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.

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.
substantially. 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.

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. The first ROI of 10.0 cm² was positioned in the posterior fossa of the cerebrum and the second ROI of 2.5 cm², 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. 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:

\[
SNR = \frac{\text{Mean HU}_{\text{cerebrum}}}{\text{SD HU}_{\text{cerebrum}}}
\]

\[
CNR = \frac{\text{Mean HU}_{\text{cerebrum}} - \text{Mean HU}_{\text{air}}}{\sqrt{\text{SD}_{\text{cerebrum}}^2 + \text{SD}_{\text{air}}^2 / 2}}
\]

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
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 Dose-4 D                             |
| Quality reference mAs        | 50 and 20                                 |
| ADMIRE strength              | 1, 3, and 5                               |
| Field of view                | 220.0 mm                                  |
| Collimation                  | $192 \times 0.6$ 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                       | $512 \times 512$                         |
| Reconstruction kernels       | Bone Hr59 d and soft tissue Hr32 d        |
| Postprocessing               | PixelShine deep learning processing       |

Table II. 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           |               |               |
| Noise (HU)     | 31.84 ± 110.87 | 24.33 ± 41.44 |
| SNR            | 0.289 ± 0.040  | 0.441 ± 0.070 |
| CRN            | 11.89 ± 0.32   | 15.71 ± 0.74  |
| PS deep learning processing | 39.54 ± 90.18 | 15.71 ± 0.74  |
| Noise (HU)     | 42.12 ± 69.14  | 42.12 ± 12.8  |
| CNR            | 0.441 ± 0.070  | 20.68 ± 1.28  |
| Soft tissue    |               |               |
| Noise (HU)     | 40.67 ± 22.93  | 40.67 ± 22.93 |
| SNR            | 1.798 ± 0.252  | 1.798 ± 0.252 |
| CRN            | 59.33 ± 5.91   | 66.39 ± 7.26  |
| PS deep learning processing | 39.54 ± 90.18 | 66.39 ± 7.26  |
| Noise (HU)     | 42.12 ± 69.14  | 42.12 ± 12.8  |
| SNR            | 2.006 ± 0.314  | 2.224 ± 0.362 |
| CRN            | 68.31 ± 8.20   | 75.06 ± 9.80  |

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.
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. 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.

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
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.\textsuperscript{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.\textsuperscript{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,\textsuperscript{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.
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. Other studies provided a potential for radiation dose reduction using an IR algorithm for soft tissue data sets of cranial CTs. 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.

Table III. Results of the linear mixed model analyses.

| Reconstruction type | B     | SE   | 95% CI       | P value | B     | SE   | 95% CI       | P value |
|---------------------|-------|------|--------------|---------|-------|------|--------------|---------|
|                      | Bone  | Soft tissue |
| Parameter type       |       |            |             |         |       |     |              |         |
| SNR                 | 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     | 0.155 | 0.013 | 0.129-0.180 | .000 | 0.228 | 0.043 | 0.142-0.313 | <.001 |
|                      | 3     | 0.447 | 0.013 | 0.421-0.472 | .000 | 0.559 | 0.043 | 0.473-0.644 | <.001 |
|                      | 5     |       |            |         |       |     |              |         |
| PS deep learning processing | No | 0.145 | 0.012 | 0.121-0.169 | .000 | 0.210 | 0.041 | 0.129-0.290 | <.001 |
|                      | Yes   |       |            |         |       |     |              |         |
| CNR                 | 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     | 3.15  | 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 | 3.54  | 0.16  | 3.23-3.84 | .000 | 9.15  | 0.98  | 7.23-11.07 | <.001 |
|                      | Yes   |       |            |         |       |     |              |         |

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.
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