CIS II Seminar Report

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CIS II Project Summary

Introducing robotics into the pelvic trauma surgery involves novel challenges, one of them being the guidance of the Kirschner wires (K-wires). K-wires are long and thin deformable stainless steel pointed rods, and due to them often bending during the insertion, impossible to track using the state of the art instrument tracking techniques which assume rigidity of the object. Instead, intraoperative fluoroscopy can be used to image the K-wires to detect and localize them relative to the patient's pelvis' anatomy. In the past, the I-STAR lab has utilized methods such as fitting a B-spline model for K-wire detection on pelvic radiographs; however, these methods were limited in the runtime and accuracy [1]. Our project's aim is to achieve better metrics for K-wire detection and 3D localization on pelvic fluoroscopic images using a deep learning approach.

Paper Selection Motivation

In the last few years, the use of deep neural networks (DNNs) has exploded in the medical image analysis field, with one of the most popular types being convolutional neural networks (CNNs) [2]. The most significant difference of DNNs compared to other image analysis techniques is the amount of data it requires to complete the analysis. To analyze one image, a network must first be trained on a large dataset of thousands of annotated images. As collecting thousands of required images and manually segmenting them is extremely expensive and often impossible, the simulated data is produced and/or existing data gets augmented to produce a much larger dataset. For our project, we have acquired a couple thousands of fluoroscopic pelvic images without k-wires, with a goal of distorting the original images to introduce variations in angles and anatomy and then projecting simulated k-wires onto them to create images with a known ground truth. The goal of our team is not to create a novel deep learning algorithm, but to apply existing architectures on the dataset that we would create. While the k-wire detection on radiographs using deep learning has not been described in the literature prior to this project, the detection of similar objects such as guidewires, which are thinner than k-wires metal wires, has been investigated. In this seminar the I will be reviewing *"Deep learning based guidewire segmentation in x-ray images"(2019)*[3] paper that focused on detecting guidewires on 2D radiographs with a deep learning network that had been trained on a dataset produced with real X-rays and simulated guidewires. As the workflow described in the paper was similar to the one suggested by our mentor, my team found this paper useful for designing our own data simulation and augmentation pipeline.

Goal of the paper

Liver embolization is a hepatocellular carcinoma treatment procedure that involves inserting a catheter into arteries feeding the tumors and injecting microspheres into them to limit their blood supply. The placement of the guidewire that is used to insert the catheter into the patient is conducted using real-time fluoroscopic imaging, which is complex due to the dynamic nature of the arteries. The paper's authors' goal was to perform guidewire segmentation on the X-ray images using deep learning and compare it to the prior methods of such as mask subtraction.

Methods

Real X-ray images were produced from 10 different pigs with 3D digital angiography (3D DSA), each pig producing between 133 and 496 2D images that were processed using 3D DSA's manufacturer's software that utilized line integral algorithms. The images were randomly rotation for ±2.5 °, translation of ±10 pix and magnified/shrank anywhere from 80 to 120%, then cropped to 1024x1024 size. For each 2D X-ray, 32 simulated guidewires were created by generating a random curve inside the reconstructed 3D arteries that was used to create a 3D shape of the guidewire. The wires were then projected onto the X-ray images, and the profile of the guidewire obtain with real fluoroscopy was overlaid onto those projections for realistic attenuation and blurring. The noise was then applied with a spatial correlation standard deviation of 1 pixel and a weighting factor of 0.07 to 0.09. A binary mask with the ground truth of guidewire's location was created for each image.

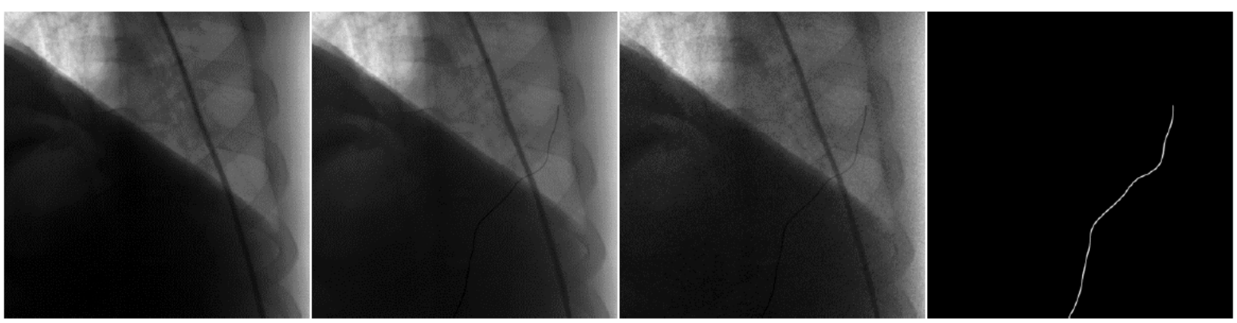

Figure 1 (from right to left): Original 2D X-ray image, 2D X-ray image with a simulated guidewire, 2D X-ray image with a simulated guidewire with noise, ground truth binary mask [3].

SegNet with VGG16 backbone with pretrained weights from Imagenet dataset based softamax optimization function was used as a deep learning network. The network was trained on 60% of the data while 20% of the data was used as validation and 20% as a test dataset. The learning rate for training of 0.001, and L2 regularization of 0.0005 were used on batches of 1 image over 56,768 iterations that overall constituted 1 epoch for the training. The implementation was done in Matlab.

To evaluate the performance of the network, Sorenson-Dice coeffiecient (SDC), false negative rate (FNR), Hausdorff distance (HSDF), and false positive rate (FPR) were calculated.

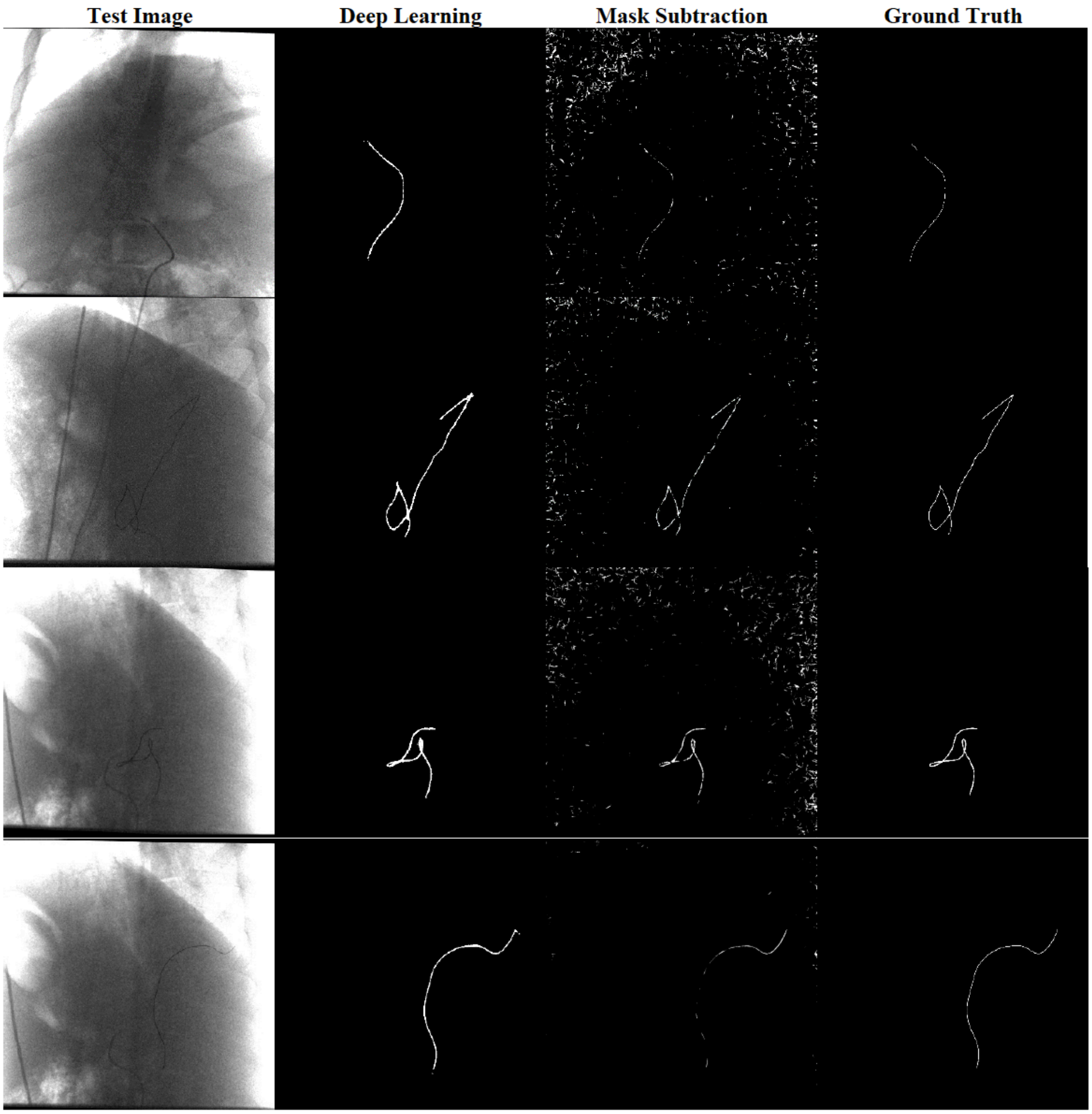

Figure 2 (from right to left): Sample of images from the dataset prediction by deep learning, prediction by mask subtraction, ground truth [3].

Results

Training the network was achieved in 29 hours while a single image prediction tool 0.5s on a single GPU. The results achieved with deep learning were significantly better than obtained with Mask Subtraction algorithm. Some error was attributed to the width of the guidewires: they were often predicted to be thicker than they actually were. However, for the liver embolization this would not constitute a problem as it still presents itself as a continuous object which is the most important quality for guidance.

	SDC	FPR	FNR	HSDF
Deep Learning	58.1%	0.1%	9.6%	16.3 px
Mask Subtraction	23.7%	2.0%	40.8%	90.6 px

Table 1: Summary of evaluation metrics comparison of Deep Learning and Mask Subtraction[3].

Assessment and Relevance

This paper has demonstrated that deep learning can be efficiently used for image segmentation of a thin deformable metal object on 2D radiographs, which is a similar goal of our team's project. They have outlined an approach for data augmentation with the parameters such as translation, rotation, and cropping we used for the design of our own workflow. We also examined their training procedure as a reference for our training of UNet with VGG16 backbone.

The major weakness of this paper is that there has been no testing on the images with real guidewires, as it has only been conducted on the simulated images. Therefore, their findings might not translate into real-life applications. Moreover, there has been no reasoning provided for selection of SegNet based on VGG16 despite there being other alternatives for encoder-decoder based CNN for image segmentation. They have also provided no explanation for the training parameters that they used, which limits their use for my team's purposes as it leaves a lot of room for experimentation. Finally, the paper mentions that all images were sized to be 1024x1024 pixels, but has no mention of the downsampling or upsampling strategy they used, which could have affected the quality of their images and masks. The code was also implemented in MATLAB, which limited the comparison in the speed of the prediction, which is one of the criteria for the success of our project.

Despite these flaws, my team found the paper useful as it provided an extensive outline of their dataset generation, which is one of the deliverables of our project. Furthermore, I found the authors' approach to simulation of the guidewires to be particularly interesting as it involved applying the real textures of the guidewires onto their projections. Although we have not done that for our simulated K-wires, it would be an alternative strategy to pursue if our current workflow that only involves a projection of the shape does not produce satisfactory results.

References

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[2] S. Minaee, Y. Boykov, et al. "Image Segmentation Using Deep Learning: A Survey" arXiv:2001.05566v4

[3] Wagner, Martin G., et al. "Deep Learning Based Guidewire Segmentation in x-Ray Images." Medical Imaging 2019: Physics of Medical Imaging, 2019, doi:10.1117/12.2512820.