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Noise-reducing algorithms do not necessarily provide superior dose optimisation for hepatic lesion detection with multidetector CT

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Objective: To compare the dose-optimisation potential of a smoothing filtered backprojection (FBP) and a hybrid FBP/iterative algorithm to that of a standard FBP algorithm at three slice thicknesses for hepatic lesion detection with multidetector CT.

Methods: A liver phantom containing a 9.5-mm opacity with a density of 10 HU below background was scanned at 125, 100, 75, 50 and 25 mAs. Data were reconstructed with standard FBP (B), smoothing FBP (A) and hybrid FBP/iterative (iDose⁴) algorithms at 5-, 3- and 1-mm collimation. 10 observers marked opacities using a four-point confidence scale. Jackknife alternative free-response receiver operating characteristic figure of merit (FOM), sensitivity and noise were calculated.

Results: Compared with the 125-mAs/5-mm setting for each algorithm, significant reductions in FOM ($p < 0.05$) and sensitivity ($p < 0.05$) were found for all three algorithms for all exposures at 1-mm thickness and for all slice thicknesses at 25 mAs, with the exception of the 25-mAs/5-mm setting for the B algorithm. Sensitivity was also significantly reduced for all exposures at 3-mm thickness for the A algorithm ($p < 0.05$). Noise for the A and iDose⁴ algorithms was approximately 13% and 21% lower, respectively, than for the B algorithm.

Conclusion: Superior performance for hepatic lesion detection was not shown with either a smoothing FBP algorithm or a hybrid FBP/iterative algorithm compared with a standard FBP technique, even though noise reduction with thinner slices was demonstrated with the alternative approaches.

Advances in knowledge: Reductions in image noise with non-standard CT algorithms do

not necessarily translate to an improvement in low-contrast object detection.

CT is a valuable diagnostic tool; nevertheless, it delivers a high radiation dose compared with other imaging modalities [1, 2]. Estimates of radiation risk from CT examinations based on dose surveys from the 1990s and data from atomic bomb survivors suggest that approximately 60–100 cancers are induced for every million CT examinations performed [3–6]. Significant global increases in collective CT dose over the past two decades [7–9] and recent direct evidence of increased cancer incidence in a cohort of patients who had CT imaging when they were 21 years of age or younger [10] indicate that optimisation of CT acquisition protocols is required [3, 7]. Unlike film-screen radiography, where excessive exposure is readily perceived by the film's optical density, there are no such visual indicators in CT, and there is a paucity of data defining appropriate dose levels while maintaining clinical effectiveness [11].

The current work endeavors to address this deficiency within the context of hepatic lesion detection. The limited attenuation difference that can often occur between hepatic lesions and the surrounding normal liver tissue [12] may compromise dose optimisation since high exposures aimed at reducing image noise and maximising low-contrast resolution may be required [13].

Two key operator-selectable parameters that affect image noise and influence the level of exposure required for accurate lesion detection are slice thickness and the reconstruction algorithm. Thinner slices reduce partial volume effects and can improve lesion detection, yet unless a compensatory increase in exposure is made, the resultant images have higher noise levels, which may offset any advantage in lesion conspicuity provided by the reduction in slice thickness. Traditional low pass or smoothing algorithms can be used in combination with thinner slices to offset noise increases; however, these algorithms also reduce spatial resolution [14]. Alternatively, recently developed hybrid reconstruction algorithms using iterative techniques have the potential to facilitate thin slices without noise increase [15]; however, studies investigating the interaction between algorithm, slice thickness and exposure when optimising hepatic CT protocols are required.

In this phantom study, we compare the dose-optimisation potential of a smoothing and a hybrid reconstruction algorithm to that of a standard algorithm at three different slice thicknesses for hepatic lesion detection with multidetector CT (MDCT).

METHODS AND MATERIALS

A liver lesion phantom (Spiral/helical CT phantom, Model 061; Computerized Imaging Reference Systems, Inc., Norfolk, VA) was scanned using a 64-slice CT system (Brilliance 64; Philips Medical Systems, Cleveland, OH). The phantom consisted of an 18-cm diameter polymer disc, which contained within its central plane three rows of spheres ranging in size from 2.4 to 9.5 mm in diameter with CT density 5, 10 or 20 HU below that of the liver-equivalent (50 HU) background (Figure 1). The focus here was on the 9.5 mm/10 HU opacity (Figure 1, arrow) because liver lesions <10 mm in size are rarely of diagnostic significance for routine abdominal CT examinations [16] and 10 HU is generally considered the minimum lesion-to-liver contrast required to be detected with CT [17].

The phantom was scanned five times at each of the five exposure settings (125, 100, 75, 50, 25 effective mAs)

Figure 1. An image of the phantom through the midline of the opacities. The opacity under investigation is indicated (arrow).

and the data reconstructed at three slice thicknesses (5, 3 and 1 mm) using the following three reconstruction methods: filtered backprojection (FBP) using the standard body (B) algorithm, FBP using a smoothing body (A) algorithm and a hybrid reconstruction method utilising FBP with the B algorithm and an iterative reconstruction algorithm (iDose⁴ with strength 3 noise reduction [18]). Data were presented with 50% image overlap and 350-mm display field of view.

An image containing the background disc and a single randomly positioned opacity was generated for each series by electronically cutting an 18-mm region of interest (ROI) containing the opacity from the image reconstructed through the midline of the phantom. This ROI was then pasted on a distal image from the same series that contained only the background disc at a position that was at an equal distance from the outer perimeter of the phantom as the cut opacity to standardise spatially dependent noise variations (Figure 2). 25-mm-diameter ROIs were then placed over the opacity and the minimum, maximum and standard deviation of the pixel values compared between the edited and the original images, which confirmed that the editing process did not change the appearance of the background or the opacity.

Five edited images were created for each algorithm/mAs/slice thickness combination, resulting in a total of 225

Figure 2. An edited image containing a pasted opacity (arrow).

images containing the opacity. These images were randomly combined with 450 background-only images.

All images were reviewed on a diagnostic display station (DS3000; Agfa, Mortsel, Belgium) by 10 observers, who marked each perceived opacity using the inbuilt ROI tool and scored their level of confidence using the following scale: 1=opacity not visible, 2=opacity possibly visible, 3=opacity probably visible and 4=opacity definitely visible. A true-positive mark-up was declared if the centre of a ROI was <20 pixels distant from the centre of the true opacity. Observers had between 6 and 20 years' experience in viewing abdominal CT images (average 12.4 years) and were blinded to the presence and location of the opacity. Images were presented to each observer in a randomised order. Ambient light in the viewing area was between 25 and 40 lux [19], and the display monitor was calibrated prior to each reading session.

Statistical analyses

The evaluation of specific exposure and slice thickness combinations for each algorithm and the assessment of different algorithms was based on comparisons with the departmental standards of 125 mAs and 5-mm slice thickness setting and the B algorithm, respectively. The comparisons used the following methods:

1. Jackknife alternative free-response receiver operating characteristic (JAFROC) analysis [20] was performed with both readers and cases treated as random samples, and figures of merit (FOMs) were compared using the analysis of variance model embedded within the JAFROC software.
2. Sensitivity was compared using the Wilcoxon matched-pairs signed rank test.
3. Image noise for each exposure, slice thickness and algorithm permutation was measured using the CT number standard deviation within a 40-mm-diameter circular ROI placed within the distal (background only) image at the same x/y location as the opacity.
4. Contrast-to-noise ratio (CNR) for each algorithm, exposure and slice thickness setting was calculated using the following formula:

$$\text{CNR} = \frac{\text{SD}_{\text{backgroundROI}} - \text{SD}_{\text{opacity}}}{\text{SD}_{\text{background}}}$$

where $\text{SD}_{\text{backgroundROI}}$ = the standard deviation of CT numbers within a 6-mm diameter (ROI placed

within the background adjacent to the 9.5-mm opacity), SD_{opacity} =the standard deviation of CT numbers within a 6-mm diameter ROI placed centrally within the opacity and $SD_{\text{background}}$ =image noise as described in (3) above.

For all statistical tests, differences of $p < 0.05$ were considered significant.

RESULTS

Comparisons between the 125 mAs/5-mm setting and other exposure/slice thickness combinations for each algorithm

The FOM was significantly reduced from the standard combination for all exposure settings at 1-mm slice thickness and for the 25-mAs exposure at all slice thicknesses for all algorithms, with the exception of the 25 mAs/5-mm slice thickness setting for the B algorithm. Significant FOM reductions, compared with the standard combination, were also noted at 50 and 75 mAs using the 3-mm slice thickness for the B and A algorithms, respectively (Table 1).

Sensitivity was also significantly reduced from the standard setting for all exposures at 1- and 3-mm slice thicknesses for the A algorithm, and for the 50- and 25-mAs exposures at all slice thicknesses for all algorithms, with the exception of the 50-mAs exposure at 5-mm slice thickness for the B algorithm (Table 2).

Comparisons between the B algorithm and the A and iDose⁴ algorithms for each exposure/slice thickness setting

The JAFROC FOM was significantly lower for the A algorithm at 75 mAs and 3-mm slice thickness ($p < 0.01$) and for the iDose⁴ algorithm at 50 mAs and 5-mm slice thickness ($p < 0.05$) (Table 1) compared with the same settings with the B algorithm.

Significant reductions were also found for sensitivity with the A algorithm at 75 mAs/3 mm ($p < 0.01$) and 50 mAs/5 mm ($p < 0.05$) and for the iDose⁴ algorithm at 50 mAs/5 mm ($p < 0.05$) and 25 mAs/5 mm ($p < 0.05$) when compared with the B algorithm, unlike the increases in sensitivity recorded at 50 mAs/1 mm ($p < 0.05$) and 25 mAs/3 mm ($p < 0.05$) with the A algorithm and at 75 mAs/5 mm ($p < 0.05$) and 50 mAs/3 mm ($p < 0.05$) when employing the iDose⁴ algorithm (Table 2).

Table 1. Jackknife alternative free-response receiver operating characteristic figure of merit (FOM) for each algorithm/exposure/slice thickness combination

Algorithm	Slice (mm)	125 mAs	100 mAs	75 mAs	50 mAs	25 mAs
B	5	0.9650 (0.9393, 0.9907)	0.9170 (0.8504, 0.9836)	0.9190 (0.8063, 1.0317)	0.9310 (0.8286, 1.033)	0.8160 (0.6656, 0.9664)
	3	0.8880 (0.7521, 1.0239)	0.9090 (0.7414, 1.0766)	0.9320 (0.8013, 1.0627)	0.7600* (0.8013, 1.0627)	0.6500* (0.4902, 0.8098)
	1	0.6740** (0.4696, 0.8784)	0.6230*** (0.4778, 0.7682)	0.7670* (0.4778, 0.7682)	0.5560*** (0.4572, 0.6548)	0.5840*** (0.4572, 0.6548)
A	5	0.9900 (0.9673, 1.013)	0.9290 (0.630, 1.046)	0.9800 (0.9560, 1.004)	0.8339 (0.6193, 1.0487)	0.7260* (0.5584, 0.8936)
	3	0.9130 (0.7342, 1.0918)	0.8829 (0.7244, 1.0415)	0.7050** ^{##} (0.5089, 0.9010)	0.8599 (0.7058, 1.0417)	0.7570* (0.5327, 0.9813)
	1	0.6390** (0.4870, 0.7910)	0.6700** (0.4910, 0.8490)	0.7220* (0.5337, 0.9103)	0.6370** (0.4683, 0.8057)	0.5200*** (0.4202, 0.6198)
iDose ⁴	5	0.9660 (0.9013, 1.0307)	0.9280 (0.9013, 1.0307)	0.9900 (0.9674, 1.0126)	0.8200 [#] (0.6326, 1.0074)	0.6420** (0.4168, 0.8672)
	3	0.9140 (0.8425, 0.9855)	0.8950 (0.8195, 0.9705)	0.9640 (0.9180, 1.0100)	0.8500 (0.6903, 1.0097)	0.6650** (0.4916, 0.8384)
	1	0.6250** (0.4884, 0.9616)	0.6850** (0.4919, 0.8781)	0.7480* (0.5790, 0.9170)	0.6090*** (0.4937, 0.7243)	0.5230*** (0.4241, 0.6219)

95% confidence levels are provided in parentheses. Significant differences in FOM compared with FOM for the 125 mAs/5-mm slice thickness setting for each algorithm are denoted by an asterisk (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Significant differences in FOM for the A and iDose⁴ algorithms compared with the FOM for the B algorithm for each exposure/slice thickness setting are denoted by a hash ([#] $p < 0.05$, ^{##} $p < 0.01$).

Table 2. Mean (median) sensitivity for each condition

Algorithm	Slice (mm)	125 mAs	100 mAs	75 mAs	50 mAs	25 mAs
B	5	0.94 (1.00)	0.86 (0.80)	0.88 (0.80)	0.88 (0.80)	0.68 (0.60)*
	3	0.84 (0.80)	0.82 (0.80)	0.88 (0.80)	0.54 (0.60)**	0.30 (0.30)**
	1	0.38 (0.40)**	0.28 (0.20)**	0.58 (0.50)**	0.16 (0)**	0.26 (0.40)**
A	5	0.98 (1.0)	0.88 (0.80)	0.96 (1.0)	0.72 (0.80)**,#	0.52 (0.60)**
	3	0.84 (0.80)*	0.78 (0.80)**	0.42 (0.40)**,#	0.72 (0.80)*	0.54 (0.60)**,#
	1	0.32 (0.20)**	0.34 (0.30)**	0.44 (0.50)**	0.32 (0.20)**,#	0.14 (0.20)**
iDose ⁴	5	0.96 (1.0)	0.88 (0.80)	0.98 (1.0) [#]	0.64 (0.70)**,#	0.44 (0.40)**,#
	3	0.86 (0.90)	0.80 (0.80)	0.94 (1.0)	0.70 (0.80)**,#	0.38 (0.40)**
	1	0.26 (0.20)**	0.38 (0.40)**	0.54 (0.60)**	0.26 (0.40)**	0.14 (0.25)**

Significant differences in sensitivity compared with that of the 125 mAs/5-mm slice thickness setting for each algorithm are denoted by an asterisk (* $p < 0.05$, ** $p < 0.01$). Significant differences in sensitivity for the A and iDose⁴ algorithms compared with sensitivity for the B algorithm for each exposure/slice thickness setting are denoted by a hash ([#] $p < 0.05$, ^{##} $p < 0.01$).

Noise and contrast-to-noise ratio

Compared with noise for the B algorithm at each exposure/slice thickness condition, noise for the A and iDose⁴ algorithms was, on average, approximately 13% and 21% lower, respectively. The details of the noise levels at each setting are provided in Table 3. CNRs were between 12% and 197% higher for the A and iDose⁴ algorithms than for the B algorithm (Table 3).

DISCUSSION

Dose optimisation of hepatic CT protocols is challenging because a complex relationship exists between lesion conspicuity, exposure, slice thickness and reconstruction algorithm. We hypothesised that a smoothing FBP algorithm or a hybrid FBP/iterative algorithm could be utilised to offset noise increases associated with the employment of thinner slices aimed at reducing partial

Table 3. Noise, with contrast-to-noise ratio (CNR) in parentheses, for each algorithm/exposure/slice thickness combination

Exposure (mAs)	Slice (mm)	Algorithm		
		B	A	iDose ⁴
125	5	5.15 (1.69)	4.31 (1.91)	3.96 (2.06)
	3	6.40 (1.26)	5.47 (1.58)	5.06 (1.61)
	1	10.61 (0.58)	10.91 (0.91)	8.12 (1.47)
100	5	5.67 (0.92)	4.76 (1.34)	4.36 (1.34)
	3	8.64 (0.93)	6.12 (1.20)	5.66 (1.20)
	1	11.89 (0.62)	12.29 (0.92)	11.23 (0.94)
75	5	6.24 (0.75)	5.29 (1.40)	4.89 (1.40)
	3	7.98 (0.90)	6.82 (1.14)	6.30 (1.11)
	1	13.42 (0.51)	11.37 (0.59)	12.21 (0.66)
50	5	7.55 (0.31)	6.39 (0.92)	5.84 (0.92)
	3	9.57 (0.89)	8.19 (1.07)	7.55 (1.05)
	1	16.80 (0.52)	14.28 (0.66)	13.07 (0.67)
25	5	10.54 (0.34)	9.00 (0.59)	8.24 (0.63)
	3	14.40 (0.41)	12.27 (0.46)	10.59 (0.53)
	1	22.49 (0.31)	19.70 (0.40)	18.83 (0.40)

volume effects, thus improving lesion detection without increasing exposures.

The lowest exposure at which sensitivity was maintained for each reconstruction algorithm at 5-mm slice thickness in the current study was 50 mAs for the standard B algorithm and 75 mAs for the A and iDose⁴ algorithms, a finding that was supported by the JAFROC data. As the slice thickness was reduced to 3 mm, performance for the B and iDose⁴ algorithms were comparable; however, the A algorithm fared worse. Further, slice thickness reduction demonstrated that neither of the alternate algorithms were able to compensate for increased noise at 1-mm slice thickness and the lack of significant differences in FOM, and sensitivity compared with the B algorithm (with a single exception in sensitivity for the A algorithm at 50 mAs) implies overall performance for all algorithms at 1-mm slice thickness was similar.

The findings for the low-pass algorithm here were not necessarily surprising. Low-pass (smoothing) algorithms reduce noise by filtering out higher frequencies; however, the filtering is indiscriminate and important object boundaries can be smoothed concomitantly [21]. Data presented here for the smoothing algorithm further support this low-pass limitation and emphasise that preservation of interfaces is required for the detection of low-contrast objects.

Iterative reconstruction techniques, on the other hand, have the potential to reduce noise while maintaining spatial resolution [22] via accurate modelling of the scanner geometry and/or photon statistics [22–24]. Unfortunately, however, although iterative techniques are ubiquitous in nuclear medicine, their acceptance by radiologists in CT is relatively slow [25], and fully iterative techniques are not yet fast enough for routine clinical use with the large volumes of data generated by MDCT [23–25]. Hybrid approaches that combine an abbreviated form of iterative reconstruction with FBP offer a potential time-effective solution where noise is reduced, important image boundaries maintained and the familiar visual properties (*e.g.* streaking) are preserved [15, 26, 27]. It is of particular interest, therefore, that, although noise reductions have been shown here by the hybrid algorithm consistent with previous studies [15, 27–31], this noise benefit does not necessarily translate to an improvement in low-contrast

object detection, even though conservation of noise textures [26, 28], enhanced lesion conspicuity [27, 32–34] and improved image quality [15, 24, 34–36] have all been reported with hybrid FBP/iterative methods compared with standard FBP reconstruction. This may be explained in part by the fact that iDose⁴ uses FBP for its initial estimate, and, consequently, the B and iDose⁴ algorithms will produce similar covariance properties resulting in similar performance for low-contrast lesion detection [37–39]. Our results support previous studies indicating that the covariance properties of images are at least as important for lesion detection tasks as the variance (noise) properties [40].

The authors acknowledge certain limitations with the current study. Firstly, the phantom-based methodology does not facilitate assessment of radiologists' interactions with patient images. In the clinical environment, a greater reduction in exposure when a hybrid iterative algorithm is used may be accepted since observers may have a greater level of confidence viewing images with less noise. Secondly, we only examined five exposure levels with a single scanner and did not explore the concomitant use of post-processing image filters or other combinations of FBP with iDose⁴. Thirdly, owing to the linear relationship with exposure and dose, our focus was on mAs rather than kVp reductions, although others [34, 41] have demonstrated improved low-contrast opacity detection with lower kVp. Our approach allowed for more discrete selections of exposure.

CONCLUSION

Superior performance for hepatic lesion detection has not been shown with either a smoothing FBP algorithm or a hybrid FBP/iterative algorithm compared with a standard FBP technique, even though noise reduction with thinner slices were demonstrated with the alternative approaches.

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