# Jin Huang

#### **Personal Information**

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**RA Period:** From 2017-02 to 2018-05

### **Biography**

I'm a Ph.D. student at University of Notre Dame. Before that, I was a research assistant in NYU Multimedia and Visual Computing Lab, advised by Professor Yi Fang. I am broadly interested in 3D Computer Vision, Pattern Recognition and Deep Learning.

# M.S. Thesis: Med-A-Nets: Simultaneous Segmentation of Multiple Organs with Deep Adversarial Networks

## 1 Description

Deep learning has become a dominant powerful technique in solving a wide variety of tasks from almost all fields as diverse as computer vision, image processing and language processing. One of the mainstream has primarily focused on the application of deep learning driven medical image analysis. In this thesis, we introduce a novel adversarial training strategy to train deep neural networks for the segmentation of multiple organs present in an image simultaneously. We developed a novel deep adversarial network, named Med-A-Nets, that jointly train a set of convolution neural network (CNN) and an adversarial discriminator for the robust segmentation of multiple organs observed in images. More specifically, the generator produces image segmentation map of multiple organs in the image by finding the optimal alignment with the ground truth segmentation map, whereas the discriminator, learned from ground truth segmentation map, tends to penalize the segmentation map produced by the generator. The generator and discriminator compete to each other in an adversarial learning process until the equivalence point is reached to produce the optimal segmentation map of multiple organs. By addressing the challenges posed by segmentation of multi- organs medical image, Med-A-Nets demonstrates superior performance on standard datasets.

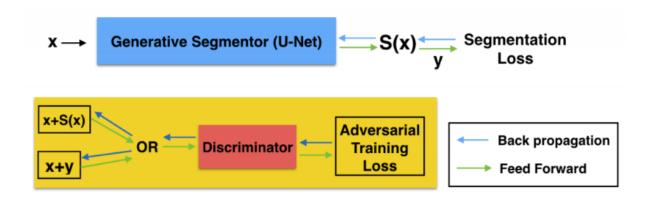


Figure 1: the pipeline of the training and the loss.

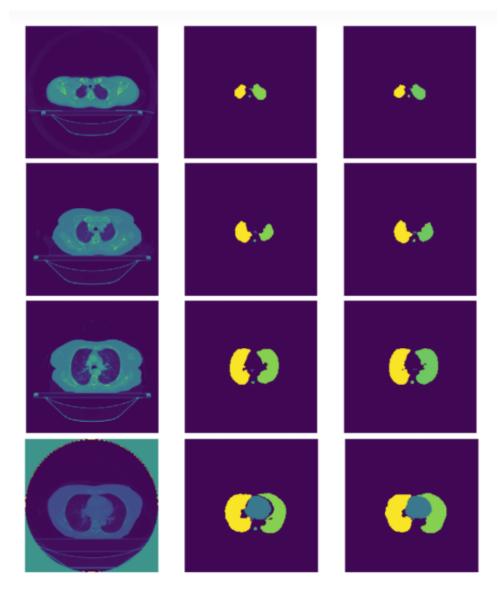


Figure 2: Good segmentation results of TICA dataset.

### 2 Method

In this project, we introduce a novel adversarial training strategy to train deep neural networks for the segmentation of multiple organs present in an image simultaneously. The adversarial training is the compete between the generator and the discrimi- nator; we construct generator loss and discriminator loss for the training process. As displayed in Figure.1, x is the input image, which is then taken by the generative segmentor (U-Net) and become a segmentation map S(x). The plus operator in the figure stands for "concatenation";input image x will concatenate with either the generated segmentation map or the ground truth mask y, and sent into the discriminator for adversarial learning (yellow region).

The green flow is the feed forward and the blue flow stands for back propagation.

### 3 Results

In this section, we demonstrate superior performance of Med-A-Nets on standard datasets by addressing the challenges posed by segmentation of multi-organs medical image. Figure.2 shows some examples of satisfied segmentation results. We can see not only the large organs e.g. Lungs are well

Dice Score (0~1), the larger the better					
	Spinal Cord	Lung_Right	Lung_Left	Heart	Esophagus
U-Net	0.4926	0.6002	0.6500	0.5927	0.2355
U-NET+GAN	0.5074	0.6418	0.7003	0.6129	0.2387
State-of-the- art	0.5701	0.6679	0.6839	0.5449	0.2778

Table 1. statistical evaluation of TICA dataset.

segmented, but also the smaller organs e.g. spinal cord can be segmented out. The first column is orig- inal image, the second column is ground truth mask, the last column is segmentation result. Table 1 shows the statistical evaluation of the TICA dataset. Overall speaking, the segmentation results on larger organs e.g. lungs and heart are better than those on smaller organs e.g. spinal cord and esophagus. This matched our intuition since it is easier to segment large area than small area. The evaluation on dice coefficient shows the model achieves 0.5074 for spinal cord, 0.6318 for right lung, 0.7003 for left lung, 0.6129 for the heart and 0.2387 for esophagus.