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Iterative reconstruction and deep learning algorithms for enabling low-dose computed tomography in midfacial trauma

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Objectives. The objective of this study was to quantitatively assess the image quality of Advanced Modeled Iterative Reconstruction (ADMIRE) and the PixelShine (PS) deep learning algorithm for the optimization of low-dose computed tomography protocols in midfacial trauma.

Study Design. Six fresh frozen human cadaver head specimens were scanned by computed tomography using both standard and low-dose scan protocols. Three iterative reconstruction strengths were applied to reconstruct bone and soft tissue data sets and these were subsequently applied to the PS algorithm. Signal-to-noise ratios (SNRs) and contrast-to-noise ratios (CNRs) were calculated for each data set by using the image noise measurements of 10 consecutive image slices from a standardized region of interest template.

Results. The low-dose scan protocol resulted in a 61.7% decrease in the radiation dose. Radiation dose reduction significantly reduced, and iterative reconstruction and the deep learning algorithm significantly improved, the CNR for bone and soft tissue data sets. The algorithms improved image quality after substantial dose reduction. The greatest improvement in SNRs and CNRs was found using the iterative reconstruction algorithm.

Conclusion. Both the ADMIRE and PS algorithms significantly improved image quality after substantial radiation dose reduction.
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Computed tomography (CT) has evolved as the imaging modality of choice for the assessment of maxillofacial injury. In recent years, particular attention has been directed toward the effects of radiation exposure within this population of patients. Novel reconstruction algorithms have been proposed to optimize and reduce the radiation dose of these CT protocols.

In recent years, iterative reconstruction algorithms and a new deep learning algorithm have emerged to provide substantial image noise reduction in CT data sets.[1] First, the iterative reconstruction (IR) algorithm was introduced as an alternative to the standard filtered back projection (FBP) reconstruction. CT vendors have released different generations of the IR algorithm.[2] First-generation algorithms were based on the image domain only, whereas second-generation or sinogram-affirmed iterative reconstruction uses both backward and forward projections to compute the differences and compare them with the actual measured CT. The newest generation, called full or Advanced Modeled Iterative Reconstruction (ADMIRE; Siemens Healthcare AG, Erlangen, Germany), is a more complex algorithm that also removes geometric imperfections and has system and noise modeling to further decrease the image noise, reduce artifacts, and improve spatial and contrast resolution.[3]

Second, a deep learning−based procedure was initiated as a postprocessing denoising algorithm. The PixelShine (PS) algorithm is a software technology developed and based on an artificial neural network, which is a deep machine learning technique (AlgoMedica Inc., Sunnyvale, CA). The algorithm is proprietary. Typical deep learning techniques for medical imaging often include convolutional neural networks, such as U-Net17 or V-Net16, which are used for medical image segmentation.[4,5] The network classifies each voxel as part of a region of interest (ROI) or background. The network is trained at the pixel level and detects voxel patterns at different resolutions to determine whether a pattern is noise or a relevant structure. Research suggests that the algorithm denoises datasets

Statement of Clinical Relevance

The introduction of the Advanced Modeled Iterative Reconstruction and deep learning algorithms can substantially improve image quality of clinical computed tomography protocols in midfacial trauma. The algorithms provide potential to maintain image quality after substantial radiation dose reduction.

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substantially.[6,7] This deep learning type of algorithm initiates a completely new concept regarding image quality optimization and should be further explored.

Adequate radiation exposure is needed to produce acceptable image quality. This is a prerequisite for the visualization of fractures in midfacial trauma CT, as well as for the assessment of soft tissue injury and subsequent treatment management. Yet, the patient radiation dose should be kept as low as reasonably possible. The IR and PS algorithms potentially improve the image quality of CT data sets, but there is not much research on this topic. The purpose of this study was to quantitatively assess the image quality of the ADMIRE and PS algorithms for CT protocols in midfacial trauma imaging after substantially reducing the radiation dose.

MATERIAL AND METHODS

The workflow of the material and method section of this study is summarized in Figure 1.

Study subjects

Six fresh frozen human cadaver heads were obtained from the anatomy section of the Department of Neurosciences at University Medical Center Groningen. The specimens were obtained according to the local legal and ethical guidelines as described in a previous study by our research group.[8]

Data acquisition

All specimens were scanned using a third-generation SOMATOM Force scanner (Siemens Healthcare AG). Each specimen was situated in a fixed position and scanned using a multitude of standardized scans of the midfacial region. The scan range was set from the upper border of the frontal sinus to the complete maxilla. Scans were produced in both the standard (reference 50 mAs) and radiation reduced (reference 20 mAs) scan protocol. Details of the scan parameters are provided in Table I.

Data reconstruction

All raw data sets were reconstructed using the ADMIRE algorithm set at strengths 1, 3, and 5. ADMIRE has up to 5 strength levels that result in less noise and reflect how aggressively the algorithm uses IR over FBP during raw data reconstruction. All data were reconstructed using both bone (Hr59d) and soft tissue (Hr32d) convolution kernels.

Post-processing

All reconstructed data sets were submitted to the deep learning PS algorithm (version 1.2.57 AlgoMedica Inc., Sunnyvale, CA) for additional image quality optimization. Both the postprocessed and original data sets were included for data analysis. All data sets were exported in a Digital Imaging and Communications in Medicine (DICOM) standard.

Image noise measurements

Image noise was assessed as Hounsfield units (HU) and standard deviation. ROI measurements were performed using a standardized template for each specimen and scan protocol using the Python software application (Python Software Foundation, Wilmington, DE). The standardized template consisted of 2 homogenous circular ROIs within each image slice as performed in a previous study.[9] The first ROI of 10.0 cm^2 was positioned in the posterior fossa of the cerebrum and the second ROI of 2.5 cm^2, the background reference, was positioned in the lateral airspace. These measurements were performed for 10 consecutive image slices.

Image quality calculations

Signal-to-noise ratios (SNRs) and contrast-to-noise ratios (CNRs) were calculated using image noise measurements.[9,10] SNR is a common way to quantify image noise, and CNR reflects how noise affects the ability to see an object in an image. The SNR was defined as the mean attenuation of the cerebrum ROI divided by its standard deviation. The CNR was defined as the difference in the mean attenuation of the cerebrum ROI and the lateral airspace ROI divided by the square root of the sum of their variances:

$$\mathrm{SNR} = \frac{\text{Mean HU}_{\text{cerebrum}}}{\text{SD HU}_{\text{cerebrum}}}$$

$$\mathrm{CNR} = \frac{\text{Mean HU}_{\text{cerebrum}} - \text{Mean HU}_{\text{air}}}{\sqrt{\frac{SD_{cerebrum}{}^2 + SD_{air}{}^2}{2}}}$$

Radiation dose estimations

An estimation of radiation dose was calculated by extracting the radiation exposure parameters from the DICOM header for each data set. The computed tomography dose index and scan range for each specimen were used to calculate the dose length products to compare the radiation dose outcomes.

Statistical analysis

The data were analyzed with the Statistical Package for the Social Sciences version 23.0 (IBM, Armonk, NY). Box plots were used to visualize the SNR and CNR outcomes. SNR and CNR normalities were examined via the Kolmogorov-Smirnov test and Q-Q plots. Linear mixed models were used to predict the fixed effects of radiation dose reduction, IR strength, and the use of the PS algorithm on image quality outcomes while accounting for repeated measures within each unique data set. The reference categories of the analyses were

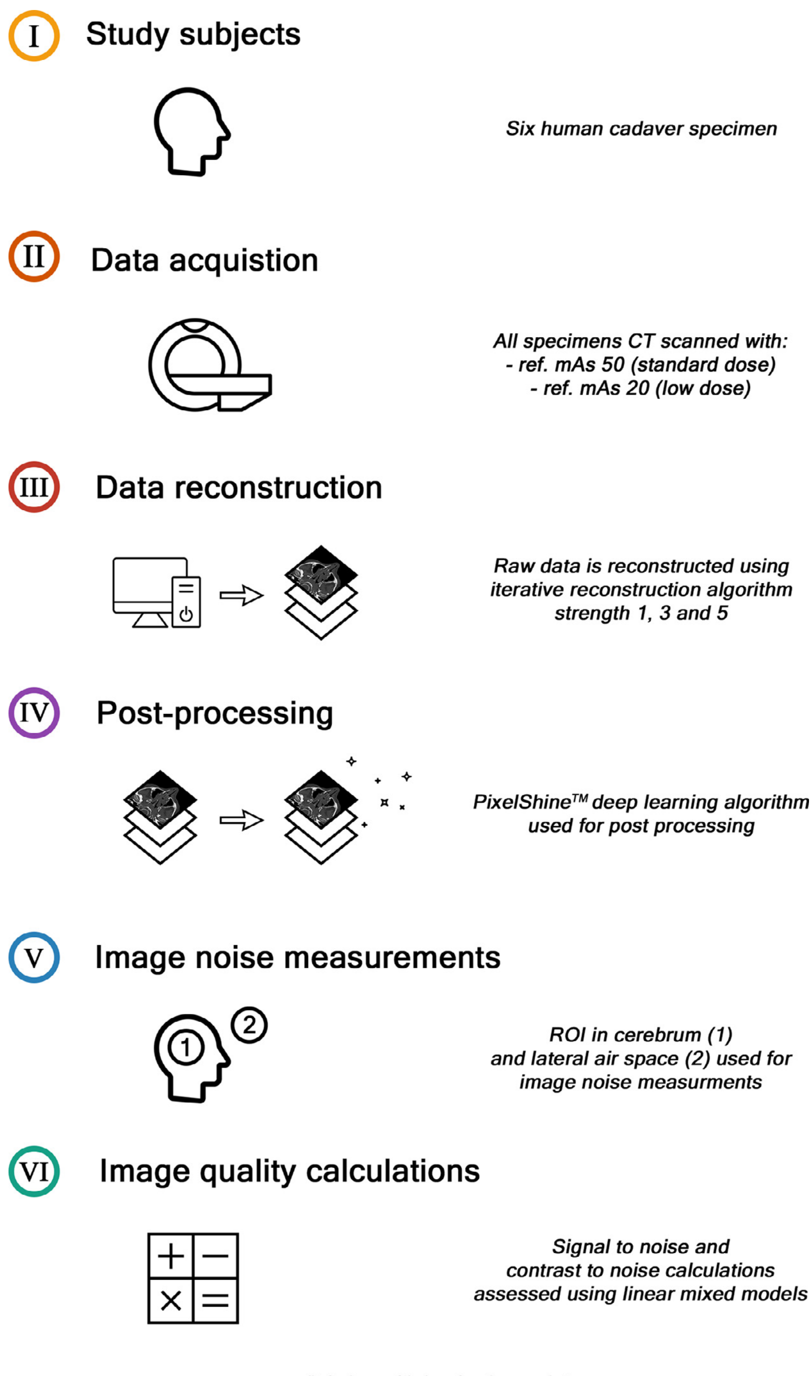

Fig. 1. Workflow of the material and methods.

low-dose reference 20 mAs scan protocol, ADMIRE strength 1, and no use of PS. The significance level was set at 5%.

RESULTS

In total, 24 unique datasets were reconstructed for each specimen. Repeated image noise measurements were taken from a total of 1440 image slices.

The radiation doses for the 2 scan protocols and the means and standard deviations of the noise, SNR, and CNR outcomes are presented in Table II. Dose reduction, IR strength, and the PS algorithm influenced the Hounsfield units (HU). The SNR and CNR outcomes of the soft tissue data sets were superior to those of the bone data sets. Overall, a radiation dose reduction from the reference 50 mAs to the reference 20 mAs protocol resulted in decreased SNR and CNR outcomes. The

Table I. CT protocol and reconstruction parameters.

CT protocol	*Reconstruction parameters*
Tube voltage	80 kV
Tube current modulation	CARE Dose4 D
Quality reference mAs	50 and 20
ADMIRE strength	1, 3, and 5
Field of view	220.0 mm
Collimation	192 × 0.6 mm
Average scan length	118 mm
Slice thickness	0.6 mm
Position increment	0.4 mm
Grayscale depth	12 bit
Pitch	0.6
Rotation time	0.5 s
Exposure time	0.5 s
Scan time	3.4 s
Matrix	512 × 512
Reconstruction kernels	Bone Hr59 d and soft tissue Hr32 d
Postprocessing	PixelShine deep learning processing

CT, computed tomography; *ADMIRE*, Advanced Modeled Iterative Reconstruction.

SNR of the bone data sets tended to increase slightly. The reduced radiation dose was equivalent to a 61.7% decrease in the dose length product (Table II). Increasing the IR strength improved the SNR and CNR outcomes of all data sets, especially the soft tissue data sets. The use of the PS algorithm further increased the SNR and CNR of all data sets (Figure 2). These effects are clearly illustrated in Figure 3 by the box plots of the comparison of the SNR and CNR for each scan protocol. The ADMIRE strength 5 reconstructed data sets and the additional use of the PS algorithm yielded the best SNR and CNR outcomes. The IR and PS algorithm improved the SNR and CNR to an extent that the outcomes for the reduced radiation protocol were well in the range of the standard protocol.

The results of the linear mixed model analyses are presented in Table III. A radiation dose reduction from the standard to the low-dose protocol did not decrease the SNR of the bone data sets significantly, but it decreased the CNR significantly. Raising the ADMIRE strength from 1 to 3 and from 1 to 5 was significantly associated with both the SNR and CNR of the bone data sets. In addition, the use of the PS algorithm was significantly associated with both the SNR and CNR bone data set outcomes. Based on the estimates, the effects of IR strength and use of PS far exceeded the effects of radiation dose on SNR and CNR outcomes.

For the soft tissue data sets, there was a significant association between both SNR and CNR and radiation dose reduction, higher ADMIRE strength, and the use of the PS algorithm. Based on the estimates, the effects of these predictors were substantially larger for the soft tissue data sets than for the bone data sets. The highest estimates were found on raising the ADMIRE strength from 1 to 5.

Table II. Radiation dose, noise, SNR, and CNR outcomes for all CT data sets.

Radiation dose, noise, SNR, and CNR outcomes for all CT data sets						
Reference mAs	50			20		
Average effective mAs	116.00 ± 10.30			36.00 ± 2.87		
Average CTDIvol (mGy)	5.26 ± 0.48			1.65 ± 0.13		
Average DLP (mGy*cm)	54.22 ± 5.30			20.79 ± 1.46		
ADMIRE strength	1	3	5	1	3	5
Bone						
Conventional processing						
Noise (HU)	31.84 ± 110.87	39.60 ± 89.10	42.00 ± 56.66	32.10 ± 109.42	39.47 ± 87.69	41.43 ± 56.59
SNR	0.289 ± 0.040	0.446 ± 0.057	0.743 ± 0.094	0.294 ± 0.044	0.451 ± 0.058	0.733 ± 0.094
CNR	11.89 ± 0.32	15.17 ± 0.55	23.93 ± 1.10	11.43 ± 0.36	14.73 ± 0.46	22.94 ± 0.71
PS deep learning processing						
Noise (HU)	39.54 ± 90.18	42.12 ± 69.14	42.14 ± 44.31	40.55 ± 83.58	41.96 ± 63.00	42.14 ± 44.31
SNR	0.441 ± 0.070	0.612 ± 0.082	0.956 ± 0.130	0.487 ± 0.071	0.669 ± 0.088	1.019 ± 0.124
CNR	15.71 ± 0.74	20.68 ± 1.28	32.15 ± 2.01	16.46 ± 0.91	21.99 ± 1.26	33.62 ± 1.65
Soft tissue						
Conventional processing						
Noise (HU)	40.67 ± 22.93	40.99 ± 20.58	41.76 ± 18.17	40.52 ± 27.13	40.83 ± 24.33	41.44 ± 21.59
SNR	1.798 ± 0.252	2.024 ± 0.297	2.347 ± 0.366	1.505 ± 0.172	1.692 ± 0.200	1.940 ± 0.239
CNR	59.33 ± 5.91	66.39 ± 7.26	75.67 ± 9.33	48.41 ± 2.98	54.02 ± 3.71	61.03 ± 4.71
PS deep learning processing						
Noise (HU)	39.54 ± 90.18	42.12 ± 69.14	42.14 ± 44.31	40.55 ± 83.58	41.96 ± 62.99	41.57 ± 40.89
SNR	2.006 ± 0.314	2.224 ± 0.362	2.516 ± 0.425	1.696 ± 0.223	1.878 ± 0.251	2.095 ± 0.277
CNR	68.31 ± 8.20	75.06 ± 9.80	83.16 ± 11.89	56.44 ± 4.64	61.79 ± 5.54	67.53 ± 6.17

SNR, signal-to-noise ratio; *CNR*, contrast-to-noise ratio; *CT*, computed tomography; *CTDIvol*, computed tomography dose index; *DLP*, dose length product; *ADMIRE*, Advanced Modeled Iterative Reconstruction; *HU*, Hounsfield units; *PS*, PixelShine deep learning algorithm.

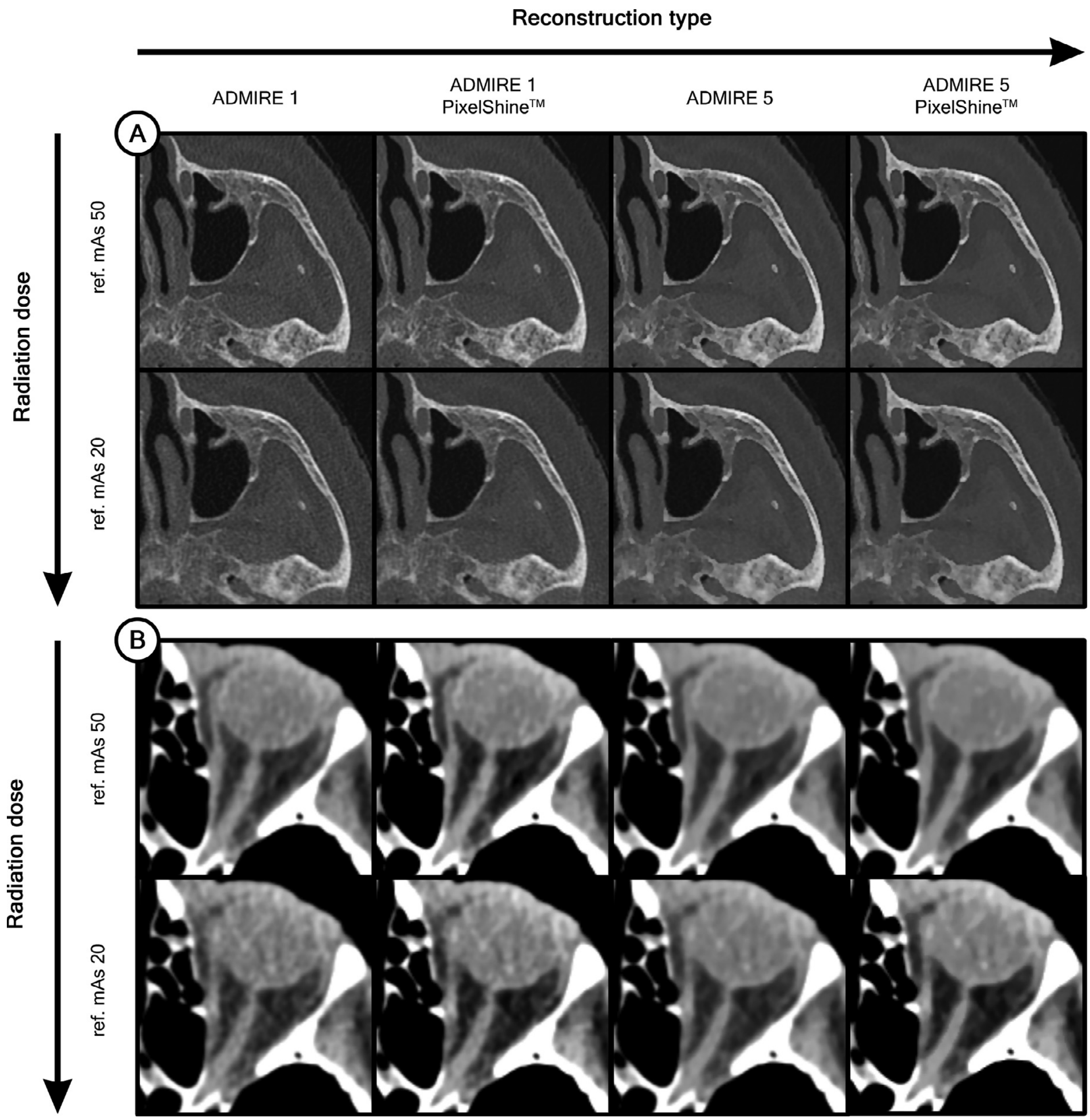

Fig. 2. Visual presentation of Advanced Modeled Iterative Reconstruction (ADMIRE) and PixelShine deep learning algorithms for **(A)** bone and **(B)** soft tissue reconstructed data sets.

DISCUSSION

This is the first study to assess the use of ADMIRE and PS algorithms to improve image quality after substantial radiation dose reduction for CT protocols to assess midfacial trauma. This study demonstrated that radiation dose reduction, increasing the IR strength, and the use of the PS algorithm were all significantly associated with SNR and CNR outcomes. Most important, the decrease in SNR and CNR due to radiation dose reduction was substantially improved using the ADMIRE and PS algorithms.

The diagnostic quality and increased availability of CT within the emergency department has led to an increased number of CT examinations. As a result, there is an expanding concern regarding the associated radiation exposure to patients.[11] In this study, the estimated radiation dose of the low-dose CT protocols was comparable to that in another human cadaver study in which a variety of scan protocols for maxillofacial fractures were assessed.[12]

We analyzed both data sets that were reconstructed using bone and soft tissue kernels. Bone data sets feature higher image noise because the slices are thinner and have a high spatial resolution. Such a sharp characteristic is required to depict fractures as small bony discontinuities. In this study, ADMIRE and PS improved

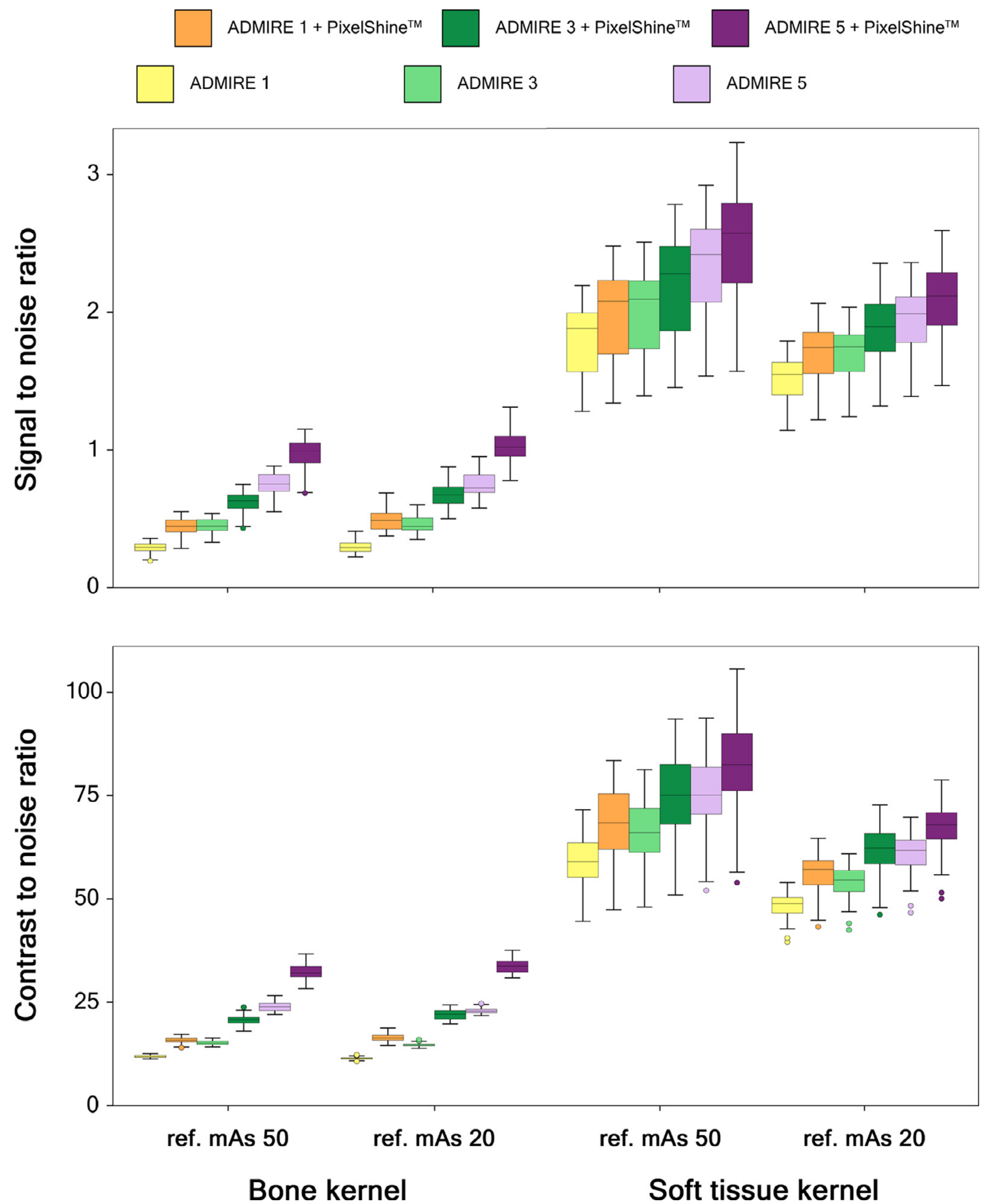

Fig. 3. Box plots showing comparison of contrast-to-noise ratio and signal-to-noise ratio outcomes. ADMIRE, Advanced Modeled Iterative Reconstruction.

the SNR and CNR after a large reduction in radiation dose. These findings are in line with previous research in which a substantial improvement in CNR was found using an adaptive statistical and model-based IR for bone kernel reconstructed data sets.[13] Image noise improvement is favorable for fracture diagnosis, and previous cadaver, phantom, and modulation transfer function studies by other IR manufacturers also revealed that spatial resolution is maintained after radiation dose reduction.[9,14,15] A known disadvantage of iterative reconstructed bone data sets is the longer reconstruction time. In addition, interpretation can be complicated by the waxy or pixelated image appearance,[16] but this was not found when using the PS algorithm. Against expectations, this study obtained only higher SNR and CNR outcomes for the bone data sets on comparing the reduced radiation protocol with the standard protocol. This finding suggests that the denoising capabilities of this algorithm are stronger for data sets with high image noise. Because the exact architecture of the PS algorithm is largely unknown, no clear explanation could be found for this outcome.

Table III. Results of the linear mixed model analyses.

Reconstruction type		*Bone*				*Soft tissue*			
Parameter		*B*	*SE*	*95% CI*	*P value*	*B*	*SE*	*95% CI*	*P value*
SNR									
Intercept		0.291	0.010	0.272-0.310	.000	1.804	0.032	1.741-1.868	<.001
Radiation dose	Ref. 50 mAs								
	Ref. 20 mAs	−0.001	0.012	−0.025 to 0.023	.914	−0.293	0.041	−0.373 to −0.212	<.001
ADMIRE strength	1								
	3	0.155	0.013	0.129-0.180	.000	0.228	0.043	0.142-0.313	<.001
	5	0.447	0.013	0.421-0.472	.000	0.559	0.043	0.473-0.644	<.001
PS deep learning processing	No								
	Yes	0.145	0.012	0.121-0.169	.000	0.210	0.041	0.129-0.290	<.001
CNR									
Intercept		12.03	0.12	11.79-12.27	.000	59.48	0.77	57.96-61.00	<.001
Radiation dose	Ref. 50 mAs								
	Ref. 20 mAs	−0.75	0.16	−1.05 to −0.45	.000	−11.00	0.98	−12.93 to −9.08	<.001
ADMIRE strength	1								
	3	3.15	0.16	2.82-3.47	.000	7.10	1.04	5.06-9.14	<.001
	5	11.72	0.16	11.39-12.04	.000	16.79	1.04	14.75-18.83	<.001
PS deep learning processing	No								
	Yes	3.54	0.16	3.23-3.84	.000	9.15	0.98	7.23-11.07	<.001

Linear mixed model analyses were performed for both bone and soft tissue separately using SNR and CNR as outcomes. Radiation dose, IR strength, and use of PS deep learning processing were added as fixed effects. The reference 20 mAs protocol, ADMIRE strength 1, and no use of PS deep learning processing were used as the reference category.
CI, confidence interval; *SNR*, signal-to-noise ratio; *ADMIRE*, Advanced Modeled Iterative Reconstruction; *PS*, PixelShine deep learning algorithm; *CNR*, contrast-to-noise ratio.

Soft tissue data sets are appreciated for the ability to visualize the intraorbital contents of midfacial trauma. Midfacial fractures are associated with soft tissue−related injuries, such as entrapment of the rectus muscles. The low contrast detectability of the soft tissue data sets is necessary to differentiate the closely related densities of the intraorbital anatomy. This study discovered that there was also a significant association between radiation dose reduction, IR strength, and PS algorithm and both SNR and CNR for the soft tissue data sets. These data sets were more prone to a decrease in SNR and CNR following a decrease in radiation dose compared to the bone data sets. The decrease in SNR and CNR appeared to be maintained with the standalone use of ADMIRE, raising the strength from 1 to 5, after radiation dose reduction. A prior study also found that both adaptive statistical IR and model-based IR produced a significantly better CNR than that obtained with FBP for the optic nerve and inferior rectus muscle.[17] Other studies provided a potential for radiation dose reduction using an IR algorithm for soft tissue data sets of cranial CTs.[18,19] Although in this investigation the PS algorithm significantly improved the soft tissue data sets, the standalone use did not seem to maintain image quality after radiation dose reduction. Nevertheless, it provided important evidence that this novel deep learning−based technology was able to substantially denoise both bone and soft tissue kernel reconstructed data sets.

This study had limitations. Human cadaver specimens were used as representations of patient cases. The postmortem status of the fresh frozen specimens could have skewed the interpretability of the data sets and the radiation dose outcomes could have been underestimated. Nevertheless, this approach allows a reliable comparison of image quality outcome. Another limitation is that SNR and CNR were the only parameters measured as an outcome of image quality. Although these outcomes are widely accepted when assessing noise-related image quality, no direct assumptions can be made regarding the effects on diagnostic outcome. Therefore, future research should focus on how these algorithms affect lesion detectability. A priori knowledge of the algorithm capabilities is needed to optimize the radiation dose of CT protocols in relation to midfacial trauma. Future research should also focus on the use of these algorithms for low-dose CT protocols in pediatrics, orthodontics, and artifact reduction.

CONCLUSION

Both advanced model-based ADMIRE and PS algorithms significantly improved SNRs and CNRs of bone and soft tissue data sets for CT protocols used for midfacial trauma. Improvements in SNR and CNR were particularly found for the soft tissue data sets. The algorithms provide potential to maintain image quality after substantial radiation dose reduction.

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