Decision Making in Orthopedic Surgery Through Hyper Low Dose Fluoroscopy

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Internal pelvic fracture fixation requires a surgeon to accurately insert K-wires into the patient's abdomen. To validate that the tool follows the desired trajectory, hundreds of digital radiographs are taken throughout the procedure. Although their only purpose is to verify placement without cortical breach, digital radiographs deliver a large dose of radiation to the patient. Additionally, the surgeon accumulates dose due to scattering over many procedures. Our aim is to decrease the radiation inflicted upon the patient and operating room staff without degrading task performance or disrupting surgical workflow. We address this by reducing the noise in hyper-low dose images, making them usable for surgical decision making.

Problem

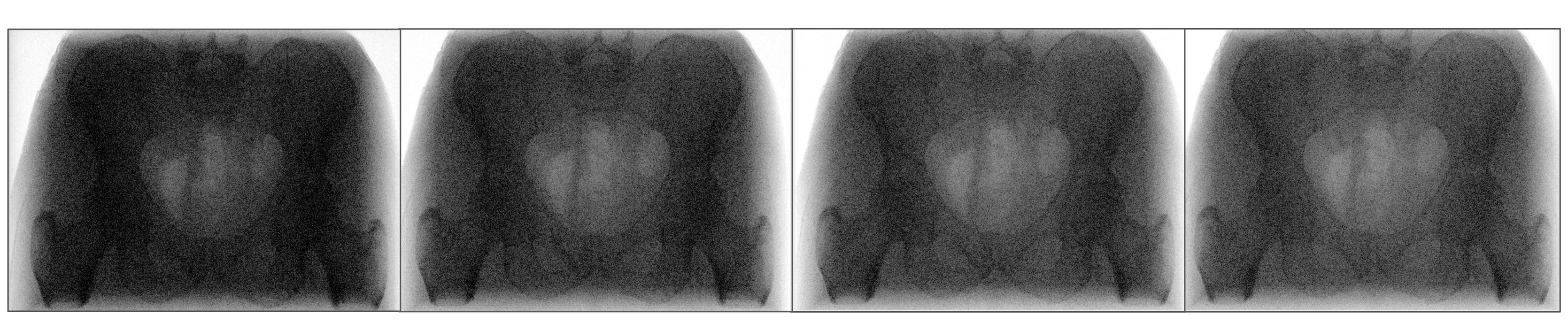
Reducing the dose is desirable because it protects the patient and surgeon, but low-dose images are noisy and make it difficult to see structures. This prevents them from being useful in surgery in their initial state.

Solution:

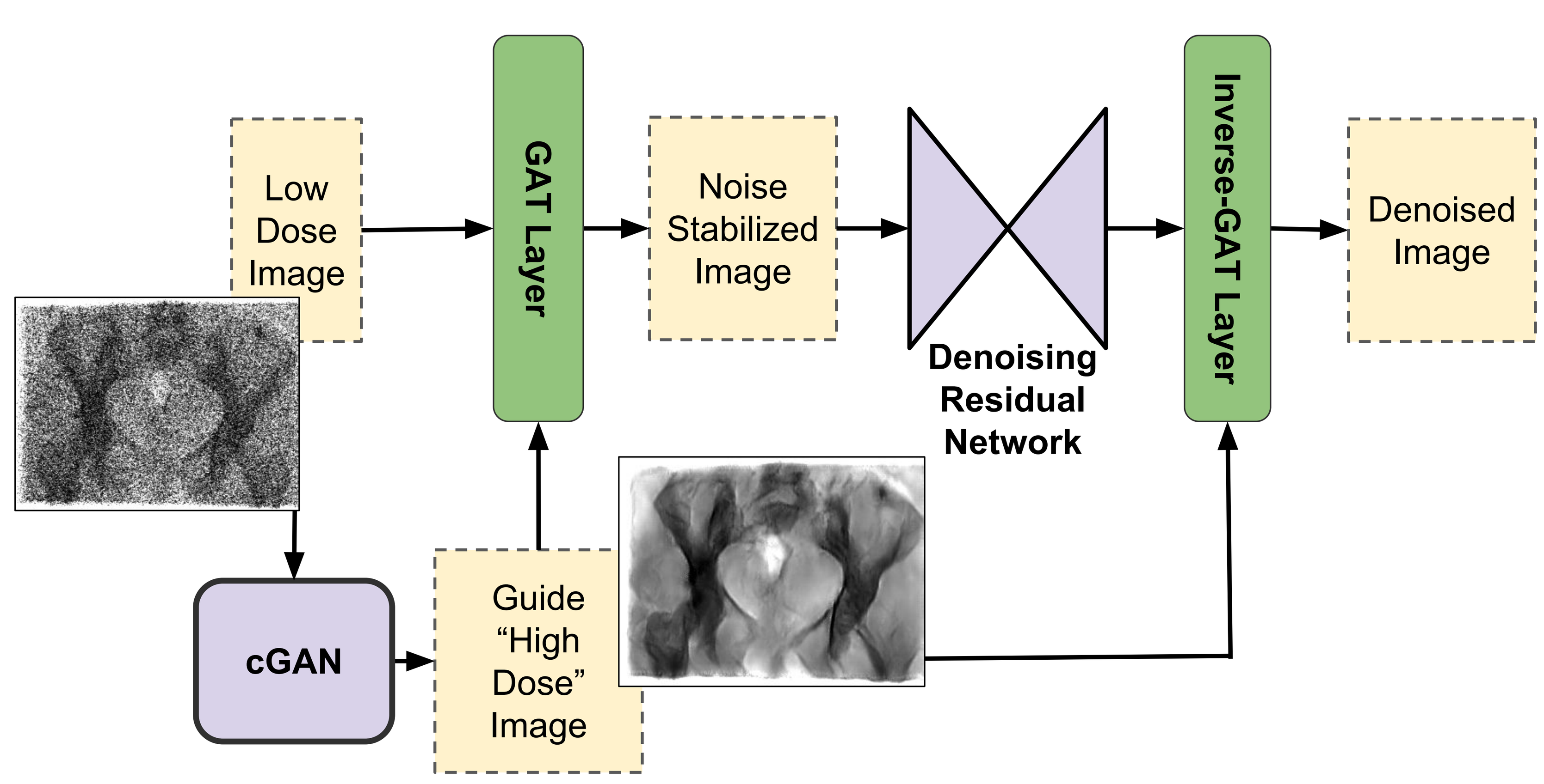
We studied the relationship between dose, spectrum, and image quality in simulated digital radiographs. This allowed us to select a dose level which would reduce risk to the surgeon and patient while still creating images containing extractable information. To accomplish our goal of reducing the noise, we have developed and implemented a deep learning pipeline which improves image quality by training on simulated low and high dose images.

Methods/Approach

-Dose quantification: We tested an array of filtration methods and their effect on dose and image quality by generating images with MC-GPU [2]. Our goal was to find a filtration profile (Al and Cu) which would maximize image quality for a given dose. This knowledge would be applied in future work and real-world testing.
-Image generation: Train and test images for the deep learning network were generated with DeepDRR [1].



Monte Carlo simulated radiographs generated at 60 kVp and **constant soft tissue dose**. From left to right, the spectrum was filtered with 0.0mm Cu, 0.1mm Cu, 0.2mm Cu, 0.3mm Cu. The copper filters out low-energy photons, increasing the contrast between bone and the background.

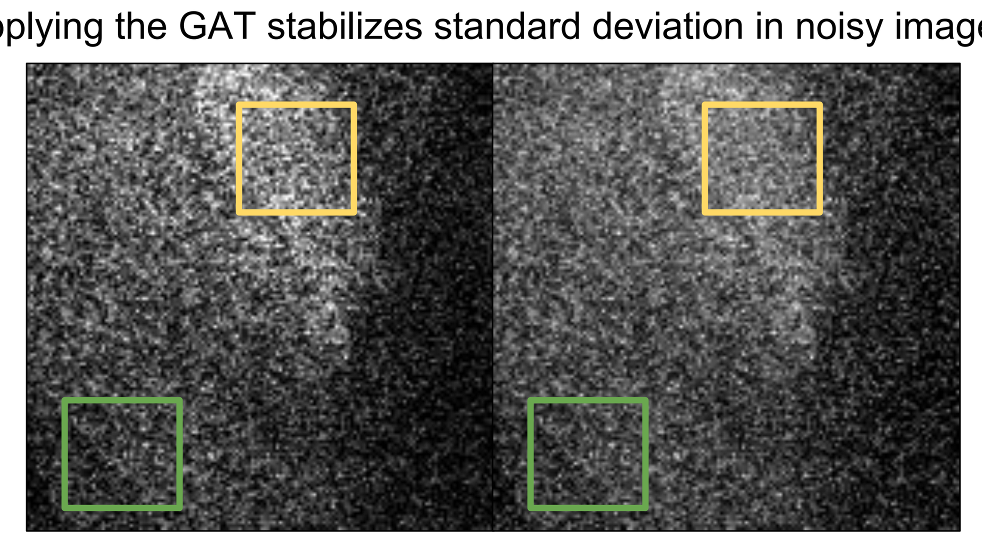


1. Conditional GAN (Generative Adversarial Network) produces estimated high-dose image from input low-dose image [3]
2. GAT (Generalized Anscombe Transform) layer stabilizes noise on low-dose image using estimated high-dose image as guide
3. Deep CNN learns noise of the stabilized low-dose image [4]
4. Inverse-GAT layer returns the denoised low-dose image to its original domain

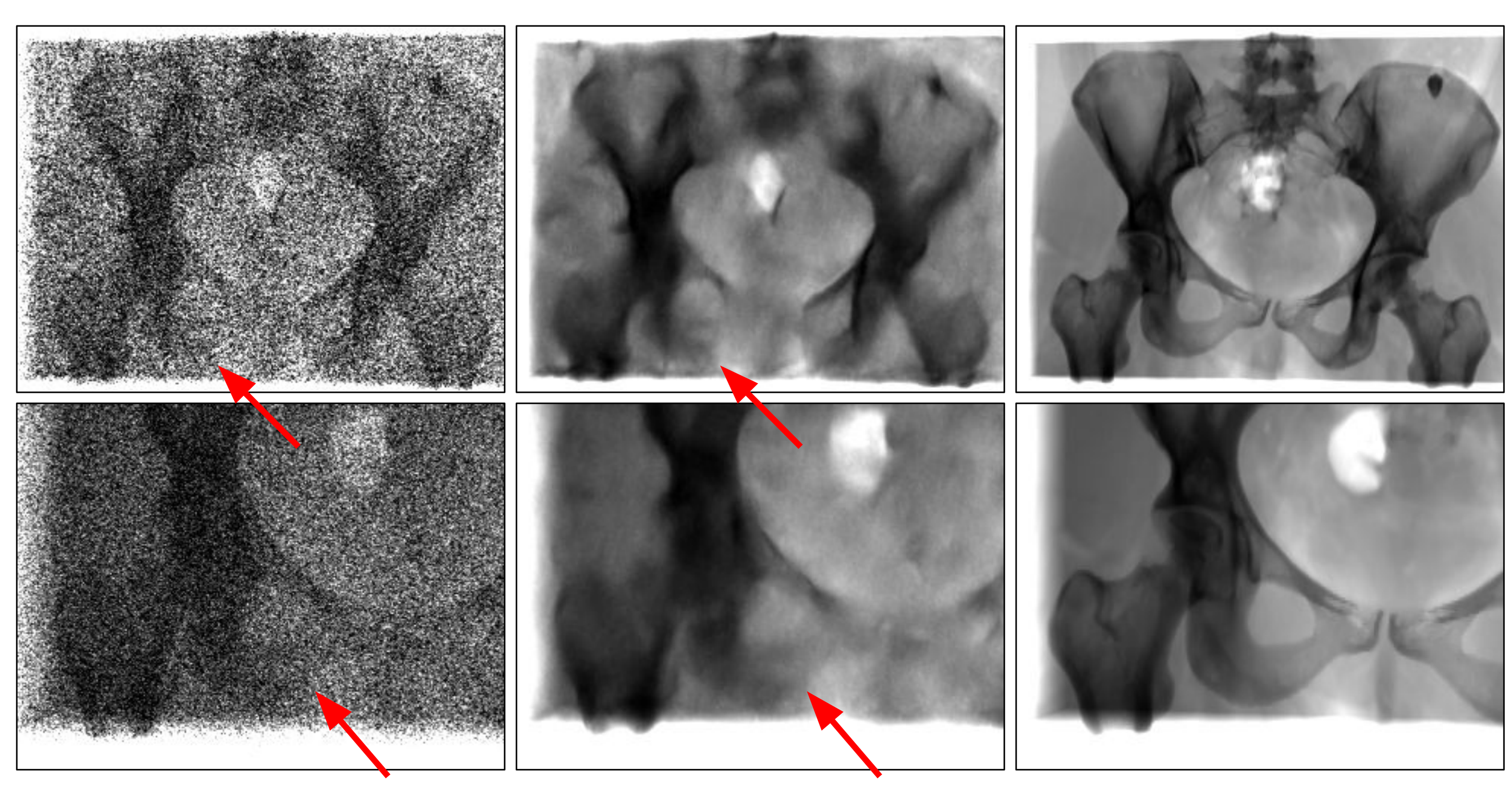
Results

-The pipeline was trained with 3,780 digital radiographs simulated from five different CT volumes. The images were taken from a variety of camera positions. Image size was 320 x 240px
-cGAN - 100 epochs
-Denoising - 100 epochs, 3,780 patches (100 x 100px)
-The addition of the GAT layer stabilizes variance in noisy images

Applying the GAT stabilizes standard deviation in noisy images.



Original Noisy (Scaled)	Noise-Stabilized
Std Dev: 1.047	Std Dev: 1.032
Std Dev: 0.670	Std Dev: 0.964



Discussion

-Substantial improvement between noisy and denoised image
-Low-contrast structures in the input images are recovered by the network
-This pipeline is a building block in the larger goal of using low-dose fluoroscopy in orthopedic surgery
-More training data would further improve model

Lessons Learned

-Noisy images still contain useful information, but finding a way to extract it can be difficult
-Errors quickly arise in neural networks when data is not normalized consistently

Credits

-Mariya: Implemented denoising pipeline
-Michael: Generated training and testing images

References

[1] Unberath, M., Zaech, J. N., Lee, S. C., Bier, B., Fotouhi, J., Armand, M., & Navab, N. (2018). DeepDRR--A Catalyst for Machine Learning in Fluoroscopy-guided Procedures. *Proc. MICCAI*
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[4] Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. (2017). Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. *IEEE Transactions on Image Processing*, *26*(7), 3142-3155.