A U-Net Framework for Detecting K-Wires in Fluoroscopic Images

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Deep Learning Application Project

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Outline

1. Introduction
2. Methods
3. Results
4. Conclusions

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Background

- Dr. Geb Thomas (IE) & Dr. Don Anderson (BME) run a research team for creating orthopedic simulators.
  - Mimic surgical procedures, score participant.
  - Long-term goal:
    - Reduce surgery training costs and risks.
    - Improve surgical skills and understanding

Motivation

- Establish methodology for objective evaluation of decisions made during surgery.
  - Requires a reliable mechanism for processing images, specifically:
    - The wire's progression across consecutive images, and
    - The final location of the wire, relative to its destination.
  - The issue:
    - Access to this data is not readily available.
    - Processing this data is time consuming.
- Objective:
  - Implement a model that identifies wire's relative wire location.
    - Do without a ground-truth dataset (use synthetic images).

Wire Example

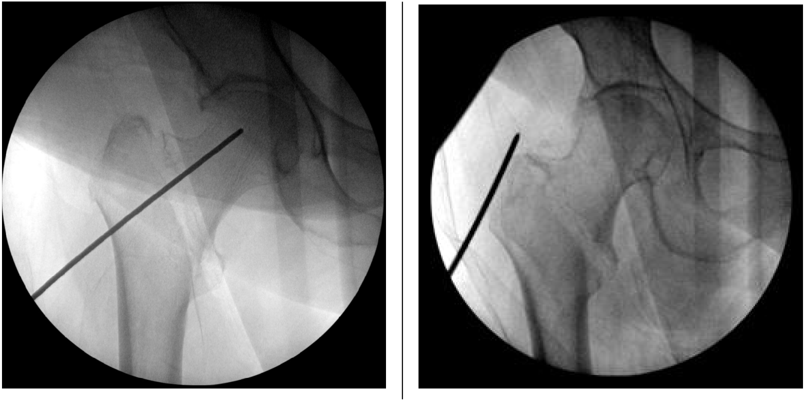

Figure: Real Image (Left); Synthetic Image, 0 Gray Intensity (Right).

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The Data

- A study revealed some merit to training biomed. models w/ **synthetic data**[1]
  - Source Images:
    1. 25% - 385 hip surgery images (in-house).
    2. 25% - 385 X-Ray images (MedPix Database, 7,470 total).
    3. 50% - 770 Random Images (Coco Dataset, 5,000 total).
  - 12,463 synthetic images.
- Random image data augmentations ($8\,\frac{aug}{img}$) include:
  - Bend ($\frac{\pi}{20}$).
  - Duplication (2 aug. wires per image).
  - Translation (x- & y- directions).
  - Reflection (x- & y- directions).
  - Assign gray intensity between 0 (black) and 128 (gray) to wire.
  - 10% chance of being "negative" (e.g. no wire).

[1] Tremblay, J., Prakash, A. Acuna, Brophy, M., et al. *Training Deep Networks with Synthetic Data: Bridging the Reality Gap by Domain Randomization*. Workshop on Autonomous Driving, CVPR-Workshops'18, https://arxiv.org/pdf/1804.06516.pdf

The Templates

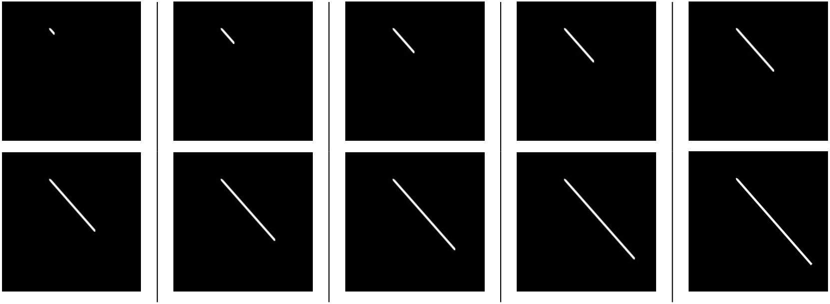

Figure: Original Wire Templates (Initial Template -> Bottom Right).

The Augmentations

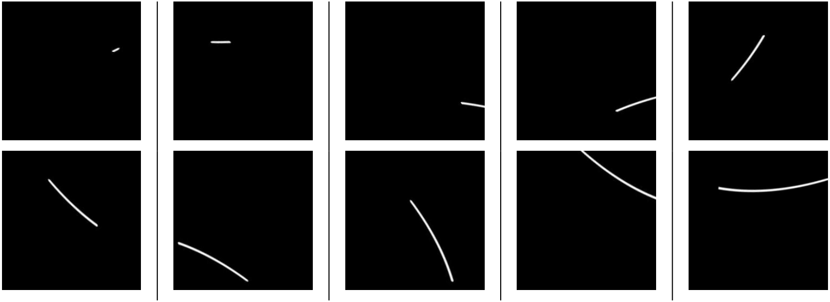

Figure: Wire Augmentations (Initial Template -> Bottom Right).

Example Augmentations

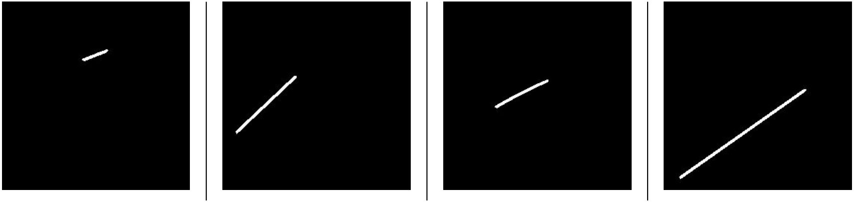

Figure: Images of Augmented Wires (Y_Train).

Example Augmentations

Figure: Images w/ Overlaid Augmented Wires (X_Train).

Heterogeneity of Augmentations

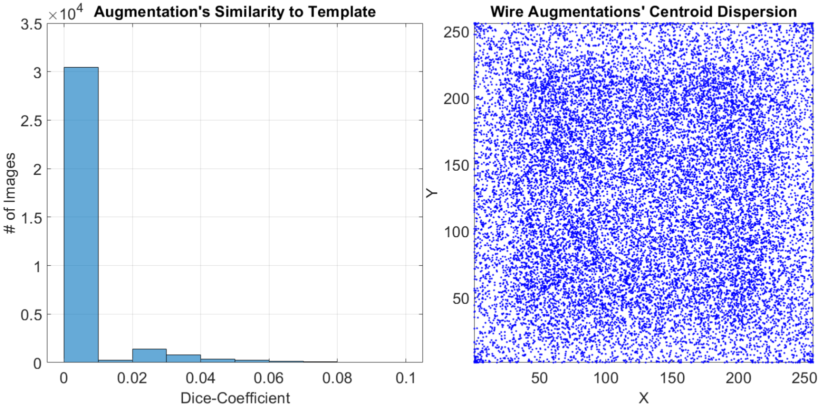

Figure: Augmentation Randomness.

The Model

- U-Net: A fully convolutional network shown to train with high accuracy in biomedical imaging applications.[2]
  - Images resized to [256, 256], normalized.
  - 50 Epochs (twice)
  - Batch Size = 32
  - Validation split = 0.20
  - Adam Optimizer, lr = .0005
  - Layers:
    1. One initial Gaussian Noise (stddev = 0.10)
    2. Contraction Path
       - Contains Dropout to prevent over-fitting
    3. Expansion Path
  - Dice Coefficient = similarity (loss) measurement

$$DSC = \frac{2|X \cap Y|}{X + Y}$$

[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. *U-net: Convolutional networks for biomedical image segmentation*. CoRR, abs/1505.04597, 2015.

U-Net: Convolutional Networks for Biomedical Image Segmentation

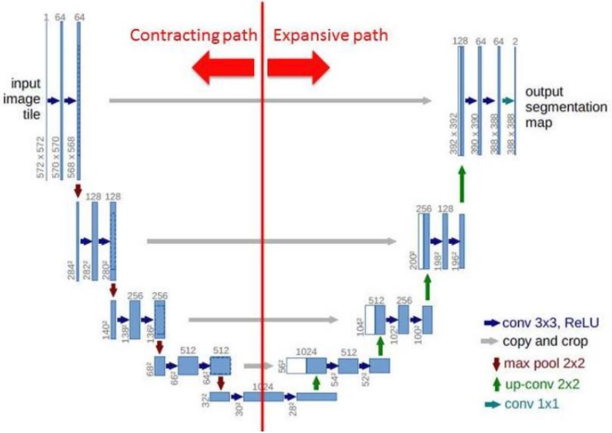

Figure: U-Net Architecture

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Results

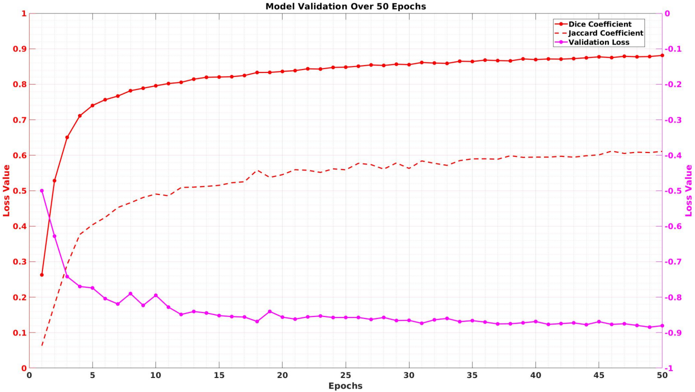

Figure: Validation & Loss per Epoch

Synthetic Data

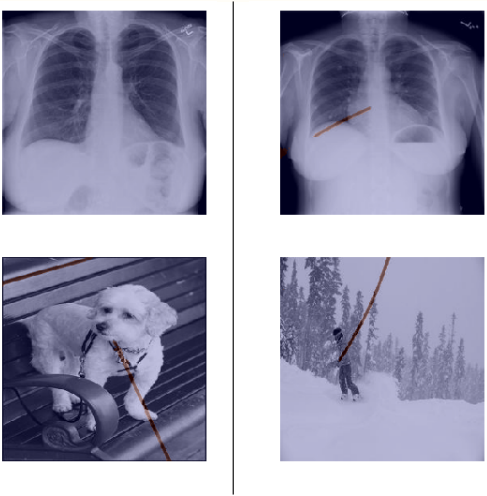

Figure: Model Predictions on Untrained Synthetic Images.

Validation Data

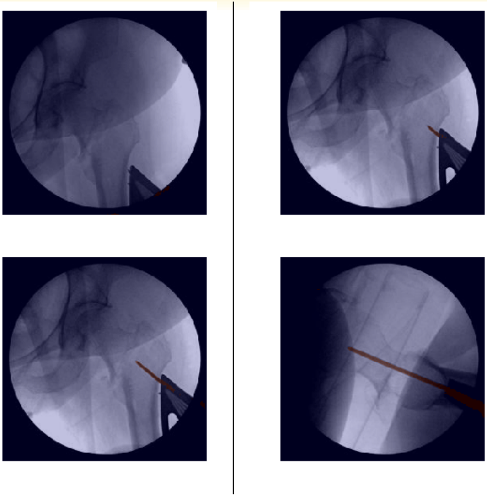

Figure: Model Predictions on Validation Images (Real, No GT).

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Implications

- Synthetic data can be used to train for real medical images (in this context).
- My research:
  - Can begin to track wire over duration of surgeries
    - Better understand decision making of surgeon.

Future Work

- Should work on methodology for generating the synthetic data.
- Should integrate other features.
  - Classify image view (AP v. Lateral).
  - Include other anatomical features.
    - Femoral Head, Neck
    - Pediatric Elbows
    - Wire Nav. etc.
- Might use larger data sets.
- Train on RGB instead of grayscale images?

Acknowledgements

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