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Feasibility of Anatomy-Specific Exposure Index in Clinical Digital Radiography Images

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MAYO CLINIC

INTRODUCTION

Exposure index (EI) and associated deviation index (DI) are useful concepts in digital radiography (DR) to provide users standardized exposure metrics [1-2].

EI is dependent on the incident air kerma in a selected area of the image detector for a standard beam quality. For each exam view, an EI target can be determined based on the image system and clinical image quality preference. Consequently a DI can be calculated and displayed on the scanner console to indicate the amount of exposure deviation of an acquired image from the EI target, through a simple equation DI = $10*\log(EI/EI_{target})$. Technologists can use EI and/or DI for trouble shooting and further image acquisition guidance when a repeated image is needed.

However, there are significant limitations in vendor implementation of EI that undermine its clinical value. One of the main issues is that selection of the area on which the detector exposure is determined is not well-defined. Some vendors use only skin line segmentation, while others also exclude metal implants; some use a center area of the detector, while others use multiple areas of the detector.

AIM

The aim of this study is to demonstrate the feasibility of anatomy-specific EI (EI_A) in clinical lateral lumbar spine images, and measure the difference between the existing vendor proprietary EI and EI_A values.

METHODS

1. EI calculation based on pixel values from DICOM For-Processing images acquired on GE Discovery XR656 DR systems was tested and confirmed.
2. A convolutional neural network based on the U-Net architecture [3] was developed to segment spines from clinical lateral lumbar spine images in the For-Processing format.
   - 80 clinical 16bit For-Processing images were obtained from the above-mentioned systems and all images were de-identified and processed for contrast enhancement;
   - Segmentation of the lumbar spines was semi-automated, including edge detection, human inspection and intervention;
   - Data augmentation was performed including horizontal and vertical translation, adding Gaussian noise, smoothing, and rotation;
   - A total of 1440 images and labels were generated, including 960 for training, 320 for validation, 160 for testing. All images were resized to 256 X 256 matrix size;
   - The network included 58 layers and was trained using a custom MATLAB program with a NVIDIA RTX 2070 GPU (Figure 1).
3. EI_A were computed and compared to the vendor EI. A number of methods for calculating EI_A were performed:
   - The median of the spine pixels
   - The first quartile of the spine pixels
   - The first peak location of Gaussian mixture model to represent the pixels corresponding to areas with high attenuation

RESULTS

- EI calculation through this formula, median(pixel value)×100/detector sensitivity, was confirmed with the vendor EI. Detector sensitivity can be found in a DICOM tag
- The network model generated a global accuracy of 0.958, a mean accuracy of 0.900, an average Jaccard index of 0.721, and a weighted Jaccard index of 0.934 using the test data
- The difference between vendor EI and EI_A taken from the median pixel values from the spines ranged from -245.9 to 42.7, corresponding to a percent difference of -42.4% to 15.3%
  - EI values from 60 datasets were plotted in Figures 2 and 3

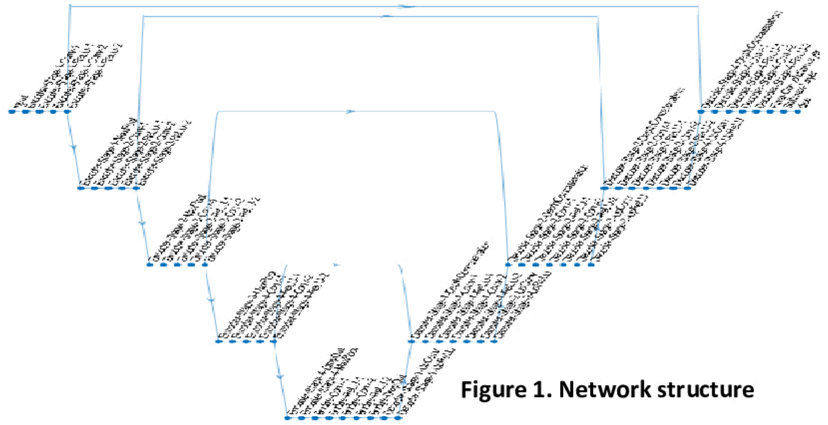


Figure 1. Network structure

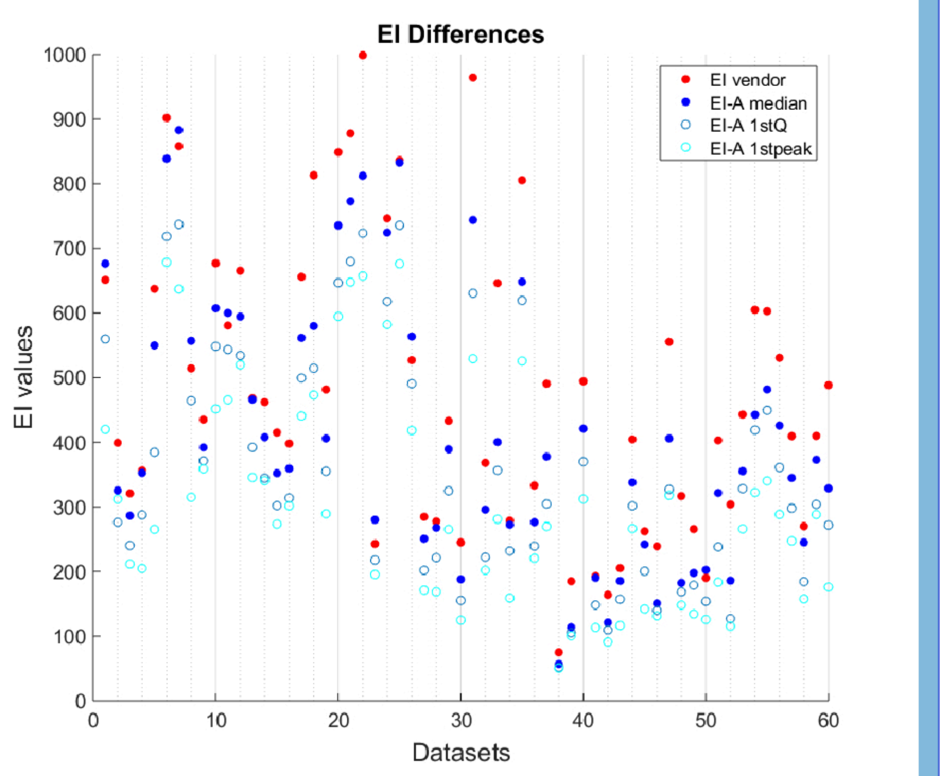


Figure 2. Scatter plot of the vendor EI and EI_A calculated using three methods from 60 datasets.

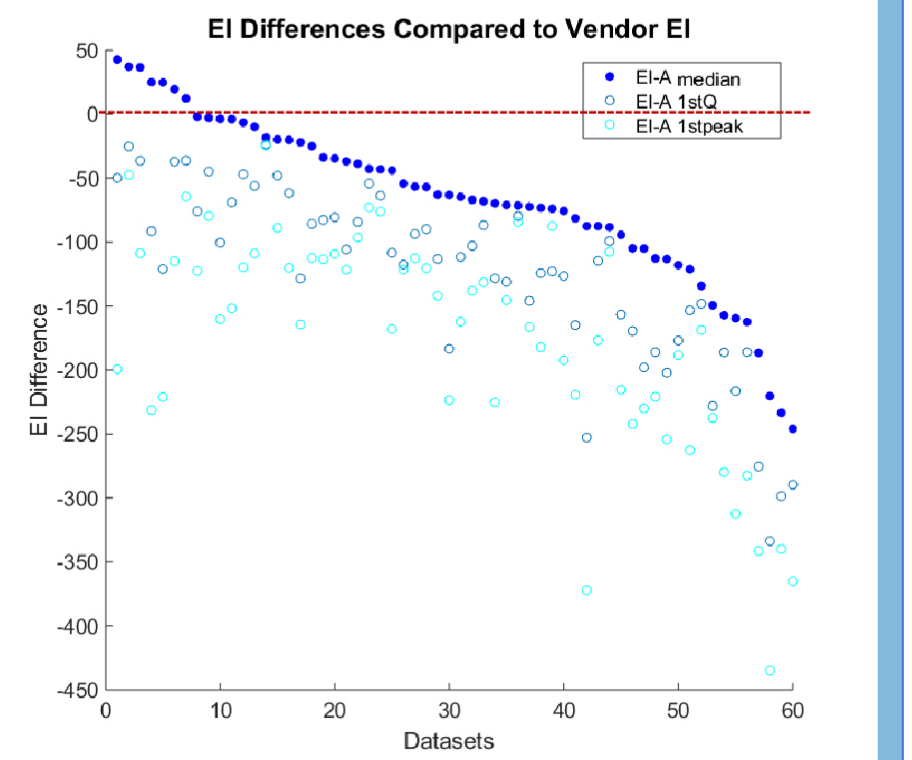
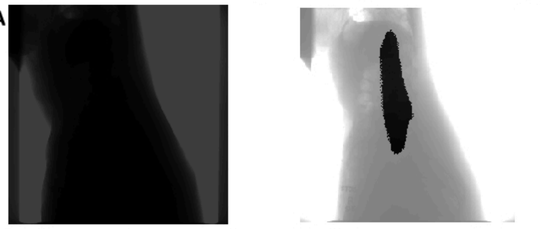


Figure 3. Differences in EI_A compared to vendor EI ordered from the highest to the lowest in results using the median method

RESULTS (*CONT.*)

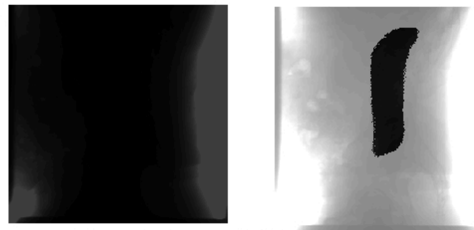
Figure 4. Image examples with vendor EI and $EI_{A\,(median)}$ values
Left: Original 16bit DICOM For-Processing Image in various matrix size, with different collimation and patient anatomy;
Right: Pair of contrast adjusted image with model segmented mask (256 by 256 matrix size);

A



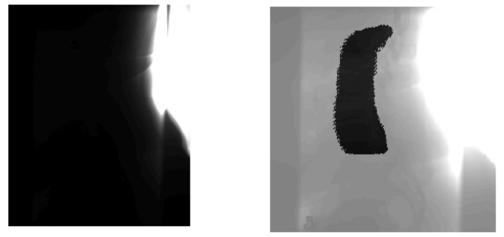
Vendor EI was 304, while EI_A was 186;
For EI target of 300, DI would be 0 and -2, respectively.

B



Vendor EI was 316.8, while EI_A was 182.5;
For EI target of 300, DI would be 0.2 and -2.2, respectively.

C



Vendor EI was 242.9, while EI_A was 280.1;
For EI target of 300, DI would be -0.9 and -0.3, respectively.

D

Vendor EI was 514.3 while EI_A was 557; Patient had spine implants
For EI target of 300, DI would be 2.3 and 2.7, respectively.

CONCLUSIONS AND DISCUSSION

- This study demonstrated the feasibility of using anatomy specific pixel information to compute EI, i.e., EI_A, in clinical lumbar spine exam setting using DICOM for-processing images
- The median EI_A method showed a wide range of difference from the vendor EI, indicating the spine areas being under- or over-exposed. The first quartile or the first peak from Gaussian mixture model fitting method showed even larger differences, because they represented pixels from high attenuation areas which might be more important for the clinical task
- EI_A would provide more relevant exposure information for specific clinical exams. It is easy to be standardized across vendors and realistic acquisition variations, such as different collimation sizes, different amount of soft tissues, bones, metal implants or other foreign objects in the images
- This approach could be useful for moving DR AEC design toward an anatomy specific scheme instead of the fixed and limited AEC cell scheme currently
- The network model is being optimized for better segmentation accuracy

REFERENCES

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2. IEC 62494-1:2008; Medical electrical equipment – Exposure index of digital X-ray imaging systems – Part 1: Definitions and requirements for general radiography.
3. Ronneberger et al. U-Net: convolutional networks for biomedical image segmentation. MICCAI 2015 pp 234-241.

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CONTACT INFORMATION

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