Project Proposal
The Domain Shift Problem of Medical Image Segmentation and Vendor-Adaptation by Unet-GAN

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November 6, 2019

1 Papers and Results:

The objective of this project is to reproduce the paper:- Wenjun Yan and Yuanyuan Wang.:*"The Domain Shift Problem of Medical Image Segmentation and Vendor-Adaptation by Unet-GAN."* arXiv:1910.13681v1. Few additional papers we would refer for background understanding:

- **To understand Unet:** Olaf Ronneberger, Philipp Fischer, and Thomas Brox.:*"U-Net: Convolutional Networks for Biomedical Image Segmentation."* arXiv:1505.04597v1.
- **To understand GAN**: Jun-Yan Zhu and Taesung Park.:*"Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks."* arXiv:1703.10593.

  Results The results we want to achieve are in terms of segmentation performances of LV Unet on datasets from different domains. In the paper, the performance of LV segmentation was evaluated in terms of Dice overlap index between the ground truth and the segmentation results. Three scenarios are compared: Clean Unet, Noisy Unet and Unet-GAN.

Dice	Clean Unet	Noisy Unet	Unet-GAN
Philips (test)	0.892 ± 0.032	0.877 ± 0.034	-
Siemens	0.474 ± 0.071	0.502 ± 0.064	0.805 ± 0.041
GE	0.727 ± 0.042	0.813 ± 0.040	0.867 ± 0.035

2 Pathwork and Tools:

- **Preliminary Path:**
  - Firstly, the Unet is trained by data from the source domain(Philips data) with sufficient annotation. The performance from the test set from the same source domain is recorded to ensure it is up to the state-of-the-art.
  - The generators and discriminators in Unet-GAN are trained alternately using unannotated data from both source and target domains(Siemens and GE data)
  - Finally, data from the target domain will be first translated to the source domain by source generator of GAN and then fed to the trained Unet for segmentation.
  - **Result Evaluation** We Perform Segmentation of the target domain by LV Unet trained on the clean source domain and then by polluted source domain (original data added with random noise). We will then translate data of the target domain by Unet-GAN to the source domain, then segment the translated data by the Unet trained on the clear source data.
- **Data:** Short-axis steady-state free precession (SSFP) cine MR images of 144 subjects acquired by three major MRI machines as three domains (44 Philips samples, 50 GE samples, 50 Siemens samples). The number of available annotated images in each domain is 4823, 2084, and 2602 for Philips, GE, and Siemens respectively.
- **Tools:** Python, Tensorflow, Tensorboard, Pandas and Numpy

3 Work Allocation:

- **Cody Crofford:** Implementation and training of Unet
- **Sonal Jha:** Implementation and training of GAN
- **Saikat Dey:** Experiments and optimizations associated with Unet-GAN segmentation
- **All**: Aggregation of results for validity