Low Dose Fluoroscopy for Orthopedic Surgery

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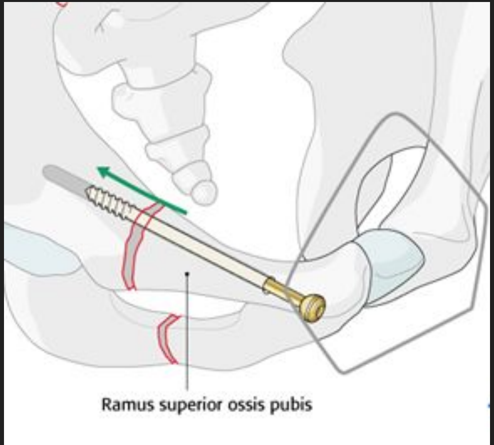
Goals

- Big picture: reduce total radiation inflicted on patient through x-ray imaging during orthopedic surgery while increasing the temporal resolution of X-ray imaging
- Enable use of low-dose live fluoroscopic video in orthopedic surgery
- Project goals:
    - Develop low dose profile for taking fluoroscopic video
    - Develop method for improving image quality of low dose fluoroscopy given initial high dose image

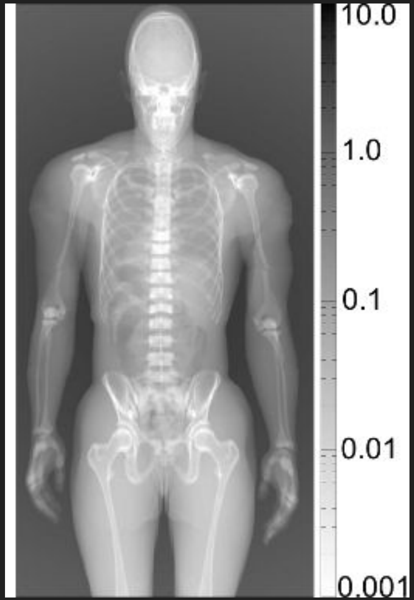
Background and Significance

- Wire driven into pelvis during orthopedic surgery
- X-ray imaging is needed to guide wire placement
- 100+ Digital Radiographs (high dose x-ray) taken during surgery (per wire)
    - Potential to affect sensitive parts of body
    - Tedious procedure
- Live fluoroscopic video (low dose) is used during some procedures, i.e. endovascular
    - Not well-suited for orthopedic surgery



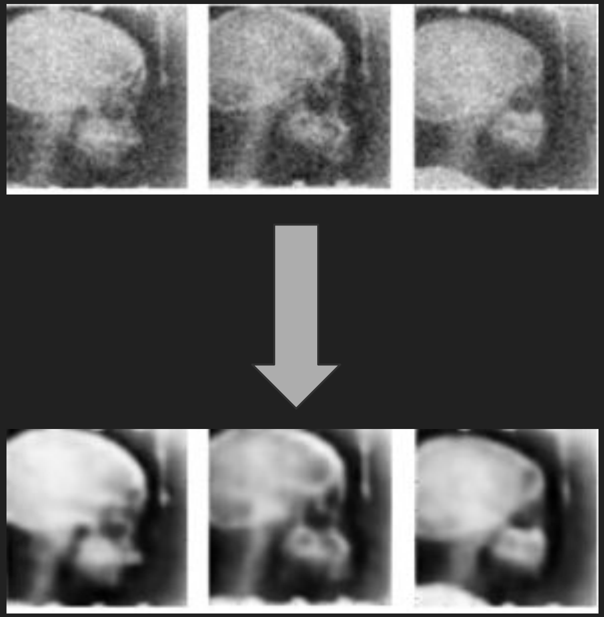
Technical Summary of Approach

- 2 main parts
  - MCGPU (Mike)
    - Monte Carlo simulations for generating x-ray images and quantifying **dose** and **image quality**
    - Alter dose parameters (kVp, mAs, filtration) to generate library of low and high dose images
  - Deep learning (Mariya)
    - Train on corresponding low and high dose image pairs
    - Use an initial DR (high dose image) as a constraint, improve image quality of subsequent low dose images
    - LSTM - “memory” to improve quality of video feed over a period of time



Technical Approach cont.

- Convolutional Denoising Autoencoder



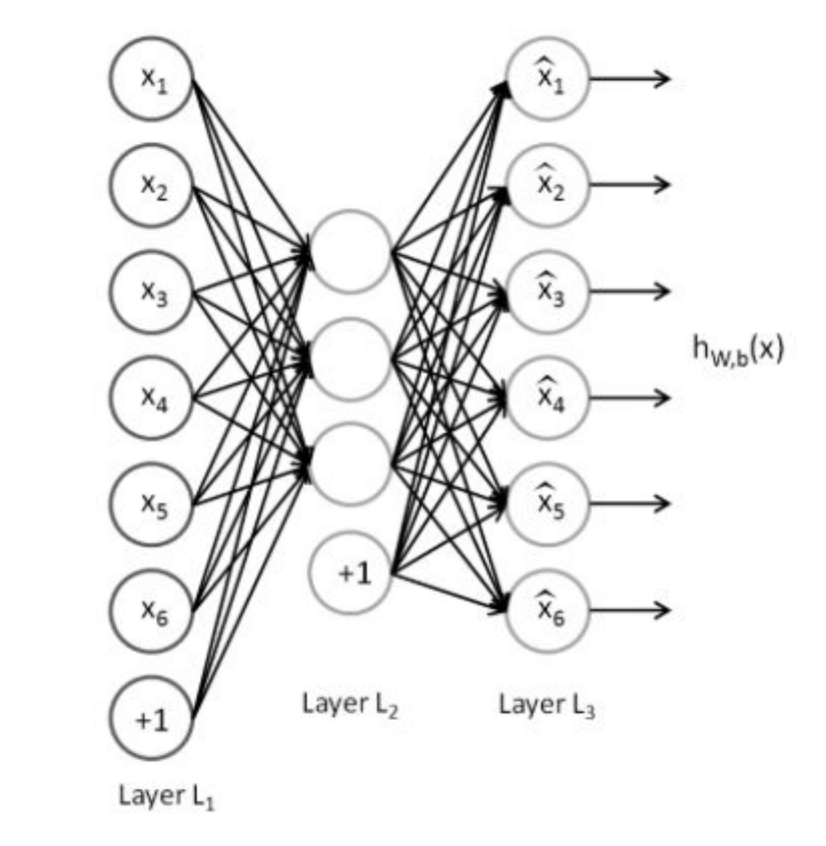


Fig. 1. A basic autoencoder

Deliverables

- Minimum:
  - Simulate a set of x-ray images with varying dose parameters
    - Quantify **dose** received by patient and **image quality**
  - Implemented neural network which can denoise a single image - no prior (Python code + doc)
- Expected
  - Functioning denoising network to improve image quality of a still low-dose image from a high-dose DR
  - Chosen dose profile to minimize dose but maximize image quality
- Maximum:
  - LSTM for continuous fluoroscopy
  - Experiment with scanner in Mock OR or Bayview Lab

Milestones

	Milestone 1	Milestone 2	Milestone 3	Milestone 4
Date	3/18/18	4/1/18	4/15/18	5/6/18
Work	- Generate comprehensive set of simulated x-ray images	- Train a NN to denoise one of the low-dose images	- Analyze image quality/dose/improvability and choose the best dose profile	- LSTM for live fluoroscopy
Deliverable (Measurable)	- Bank of images - Quantified dose/quality relationship for each profile	- An improved low-dose image that can be used in a surgical setting - NN code and documentation	- Chosen dose profile that is realistic, lessens dose received by patient, works with NN	- Set of continuous images improved by the network - Time-analysis of NN performance - Code and documentation
Backup Plan	- Get at least one low-dose profile to work with	- Experiment with various NN architectures, use an established network	- Choose the best profile, go back to milestone 1 and rework parameters	-Improve small sequences of images, move up to video feed

Schedule

PHASE		DETAILS
	Milestone:	
1	Setup and Initial Exepriments	- Read about MCGPU - Access to MCGPU - Preliminary images created
2	NN Research and Initial Architecture	- Research on denoising NNs - Code and documentation - Evaluate results
3	Best dose profile	- Variation of kVp, mAs, filtration - Generation of images - Consulting with physician
4	LSTM	- Research LSTM - Code/train and documentation - Organize produced images + consult physician

FEB				MAR				APRIL					MAY			
4	11	18	25	4	11	18	25	1	8	15	22	29	6	13	20	27

Dependencies

Dependency	Plan to Resolve	Date Expected	Date Needed	Contingency Plan
MCGPU/Python Software	Downloaded (Free)	Complete	-	-
GPU Access for Running MCGPU/Neural Net	Machines (with software) in Navab lab	3/2/18	3/4/18	Work with CPU (slower) until we get access
CT Volumes for Generating X-Ray Images	Downloaded from NIH Cancer Imaging Archive	Complete	-	-

Management Plan

- Weekly meetings with Mathias (when available), Bastian, and Nico
- Team meetings -- biweekly (Monday and Friday)
    - Bitbucket for code management
- Meeting with Prof. Navab/Dr. Osgood when expert knowledge is required
    - i.e. determining whether an image is clear enough for use in surgery

Reading List

- 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.
- 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.
- Dong C., Loy C.C., He K., Tang X. (2014) Learning a Deep Convolutional Network for Image Super-Resolution. In: Fleet D., Pajdla T., Schiele B., Tuytelaars T. (eds) Computer Vision – ECCV 2014. ECCV 2014. Lecture Notes in Computer Science, vol 8692.
- Badal, A. and Badano, A. (2009), Accelerating Monte Carlo simulations of photon transport in a voxelized geometry using a massively parallel graphics processing unit. Med. Phys., 36: 4878–4880.
- 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.
- J. Baro, J. Sempau, J.M. Fernandez-Varea, F. Salvat, “PENELOPE: An algorithm for Monte Carlo simulation of the penetration and energy loss of electrons and positrons in matter,” Nuclear Instruments and Methods in Physics Research Section B: Beam Interactions with Materials and Atoms, Volume 100, Issue 1, 1995, Pages 31-46.
- L. Gondara, "Medical Image Denoising Using Convolutional Denoising Autoencoders," 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW), Barcelona, 2016, pp. 241-246.