Pediatric image quality and dose reduction potential using a deep learning CT reconstruction algorithm

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INTRODUCTION

- The management of diagnostic image quality and radiation dose reduction is an inherently antagonistic process in which dose reductions are typically achieved at the cost of image quality.
- Statistical-based iterative reconstruction (**SBIR**) and model-based iterative reconstruction (**MBIR**) reconstruction algorithms primarily allow for quantum noise reduction, but affect noise texture that leads to lower radiologist confidence in the images.
- With recent advances in artificial intelligence (**AI**), investigations into the use of deep learning CT image reconstruction (**DLR**) have demonstrated potential for improved image quality and dose reduction without deleterious changes in noise texture.

AIM

Investigate the use of a **DLR** algorithm (**AiCE**, Canon Medical Systems) for dose reduction and image quality improvement in pediatric CT.

METHOD

- DLR was compared to filtered back projection (FBP), SBIR, and MBIR in a retrospective study of 19 patients (3 mo -19 yr; 6.5 - 92.2 kg; male/female: 9/10).
- Transaxial image thickness was reconstructed at 0.5 mm and 3 mm.
- An objective comparison of the algorithms was performed using a non-prewhitening-matched mathematical-observer model with eye filter (d'_{NPWE}), task transfer function (TTF), and noise power spectrum (NPS) analysis.

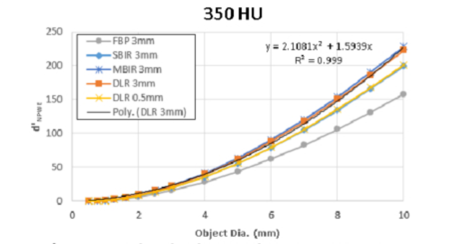
$$d'_{NPWE} = \frac{\left[2\pi \cdot \int_0^{Nyquist} |W(f)|^2 \cdot TTF(f)^2 \cdot E(f)^2 \cdot df\right]^2}{2\pi \cdot \int_0^{Nyquist} \left[|W(f)|^2 \cdot TTF(f)^2 \cdot E(f)^4 \cdot NPS(f) + N(f) \cdot NPS(f)\right] df}$$

- Detection accuracy of 15 objects ($W(f)$: 0.5-10mm diameter) at four contrast-to-background levels (50, 150, 250, and 350HU), for each reconstruction algorithm was assessed using area under the curve (AUC) analysis.

$$AUC = \frac{1}{2} \cdot \left[1 + \frac{2}{\sqrt{\pi}} \cdot \int_0^{d'_{NPWE}/2} e^{-x^2} dx\right]$$

- Additionally, three Pediatric Radiologists performed a subjective observer study.
- Small anatomic structures with low object-to-background SNR and CNR structures were reviewed: Azygos vein, right hepatic vein, common bile duct, and superior mesenteric artery.
- Observers scored from 1 to 10 (worst to best) for: edge definition, quantum noise level, and object conspicuity.

RESULTS

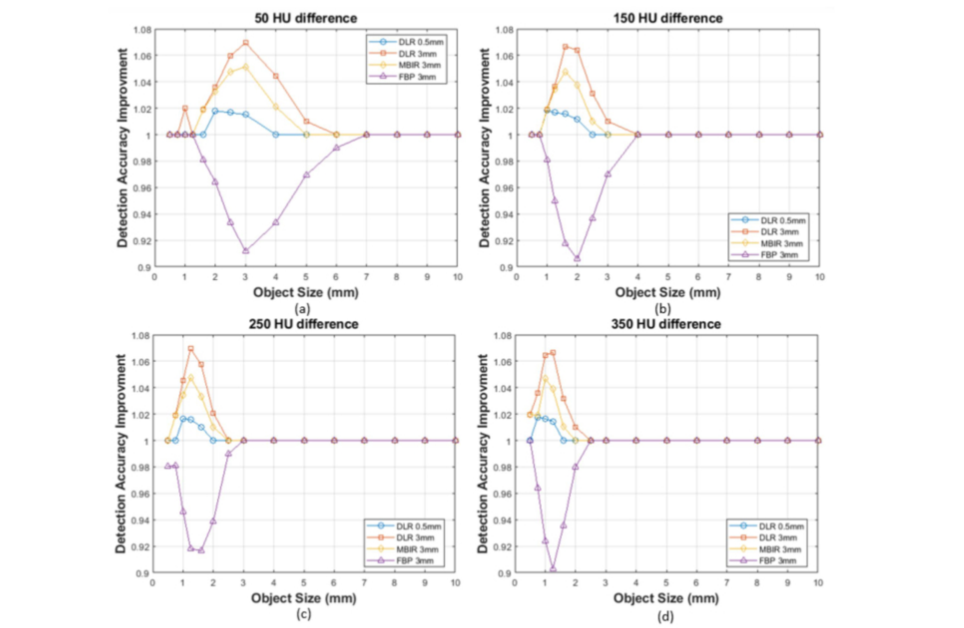


- d'_{NPWE} calculations demonstrate increasing overall object detectability as a function of object diameter and contrast for all reconstruction types.
- For all patients, 3 mm thick DLR images had object detectability ≥ 3 mm MBIR.
- For all patients, 0.5 mm thick DLR images had object detectability ≥ 3 mm SBIR.

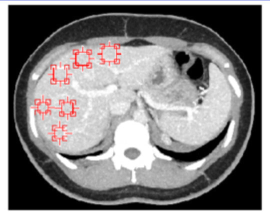
- Dose reduction estimates were performed by calculating differences between 3 mm thick CT slices of DLR and SBIR quantum noise ($\Delta noise$), as measured by the standard deviation (SD) of an ROI placed over the liver parenchyma, and was used as a first order approximation for patient dose:

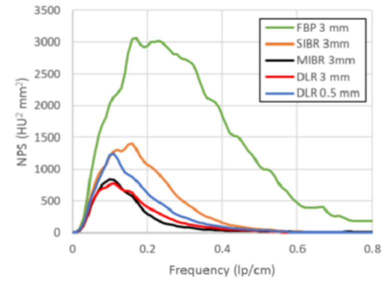
$$dose_{patient} \propto \frac{1}{\Delta noise^2}$$

- Noise magnitude in the 3 mm DLR images was on average 30% lower than SBIR images; range: 9% to 49%.
- First order patient dose reduction estimate of 41% (range: 16 - 49%).

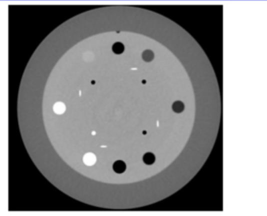


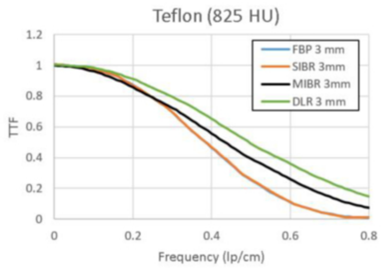
- AUC for each reconstruction algorithm was normalized by the SBIR results since image quality and dose for the 19 patients were established for SBIR.
- The median AUC mathematical observer score for all patients demonstrated that 3 mm DLR images were superior for detection accuracy for object diameters ≤7 mm followed by 3 mm MBIR and then 0.5 mm DLR images.
- The median value for all 19 patients for each reconstruction algorithm was plotted as a function of absolute contrast differences: (a) 50 HU, (b) 150 HU, (c) 250 HU, and (d) 350 HU, above that of the background contrast-enhancing liver parenchyma.



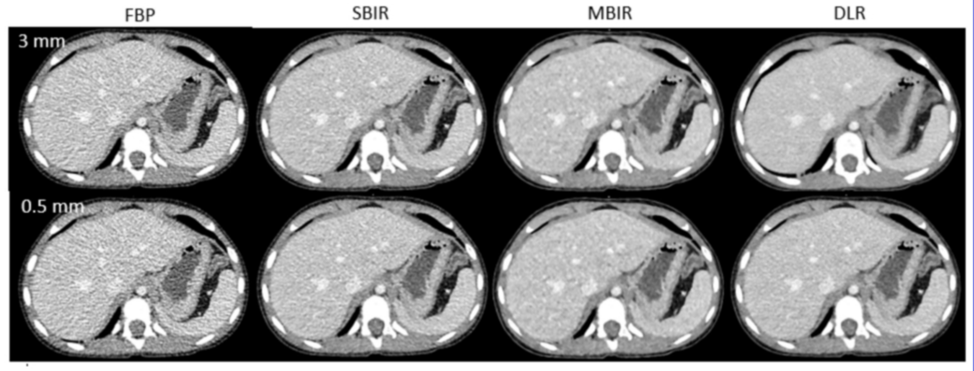


- The NPS of the DLR algorithm more closely matched SBIR than did the MBIR algorithm, which mathematically demonstrates the DLR algorithm is more closely matched in noise texture to SBIR than was MBIR to SBIR.





- For each sensitometry insert ranging from 25 HU to 850 HU (Teflon-Shown), the DLR algorithm had greater object contrast differentiation at all spatial frequencies compared to MBIR, which in turn was calculated to be greater than SBIR and FBP.



- The three observers favored DLR reconstructions for all three evaluation metrics (i.e., edge definition, quantum noise level, and object conspicuity).
- The mean response was significant (3-way ANOVA, p<0.001) for each of the three observers and for the four anatomic structures.
- An intra-class correlation coefficient calculated for 30 repeat-image observer scores was 0.89 (95% confidence: 0.83 - 0.93).
- Overall mean (±SD) image quality scores were 7±1 (DLR), 6.2±1 (MBIR), 6.2±1 (SBIR), and 4.6±1 (FBP).
- A 2-way ANOVA calculated a significant difference based on reconstruction type (p<0.001).

CLINICAL APPLICATION

The analysis of DLR images reconstructed at 0.5 mm and 3 mm in our study demonstrated equal or better object detection accuracy than 3 mm SBIR images. This provides end-users of the DLR algorithm multiple options:

1. **Improve image quality:**

   Implement DLR at current patient radiation dose levels and at standard image thickness (i.e., 3 - 5 mm) for reduced quantum noise, but with noise texture similar to SBIR.

2. **Reduce patient dose:**

   Reduce radiation output in a manner to match noise magnitude of 3 mm DLR with 3 mm SBIR images, and then implement DLR as the primary algorithm for clinical diagnosis. In this scenario, CT image quality should be equivalent, or better at 3 mm image thickness with DLR to that with 3 mm SBIR reconstruction, but allow for patient radiation dose reduction.

3. **Improve image quality and reduce patient dose:**

   A hybrid model of both options may allow users to reduce radiation dose to a lesser degree, but increase image quality by reducing quantum noise.

4. **Improve spatial resolution and reduce artifacts:**

   End-users may wish to acquire images at a decreased image thickness, such as 0.5 mm, for improved z-axis (i.e., long-body axis) resolution and partial volume artifact reduction, but with similar quantum noise as that of their current 3 mm SBIR images.

CONCLUSIONS

Deep learning CT reconstruction has the potential to improve patient care by improving CT image quality, which may allow increased detection lesion accuracy, and radiologist confidence while providing the opportunity to further reduce patient radiation dose.

1. Deep learning CT reconstruction improves overall image quality and object detection accuracy for objects of differing contrast-to-background levels (50 HU to 350 HU differences) and object diameters (0.5 mm to 10 mm).

2. Deep learning CT reconstruction demonstrated improved quantum noise mottle control without the loss of noise texture characteristics typically seen in model-based iterative reconstruction, which was associated with greater Radiologist preference and higher confidence scores.

3. Substantial dose reduction potential (16% to 49%) of deep learning CT reconstruction was demonstrated beyond that already reported for statistical-based iterative reconstruction.

CONTACT INFORMATION

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