Team members : Michael Mudgett, Mariya Kazachkova
Project: Low Dose Fluoroscopy for Orthopedic Surgery
Mentors: Mathias Unberath, PhD, Bastian Bier, Nico Zaech, Nassir Navab, PhD, Greg Osgood, MD

Stated Topic and Goal

The overall goal of using low dose fluoroscopy in orthopedic surgery is to reduce the radiation inflicted on a patient by x-ray imaging while increasing the temporal resolution of the images. Our project goal is to make fluoroscopy possible for orthopedic surgery, specifically pelvic fracture treatment, by developing a low dose profile for taking fluoroscopic video as well as improving the quality of the low dose fluoroscopy, given an initial high dose image.

Relevance/Importance

We will be focusing on orthopedic surgery with pelvic fracture repair as the main focus. In this surgery a wire is driven into the pelvis, and x-ray imaging must be used in order for the surgeon to correctly place this wire. This process requires 100+ digital radiographs (high dose images) per wire, which can be harmful to the sensitive body parts located near the pelvic area. Thus, it would be beneficial to use live fluoroscopic video (low dose) while placing the wire. This is difficult to do because the large amount of soft tissue in the pelvis prevents fluoroscopy from creating the high-resolution images needed for accurate wire placement. Our project will improve the quality of the low dose fluoroscopy so that the patient receives less radiation. Furthermore, by replacing the still digital radiographs with live video, our project will allow the surgeon to perform this procedure more quickly.

Technical Summary of approach

We have broken down our technical approach into two parts:

MC-GPU (Mike):
This part of the project will involve performing Monte Carlo simulations to generate x-ray images. Dose parameters (kVp,mAs, filtration) will be altered in order to generate a library of low and high dose images. This will allow us to quantify dose and image quality and ultimately lead to a chosen dose profile which maximizes quality and minimizes patient dose. Likewise, it will provide a training and test set for the neural network.

Deep Learning (Mariya):
In order to actually improve the usability of the low dose fluoroscopy we will use deep learning. The training will be done on the corresponding low and high dose image pairs from the library that will be created using the Monte Carlo simulations. Additionally, an initial digital radiograph (high dose image) will be used as a constraint when improving the quality of the subsequent low dose images. Ultimately, we will use an LSTM network to introduce the concept of "memory" into our network, allowing us to use information from the previous timesteps when generating our high dose image rather than just relying on the initial taken (since the position of the wire will be changing we want to avoid always using the outdated constraint and instead incorporate information more relevant to the current image).
Our first step with the deep learning part of our project is to just create a neural network that can denoise an image. We will use a convolutional denoising autoencoder (since autoencoders are often used for denoising and convolutional layers work best for images).

Deliverables

Minimum:
A single set (~500, for neural network training) of simulated x-ray images for a particular dose with clear documentation of the dose received by the patient and the image quality.
Implemented neural network that can denoise a single image with documentation on the number of layers, activations, and loss function.

Expected:
A functioning denoising network that can improve the quality of a still low-dose image from an initial high dose DR with documentation.
A chosen and documented dose profile that minimizes dose and maximizes image quality when improved by the denoising network and the initial high dose DR.

Maximum:
An LSTM network that can be used on continuous fluoroscopy with an initial DR; documentation.
Experiments with a scanner in Mock OR or the Bayview Lab

Milestones

3/18/18 -
We will have our bank of low-dose and high-dose image pairs for various doses complete as well as a quantified dose/quality relationship for each profile.

If this proves to be unattainable in the time allotted we will generate a bank of low-dose and high-dose image pairs for a single dose profile.

4/1/18 -
We will have code and documentation written for a neural network that can denoise a single image (this will be our convolutional denoising autoencoder). If we are unable to complete this we will try an established network instead and train/test it with our generated images.

4/15/18 -
A profile will be chosen for the ideal dose profile to use for reducing the dose received by the patient while also obtaining good results using the neural network. If needed, we will return to milestone 1 here and do more altering of parameters to obtain a profile that works with our neural network while also minimizing dose.

5/6/18 -
We will have our LSTM network for live fluoroscopy coded, documented, trained, and tested. We also want to have a time analysis of the network's performance (to see how much it worsens over time). If the LSTM network for the full feed does not work, we will work on improving small sequences of images instead.

Dependencies

The one dependency that has not yet been resolved is access to a fast GPU in the Navab lab for x-ray image generation and neural network training. We will be given access on March 2. Should this date be pushed back, we are prepared to run the software on our CPUs. Progress will continue, albeit slowly.

The other dependencies are obtaining Python/PyTorch as well as the MC-GPU software. Both of these have been completed. In addition, our mentors have downloaded and processed pelvic CT volumes which we will use to generate images.

Management Plan

As a team, we (Mariya and Mike) plan to meet bi-weekly, each Monday and Friday, to discuss each other's current progress and any resolve any issues. The plan is to work on our separate tasks alone but as the plan progresses and the generated images and neural network become more intertwined, we will work together. We will use a private BitBucket repository to manage our code and documentation.

We have scheduled weekly meetings with Mathias and will meet with Nico and Bastian whenever Mathias is unavailable or if any urgent problems arise. No meetings are planned with Prof. Navab or Dr. Osgood but if an expert opinion is required, (i.e. for determining the "usability" of an x-ray image during a surgery) we will contact them.

Reading List

- A. Badal and A. Badano, "Monte Carlo simulation of X-ray imaging using a graphics processing unit," 2009 IEEE Nuclear Science Symposium Conference Record (NSS/MIC), Orlando, FL, 2009, pp. 4081-4084.
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- H. Chen et al., "Low-dose CT denoising with convolutional neural network," 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017), Melbourne, VIC, 2017, pp. 143-146.
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- L. Gondara, "Medical Image Denoising Using Convolutional Denoising Autoencoders," 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW), Barcelona, 2016, pp. 241-246.
- J. M. Wolterink, T. Leiner, M. A. Viergever and I. Išgum, "Generative Adversarial Networks for Noise Reduction in Low-Dose CT," in IEEE Transactions on Medical Imaging, vol. 36, no. 12, pp. 2536-2545, Dec. 2017.