P \in N$ is divided into 4×4 blocks. Each block is covered with any four free tetrominoes, which is responsible for enhancing the local structure using properties of rotations and reflections. These four tetrominoes (I_o, I_1, I_2, I_3) are mapped in a unique order (0, 1, 2, 3) by applying bijective mapping (L) with their corresponding order. For each tetromino subset (I_v), the discrete basis functions (Krommweh, 2010) are defined as follows:

$$\phi_{I_v}[i,j] := \begin{cases} 1/2; & (i,j) \in I_v \\ 0; & \text{otherwise} \end{cases}$$

$$\psi^l_{I_v}[i,j] := \begin{cases} \in [l, L(i,j)]; & (i,j) \in I_v \\ 0; & \text{otherwise} \end{cases}$$

for $l = 1,2,3$, $\psi^l_{I_v}$ represents tetrolets and ϕ_{I_v} is scaling function. Haar wavelet transform matrix W has four fixed 2×2