Image Denoising Methods for Tumor Discrimination in High-Resolution Computed Tomography

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Pixel accuracy in images from high-resolution computed tomography (HRCT) is ultimately limited by reconstruction error and noise. While for visual analysis this may not be relevant, for computer-aided quantitative analysis in either densitometric, or shape studies aiming at accurate results, the impact of pixel uncertainty must be taken into consideration. In this work, we study several denoising methods: geometric mean filter, Wiener filtering, and wavelet denoising. The performance of each method was assessed through visual inspection, profile region intensity analysis, and global figures of merit, using images from brain and thoracic phantoms, as well as several real thoracic HRCT images.

KEY WORDS: Denoising methods, tomographic reconstruction, Poisson noise, computed tomography

INTRODUCTION

Computed tomography (CT) is an imaging modality that allows for data acquisition of the organ under study. CT has been long recognized as an invaluable imaging tool assisting medical diagnosis.¹ Since the early 1970s, several technological breakthroughs have marked the way to the current sophisticated sub-second multi-slice CT systems. One of the most important achievements enabled volumetric data acquisition through helical scanning leading to what is known today as spiral or helical CT. This scanning technology, when combined with the multi-slice detection, provides a means for almost isotropic volume imaging aiming at sub-millimeter voxels, minimizing the blur due to moving structures (respiration, cardiac beat, blood circulation, etc.), being able to detect small variations in density that might correspond to physical anomalies.

The quest for isotropic resolution and the need to minimize partial volume artifacts in many diagnosis assessments have been contributing for

an ever-increasing pool of thin slices. However, due to the fact that radiation dose should always be limited to clinically acceptable levels and the inverse relation between noise and slice thickness, transaxial images of thin slices always exhibit anatomic details overlaid by random grainy-like fluctuations.

In most cases, this type of noise even if emphasized by a high spatial resolution reconstruction kernel does not impair qualitative evaluations supporting diagnosis tasks. In fact, visual inspection is often sufficiently effective in distinguishing morphological details specially those that might reinforce diagnosis. However, with computer-aided quantitative analysis in either densitometric, or shape studies aiming at accurate results, the impact of this type of noise must be taken into consideration.

Noise in CT is a multi-source problem, but the ultimate physical factor that determines image quality particularly in thin slices may be modeled

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as a Poisson process parameterized by the X-ray photon counting statistics.

In this work, we present several denoising methods that may be helpful as a pre-processing step of a higher-level specific computer-aided image analysis task. These methods comprise the following approaches: geometric mean filtering, adaptive filtering, and wavelet denoising.

The performance of each method was assessed through visual inspection and figures of merit on both head and thoracic phantom images with induced Poisson noise. Moreover, real high-resolution (HR) thoracic CT images were used to visually assess the effect of those methods.

IMAGE FORMATION CONCEPTS

It can be shown² that an analytical model for the tomographic reconstruction process is a regularized version of the ill-posed problem:

$$\hat{f} = Q^{**} \left(f^{**} \frac{1}{r} \right) \quad (1)$$

where $\hat{f}$ is the reconstructed image, f is the true image, r is the distance to the center of the reconstruction field, $**$ denotes 2D convolution, and Q is a regularization operator or filter. Note that $f^{**} \left(\frac{1}{r} \right)$ models the back-projection process.³ In practice, Q is a windowed ramp filter, and the numerical implementations of Eq. 1 are normally known by convolution-back-projection methods.

Most of the reconstruction error is due to imperfect regularization achieved by Q . This operator is normally chosen as a trade-off between spatial resolution and tolerated noise level required for imaging a particular anatomic part.

In practice, what is actually available is a finite and discrete set of projections of f or, in other words, a sampled version of its Radon transform or also its sinogram. Moreover, as a physical projection process, each sample is determined by a photon counting process with underlying Poisson statistics.⁴ The Lambert–Beer law is only able to predict average values given by

$$\bar{N}_d(i) = N_{in} e^{-\int_L f(p) dp} \quad (2)$$

where N_{in} is the radiation intensity at the source, $\bar{N}_d(i)$ is the average intensity recorded at the i th

detector after traversing the object along a straight line path L . The measurement of P_i^m may be regarded as a realization of a Poisson process such that

$$P_i^m = \ln \frac{N_{in}}{\bar{N}_d(i)} = \frac{N_{in}}{\text{Poisson}(\bar{N}_d(i))} \quad (3)$$

This simplified model enables consistent prediction of noise influence in image quality associated with acquisition parameters such as scanning time, tube current, slice thickness, and others that may determine the overall dose.

METHODS

In many medical applications, images are often corrupted by noise due to data acquisition or data transmission. Therefore, the problem of recovering an original image from noisy data has received increasing attention in recent years.^{5,6}

We had to make a selection of the denoising methods we wished to compare. Here, a problem arises as most original methods have caused an abundant literature proposing many improvements. So, we tried to get the most representative methods, but keeping the simple and genuine character of the original methods: no hybrid methods.

Most denoising methods were tested in the presence of generic noise (white noise), but their conclusions do not take into account the Poisson noise that corrupts sinogram data. We also take into consideration the denoising methods without high computational costs (processing time) and their availability in high level programming language, such as the Matlab, among others.

This section is divided in two parts: First, we give details of the used denoising methods; in the second part, we describe the method used for the performance evaluation.

Denoising Strategy

Several denoising methods, a geometric mean filter, an adaptive filter, and a Wavelet denoising method were tested using neighborhoods of 3×3 and 5×5 .

– Geometric mean filter

In this filter, each pixel is the result of the product of all gray levels in a $m \times n$ neighborhood raised to the power of $1/(m \times n)$. This filter tends to maintain more detail than the arithmetic mean filter.⁷ We include this

filter because in a preliminary test, we were positively surprised with the capability of this filter in noise attenuation; in specific cases, it was able to surpass the results of the other filters compared in this work.

– Wiener filter

The Wiener filter was also used due to its adaptive properties to the image noise. It adapts itself to the local image variance. Where the variance is large, it performs little smoothing. Where the variance is small, it performs more smoothing.^{7,8} This approach often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image.

– Wavelet denoising

Another approach for denoising is using wavelet transforms. Wavelet denoising reduces multi-band noise. A direct wavelet transform is computed from the original image. The noise level at each wavelet scale is estimated separately. This defines a threshold for zeroing wavelet coefficients. Other wavelet coefficients are shrunk according to local variance estimation. After inverse wavelet transform, the image is renormalized. The wavelet decomposition was performed up to level 2 with the Haar basis function for a soft threshold with automatic default value.⁷⁻⁹

Performance Analysis

In order to compare the performance of the denoising methods, we have visually inspected the

filtered images and some gray level profiles. For a global analysis, we have also used a quantitative approach based on several figures of merit.

Visual Inspection

Denoised images were visually inspected to assess if the methods have significantly changed some of the global properties, such as the shape, size, and position of relevant structures on the images, as low contrast brain tumors and air bubbles in the pulmonary fields.

Several gray level profiles of regions containing the above-mentioned relevant structures were defined on images produced from phantoms (“original images”), after noise insertion and after denoising. These profiles were visually compared.

Quantitative Comparison

In order to measure the differences between original phantom image (I_{orig}) and denoised image (I_{reconst}), the following figures of merit were used:

- Normalized root mean square error (nRMSE)^{2,4} where I_{orig} is the original image and I_{reconst} is the image after applying the noise attenuation filter:

$$\text{nRMSE} = \sqrt{\frac{\sum_{i=1}^N (I_{i,\text{orig}} - I_{i,\text{reconst}})^2}{\sum_{i=1}^N |I_{i,\text{orig}} - \bar{I}_{\text{orig}}|^2}} \quad (4)$$

A large difference in a few pixels causes the value of nRMSE to be large.

Fig 1. a Brain phantom image with low contrast tumors in lower left region. b Thoracic phantom image with an air bubble in the lung on the right. c Real high-resolution computed tomography image of a patient with a large air bubble.

Fig 2. Profile intensities for comparison among filters, a–c correspond to Figure 1a–c, respectively. The x-axis corresponds to tumor/bubble region and y-axis is in Hounsfield units.

- Normalized mean absolute error (nMAE)^{2,4}:

$$\text{nMAE} = \frac{\sum_{i=1}^N |I_{i,\text{orig}} - I_{i,\text{reconst}}|}{\sum_{i=1}^N |I_{i,\text{orig}}|} \quad (5)$$

As opposed to nRMSE, nMAE emphasizes the importance of a lot of small errors rather than a few large errors.

- Worst case error (WCE) over smoothed error image^{2,4}:

$$\text{WCE} = \max_{1 \leq k \leq N} \left(\text{mean}_{2 \times 2 \text{ neighborhood}} (|I_{k,\text{orig}} - I_{k,\text{reconst}}|) \right) \quad (6)$$

The maximum intensity value is computed after a slight smooth with a mean filter in a neighborhood of 2×2 .

Image Data Set

Three types of images were used (Fig. 1):

- (a) Tomographic reconstructions of a brain phantom with a resolution of 512×512 , obtained from sinograms with 1,200 projections and 729 detectors per projection. Reconstruction was accomplished by inverse Radon transforming the sinogram data using Ram–Lak filtering and linear interpolation in the back-projection phase^{4,10,11};

Table 1. Results obtained for the Brain Phantom

Filter	nRMSE	nMAE	WCE
Geometric mean	0.155	0.024	1,506
Wiener	0.060	0.011	365
Wavelet	0.061	0.010	366

Table 2. Results obtained for the Thoracic Phantom

Filter	nRMSE	nMAE	WCE
Geometric mean	0.191	0.025	657
Wiener	0.174	0.032	431
Wavelet	0.180	0.032	459

- (b) Tomographic reconstructions of a thoracic phantom with a resolution of 256×256 , using 256 detectors, 512 projections, and a thickness of 2.3 mm^{12,13};
- (c) Real HR thoracic CT images with a resolution of 512×512 and 1-mm thickness, obtained from patients having pulmonary bubbles.

Brain tumors having an attenuation contrast from the neighboring tissue of 0.5% are considered relevant in medical diagnosis and should be detectable on the images¹⁴; thus, we have inserted in our brain phantom three low contrast tumors, two with this contrast and another one with a lower value (0.25%).

In air-filled regions, noise level may be an impairing factor for the success of subsequent automated segmentation tasks. This problem is even more serious with thin slices where photon collection statistics are rather weak. Thus, we have inserted in the thoracic phantom one air bubble.

On the images obtained from phantoms, we have added Poisson noise to the image projections in the Radon space, during phantom reconstruction phase, with a level similar to the noise of real HRCT images. Thus, we considered for simulation purposes and, according to the underlying principles described in “Image Formation Concepts,” a source intensity of 10^7 photons per X-ray beam.

RESULTS AND DISCUSSION

From a global analysis of the gray level profiles, we have noticed that all methods considerably reduce the noise in the processed images, either real or reconstructed from the phantoms (see Fig. 2).

Comparing the gray level profiles of Figure 2, we observe that:

- For tomographic reconstructions of the thoracic phantom, the geometric mean filter and the Wavelet denoising seem to yield better results.
- For the brain phantom, only the wavelet denoising method seems to produce better results than all the other methods, with possible impact in tumor discrimination.
- Finally, for real thoracic images, the geometric mean filter results in a “flatter” profile in the region of the air bubble.

Analyzing figures of merit obtained for the denoising of tomographic reconstructions of the

brain phantom (Table 1), we notice that the geometric mean filter seem to have a performance significantly different from the other two filters (which exhibit similar values among them). Yet, this is not the case for the thoracic phantom (Table 2).

These results seem to suggest that it is not possible to select a globally optimal method for denoising tomographic reconstructions regardless of the specific diagnosis task. They also reinforce the idea that the consistency between visual assessment and numerical figures of merit computed without any perceptual constraint is hard to achieve.

CONCLUSIONS

We have studied several denoising methods that may be helpful as a pre-processing step of a higher-level specific computer-aided image analysis task. Geometric mean filter, Wiener filter, and wavelet denoising were applied to real HRCT images, as well as tomographic reconstructions obtained from phantoms having Poisson noise generated in Radon space, during reconstruction phase.

In order to compare the results yielded by these denoising methods, we have carried out a performance analysis using visual inspection of gray level profiles containing structures relevant to diagnosis and three widely used global figures of merit. The results of this analysis suggest that perhaps the Wavelet method is a good candidate for denoising strategies before further image processing tasks; however, it may not be possible to find a method that is globally optimal for denoising tomographic reconstructions regardless the location and diagnosis task involved.

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