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Image quality assessment of an iterative reconstruction algorithm applied to abdominal CT imaging

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Abstract

Purpose: To compare the noise and accuracy on images of the whole porcine liver acquired with iterative reconstruction (IMR, Philips Healthcare, Cleveland, OH, USA) and filtered back projection (FBP) methods. **Materials and methods:** We used non-enhanced porcine liver to simulate the human liver and acquired it 100 times to obtain the average FBP value as the ground-truth. The mean and the standard deviation (“inter-scan SD”) of the pixel values on the 100 image acquisitions were calculated for FBP and for three levels of IMR (L1, L2, and L3). We also calculated the noise power spectrum (NPS) and the normalized NPS for the 100 image acquisitions.

Results: The spatial SD for the porcine liver parenchyma on these slices was 9.92, 4.37, 3.63, and 2.30 Hounsfield units with FBP, IMR-L1, IMR-L2, and IMR-L3, respectively. The detectability of small faint features was better on single IMR than single FBP images. The inter-scan SD value for IMR-L3 images was 53% larger at the liver edges than at the liver parenchyma; it was only 10% larger on FBP images. Assessment of the normalized NPS showed that the noise on IMR images was comprised primarily of low-frequency components.

Conclusion: IMR images yield the same structure informations as FBP images and image accuracy is maintained. On level 3 IMR images the image noise is more strongly suppressed than on IMR images of the other levels and on FBP images.

Keywords

Iterative reconstruction; Image quality; Porcine liver; Filtered back projection; Abdominal CT

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Introduction

Advances in the computational capability of processors facilitated the development and implementation of complex reconstruction algorithms for CT imaging [1–4]. These algorithms play a major role in achieving an effective dose of less than 1 mSv in routine CT examinations [5]. Iterative reconstruction algorithms may help to reduce the radiation dose while maintaining image quality. Most vendors of CT scanners have released first-generation iterative methods [6–10] that apply combined filtered back projection (FBP) and statistical iterative techniques to both projection and image data to generate CT images with lower image noise. A prototype of a second-generation algorithm, “iterative model reconstruction” (IMR), has been developed (Philips Healthcare, Cleveland, OH, USA) for image reconstruction. Unlike first-generation methods (i.e. iDose), it is an iterative reconstruction algorithm that uses a knowledge-based approach to yield improved image quality and virtually noise-free images via the iterative minimization of the penalty-based cost function. As second-generation methods model the X-ray physics more accurately than first-generation iterative techniques [11–14], compared to FBP methods, they may result in a marked decrease in image noise while maintaining or improving the image quality.

Iterative reconstruction algorithms such as IMR are nonlinear, therefore, their performance depends on the imaged object. Consequently, when simple phantoms such as wires, bars, or cylindrical inserts in a water tank are used in phantom studies their results do not reflect the image quality nor do they predict the performance in clinical studies [15]. As task-specific performance tests involving tumor detection and characterization are time-consuming and difficult, a hypothesis is needed for the creation of tests that identify candidate tasks suitable for performance tests under application-specific conditions. Moreover, when tests are performed on clinical cases, the lack of ground-truth information renders the objective assessment of image accuracy highly difficult.

Focusing on abdominal CT images, we performed a hypothesis-generating study using ground-truth values obtained with a whole porcine liver. We acquired the specimen 100 times to obtain an average CT image with very low image noise and used the obtained values as our ground-truth. Then we compared the performance of IMR and FBP methods with respect to image noise and the accuracy of image features.

Materials and methods

Phantom

We used a non-enhanced liver phantom produced in-house. A whole porcine liver weighing 1.0 kg was placed in the center of a 20 × 20 cm (diameter × height) acrylic cylindrical container filled with agar gel (Wako Pure Chemicals Industries Ltd., Osaka, Japan). The agar concentration was 2% weight/volume, resulting in a pixel value of approximately 12.0 Hounsfield units (HU).

Step-and-shoot acquisition and image reconstruction

We used a 256-slice CTscanner (iCT, Philips Healthcare, Cleveland, OH) and the axial (step-and-shoot) acquisition mode. The same area that included the porcine liver was acquired 100

times without automatic exposure control modulation. The acquisition parameters were detector configuration, 64×0.625 mm, gantry rotation time 1.0 s, tube voltage 120 kV, tube current–time product 200 mA s. From each axial acquisition we reconstructed 37 slice images, thus obtaining 3700 images. The slice thickness and interval were 1.0 mm and the display field-of-view diameter was 200 mm. FBP images were reconstructed using the standard kernel/filter (B). We reconstructed IMR images at 3 noise reduction levels, L1, L2 and L3, using the IMR soft-tissue setting and an off-line, dedicated image reconstruction system. The soft-tissue setting is designed to maximize low-contrast detectability; as it aggressively enforces the edge fidelity term in the cost function, enhanced spatial resolution is not the goal of soft-tissue reconstruction. For quantitative image analysis we chose one axial slice level near the middle of the liver that contained both low- and high-contrast structures, i.e. the liver, agar, blood vessels, and air holes produced by the drainage of blood vessels, and applied each image reconstruction technique to the 100 images.

Image analysis

Mean and subtraction images—The mean image pixel value for each pixel location on the 100 acquisitions was calculated for FBP, IMR-L1, IMR-L2, and IMR-L3 images and 3 subtraction images were obtained by subtracting the mean FBP image from the mean IMR-L1, mean IMR-L2, and mean IMR-L3 images.

Power spectrum of the mean images—A central portion of the mean images containing 300×300 pixels was chosen as the region-of-interest (ROI) and the power spectrum of the ROI was calculated.

Standard deviation (SD) images—The SD of the image pixel values derived from the 100 data acquisitions performed at each pixel location was calculated for FBP, IMR-L1, IMR-L2, and IMR-L3 images. Our term for this value is “inter-scan SD” or “ σ_{nr} ”. We also calculated the SD of the image pixel values for ROIs comprised of 11×11 pixels in the center of each pixel location on FBP, IMR-L1, IMR-L2, and IMR-L3 images. The mean of SD at the pixel values derived from the 100 acquisitions was then calculated; we term this the “spatial SD” or “ σ_{xy} ”. Finally σ_r , the ratio of σ_{xy} to σ_{nr} , was calculated; we posited that this value shows the non-linear or adaptive nature of the image reconstruction algorithms.

Image profile curves across the edges—On all FBP and IMR images we measured the image profiles across the edges at the site of an air hole in the liver parenchyma (high-contrast edge) and at the edge of the liver (moderate-contrast edge). The profiles were then averaged over the 100 images.

Noise power spectrum (NPS) and normalized NPS—For each reconstruction method we produced 100 noise images by subtracting the corresponding mean image from the 100 images. The ROI was a central portion of the noise images consisting of 300×300 pixels. The power spectrum of the ROI was obtained by dividing the squared magnitude of the two-dimensional Fourier transform of the noisy ROI image by the physical area of the ROI [16,17]. This process was applied to 100 noise images, the mean of the spectrum was calculated and called “NPS”.

We calculated the normalized NPS by dividing the NPS value by the area-under-the-curve of the NPS. As the 100 noise images were devoid of signals (zero-mean), both the NPS and the normalized NPS values featured only the image noise characteristics and were not affected by anatomical structures.

Normalized covariance map—To characterize the patchy nature of the image appearance we prepared a normalized covariance map using the equation:

$$nCov_i = \frac{1}{n-1} \sum_{\text{all } j \in S_i} \frac{Cov_{ij}}{\sigma_i \cdot \sigma_j}$$

where i is the image pixel index at the central portion of images with 300×300 pixels, j is a working image pixel index except i within a sub-region S_i (i.e. a rectangular region with 11×11 pixels) which was set centering at the image pixel i , n is the number of pixels within S_i excluding i , σ_i and σ_j are the standard deviation over 100 acquisitions measured at pixels i and j , respectively, and Cov_{ij} is a covariance of pixel values at i and j over 100 images.

Results

Single and subtraction images

Figure 1 shows FBP and IMR images obtained from the 51st acquisition. In these slices the spatial SD (or σ_{xy}) at the liver parenchyma was close to the σ_{nr} value at 9.92, 4.37, 3.63, and 2.30 HU with the FBP, IMR-L1, IMR-L2, and IMR-L3 technique, respectively (Table 1). The noise texture of images reconstructed with IMR-L1 and FBP appeared similar. The noise pattern of IMR-L3 images exhibited the greatest difference from FBP images. Figure 1e presents the mean image acquired with the FBP reconstruction method. We used the mean FBP image because it represents the most accurate CT image of the object as the ground-truth based on the consideration that FBP is a linear algorithm that reflects acquired projection data onto an image in a straightforward fashion and that non-linear effects such as soft-tissue-induced beam hardening effects on the projection data were minimal under the conditions we used.

Calculation of the power spectrum of the mean images confirmed our observations (Fig. 2). The low to high frequency components of all mean images were identical.

Our observation that IMR images obtained by subtracting the mean FBP image from the mean IMR images were different from the ground-truth (Fig. 3) confirms our observations. Most of the pixel values were close to zero, indicating that the mean IMR images were accurate. In the presence of small low-contrast structures the difference was relatively large due to differences in the contrast of the averaged IMR images.

Image profile curves across the edges

The image profiles at three different locations on mean or single images reconstructed with FBP and IMR methods are shown in Fig. 4a and b. The profiles through a high-contrast feature (e.g. an air hole) on single image were identical among all algorithms (Fig. 4a, right).

All profiles were identical on mean and reconstructed images (Fig. 4a, left). The mean profiles through a wide gap with moderate contrast (approximately 40 HU) from the liver edge to the agar region were identical on FBP and IMR images (Fig. 4b, left) even though single profiles were slightly different due to noise variability (Fig. 4b, right).

NPS and normalized NPS

The NPS presented in Fig. 5a reflects the improvements in image noise. The NPS of IMR was lower than of FBP images over the entire frequency range. With IMR-L3 the greatest and with IMR-L1 the least decrease in image noise was obtained (Fig. 5a). The normalized NPS showed that, different from FBP images, the noise on IMR images consisted mostly of low-frequency components (Fig. 5b). The difference from FBP was greatest with IMR-L3 and smallest with IMR-L1.

SD images

Figure 6 shows the inter-scan SD (or σ_{nr}) images obtained with FBP and IMR methods. The inter-scan SD image with FBP was spatially uniform regardless of anatomical structures although the SD was higher in some air-filled regions due to the movement of small air bubbles during the acquisition of 100 images. In contrast, as reported by Kohler and Proksa [18], the inter-scan SD values on IMR images exhibited relative spatial variations; they were larger in areas with a change in the pixel value, i.e. at the border between the liver parenchyma and the agar, in hypo-dense lesions, and near thin and faint structures (see Fig. 3). The spatial variation was greatest on IMR-L3 images. To quantify this observation we measured the σ_{nr} values at the liver parenchyma, in the agar, and at the border between the parenchyma and agar (Table 1). While with FBP the σ_{nr} value at the liver edge was as little as 10% higher than in the liver ($= (10.88/9.92 - 1) \times 100$) it was increased by 26% ($= (5.49/4.37 - 1) \times 100$), 32%, and 53% with IMR-L1, IMR-L2, and IMR-L3, respectively. The value of σ_{xy} and σ_r measured at the same three locations is also shown in Table 1. With all reconstruction methods the σ_r value was close to 1 in the liver parenchyma and in agar; with FBP and IMR-L3 edge σ_r value was 1.11 and 1.73, respectively.

Normalized covariance map

Our normalized covariance maps are shown in Fig. 7. In Table 1 we list the values measured at the liver parenchyma, in the agar, and at the border between the parenchyma and agar. On all IMR images the $nCov$ value was larger than on FBP images. On IMR-L3 images it was as much as 7.14 and 9.88 times larger in the agar and the parenchyma, respectively, than on FBP images. The ratio remained large at the edges (4.78) but smaller than in the two flat regions, indicating the complex non-linear nature of IMR methods. The large $nCov$ value may be attributable to the low-frequency noise on IMR images.

Discussion

We compared the performance of IMR and FBP with respect to image noise and image accuracy. As iterative methods are nonlinear, we designed a phantom study to evaluate performance under conditions mimicking clinically relevant settings and to obtain ground-truth information. Our phantom was a whole porcine liver immersed in agar, this provided

realistic low-, moderate-, and high-contrast features because unlike homogeneous water phantoms, the tissue structure and texture of the porcine and human liver are similar. We acquired the phantom 100 times and the mean FBP image we obtained served as the ground-truth. NPS measurements were obtained on the whole porcine liver under clinically relevant settings.

On single-scan images reconstructed with IMR methods the image noise was remarkably lower (by more than 75% at the liver parenchyma) than on FBP images and the delineation of object features was as good as on FBP images (Fig. 1). However, the noise on IMR images had a somewhat different appearance, the pattern was patchy and granular with more low-frequency components. As image readers may not be familiar with this pattern, adaptation to this new noise pattern is necessary.

With respect to high-contrast features such as air holes, the IMR soft-tissue setting retained the image profile and contrast of structures. Image noise near the liver edge was reduced, thereby improving the visibility of the structures. Both the spatial- and the inter-scan SD were markedly decreased from 12.10 HU on FBP to 6.10 HU on IMR-L3 images (decreased by 50%) with σ_{xy} , and from 10.88 HU to 3.53 HU (by 68%) with σ_{nr} . These noise reductions were substantial, although they were less than that (by 75%) in the flat region, possibly because image pixels are filtered with a fewer number of pixels along the edges. If the 11% noise increase with FBP is due to the slope of the pixel values at the border between the liver and agar (a factor involved only in σ_{xy}), we attribute the additional increase with IMR methods to the non-linearity of the algorithms. Overall, the edges with moderate contrast on IMR images looked sharper than the edges on FBP images. We are in the process of performing task-specific human observer studies to evaluate the effect of the edge appearance on observer performance.

With respect to small low-contrast features, contrast and peak-to-peak amplitudes were lower with IMR methods (Fig. 3). We need to test our hypothesis that this is due to the edge-preserving nature of non-linear algorithms such as IMR. The visibility of faint structures may be retained or improved by IMR methods because the noise in the surrounding area is decreased (see Fig. 1). Careful task-specific observer studies must be performed to evaluate the effect of tradeoff factors.

Our findings suggest that in combination, the use of a lower tube current and IMR methods may make it possible to reduce the radiation dose substantially without reducing the image quality. This suggestion must yet be carefully examined by using task-specific performance tests at various dose levels. It is important to note that due to the non-linearity of IMR methods, an image noise reduction from 1 to a (<1) does not indicate that the radiation dose can be reduced from 1 to a^2 at the same noise level. Our study provides ground-truth information on the potential of a maximum radiation dose reduction in such performance tests.

Our study has some limitations. We used a whole porcine liver to simulate the human liver. Although our simulation was successful overall, because we drained the blood vessels there were air holes in the porcine liver. Nonetheless, we suggest that our findings can be

extrapolated to clinical hepatic CT imaging using various reconstruction algorithms. In addition, we applied the IMR soft-tissue setting at non-enhanced hepatic CT imaging because it yielded a substantial noise reduction and better image quality. With respect to the contrast-enhanced liver, spatial resolution may become more important than a substantial noise reduction and the image appearance. Therefore, a different kind of “flavor” for IMR reconstruction may be useful. While the helical acquisition mode is used in clinical protocols for abdominal CT studies, we used the step-and-shoot mode in this study. However, if the reasonably accurate cone-beam (Wedge) algorithm commonly used with both acquisition modes is applied, we think that the difference in the acquisition modes will not affect our conclusions. Use of the NPS assumes the algorithms to be linear although IMR algorithms are non-linear. We chose the NPS to demonstrate differences from the linear FBP algorithm. We focused on measuring physical performance indices and did not assess the effects on clinical tasks because ours was a hypothesis-generating study to identify potential benefits and risks associated with the use of iterative methods. In our ongoing observer performance tests that include low-contrast lesions we are focusing on the detectability of low-contrast lesions on unenhanced and equivalent-phase hepatic CT images.

In conclusion, we used a non-enhanced whole porcine liver phantom and evaluated the soft-tissue “flavor” at 3 different noise levels of the iterative reconstruction (IMR) algorithm. IMR images yield the same structure informations as FBP images and image accuracy is maintained. On level 3 IMR images the image noise is more strongly suppressed than on IMR images of the other levels and on FBP images.

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Figure 1. FBP (a) and IMR-L1 (b), IMR-L2 (c), and IMR-L3 (d) images obtained from a single acquisition and mean image reconstructed by FBP (e). The window width and level were 130 HU and 65 HU. Each region-of interest (ROI) represents the measurement point of standard deviation in the image.

Figure 2.
Power spectrum of the mean images obtained from FBP and IMR methods.

Figure 3.

Images obtained by subtracting the mean FBP image from the mean IMR images (IMR-L1 (a), IMR-L2 (b), and IMR-L3 (c)), present the differences in the mean IMR images from the ground-truth (d). The window width and level were 26 HU and 0 HU. Most of pixel values were close to zero, indicating that the mean IMR images were accurate. When small structures with small contrasts are present, differences were relatively large (arrows).

Figure 4.

Profiles at three different locations measured with the mean (left) or the single (right) image acquisitions reconstructed by FBP and IMR methods: high contrast feature (i.e. an air hole (a)) and moderate contrast, i.e. ~40 HU, from the edges of the liver to the agar region (b).

Figure 5.

Noise power spectrum (NPS) and normalized NPS obtained from FBP and IMR methods. (a) NPS reflected the improvements in image noise. (b) The normalized NPS showed that the noise of IMR images consisted mostly of low-frequency components, which were different from that of FBP images.

Figure 6.
The inter-scan SD (or σ_{nr}) images with FBP (a), IMR-L1 (b), IMR-L2 (c), and IMR-L3 (d) methods. The window width and level were 2σ and σ HU.

Figure 7. Normalized covariance maps obtained from FBP (a), IMR-L1 (b), IMR-L2 (c), and IMR-L3 (d). The πCov values (see Table 1) with IMR methods were larger than those with FBP method throughout the images. The window width and level were $2 \times \text{mean}$ and “mean” HU.

Table 1

Standard deviation and normalized covariance values for liver, agar and edge.

		σ_{nr}		σ_{xy}		σ_t		$nCov$	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Liver	FBP	9.92	0.77	9.76	0.30	0.98	0.07	0.028	0.019
	IMR1	4.37	0.39	4.24	0.16	0.97	0.08	0.076	0.024
	IMR2	3.63	0.37	3.49	0.18	0.96	0.09	0.100	0.026
	IMR3	2.30	0.35	2.15	0.24	0.94	0.11	0.200	0.034
Agar	FBP	10.69	0.86	10.61	0.20	0.99	0.08	0.024	0.019
	IMR1	4.43	0.38	4.41	0.22	1.00	0.09	0.073	0.026
	IMR2	3.59	0.31	3.59	0.25	1.00	0.09	0.101	0.029
	IMR3	2.12	0.21	2.15	0.34	1.02	0.12	0.237	0.041
Edge	FBP	10.88	0.75	12.10	0.31	1.11	0.06	0.032	0.018
	IMR1	5.49	0.43	7.42	0.33	1.35	0.06	0.080	0.023
	IMR2	4.79	0.42	6.90	0.35	1.44	0.06	0.097	0.024
	IMR3	3.53	0.43	6.10	0.38	1.73	0.06	0.153	0.031

After these values were obtained on a pixel basis following the procedure described in Section 2, the mean and S.D. of the values were calculated over pixels within a ROI manually drawn at liver, agar, and edge, respectively.