ARUNA: Generative Adversarial Networks for head and neck CT Image Auto-Segmentation

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♦ Introduction

Accurate segmentation of organs at risks (OARs) is an essential step for the planning of radiation therapy for head and neck (H&N) cancer treatment. However, this procedure is mostly carried out manually in the clinic, and the average physician's time to fully contour a single head and neck case is approximately 2.7 hours[1]. Automatic segmentation of OARs is a challenging task due to the low contrast of soft tissue, artifacts in CT images, and limited labeled slices for training. To deal with the problems, we propose the first conditional generative adversarial network (cGAN)[2] based algorithm, for automatic segmentation of OARs in H&N CT images.

♦ Methods & Materials

Network

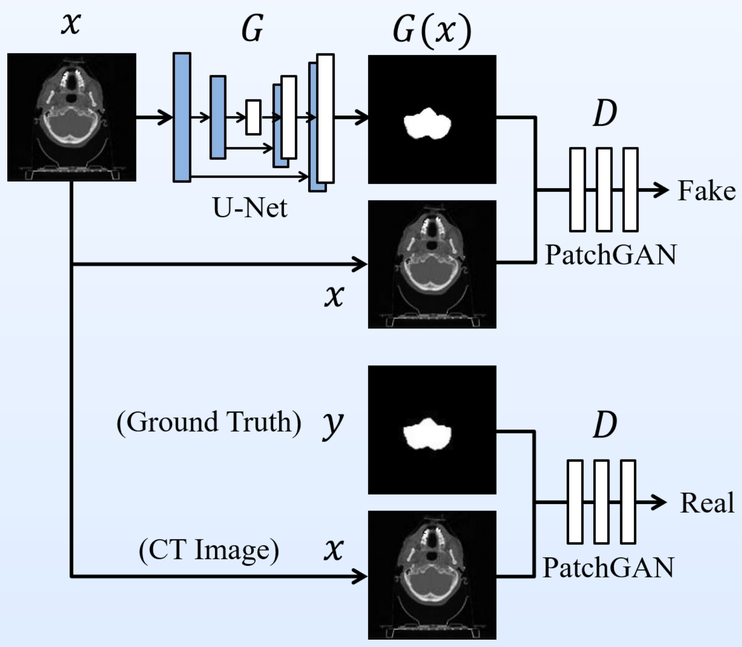

Fig.1 Network structure

- Conditional generative adversarial networks learn a mapping from observed image x and random noise vector z, to output image y. The generator network *G* tries to generate realistic segmentation slices given a CT slice. The discriminator network *D* is shown a CT slice and a segmentation slice, and must determine if the segmentation slice is real or generated.
- The objective function of our network is:

$$G^* = argmin_G max_D L_{cGAN}(G,D) + \lambda L_{L1}(G)$$
$$= argmin_G max_D \left(\mathrm{E}_{x,y}\left[\log\left(D(x,y)\right)\right] + \mathrm{E}_{x,z}\left[\log\left(1 - D\left(x, G(x,z)\right)\right)\right]\right)$$
$$+\lambda \mathrm{E}[\|y - G(x,z)\|_1]$$

- The network was trained on slices which were resized to 256x256.

Dataset

- 39 patients' H&N CT images were acquired from the clinic.
- 27 were used for training, 6 were used for testing, and another 6 were used for validation.
- Each image was provided with a manual segmentation of the organs it contained, which was used as a ground truth in this work.

♦ Acknowledgements

I would like to thank the UCLA CSST Program for offering this opportunity of cross-disciplinary research.

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♦ Results

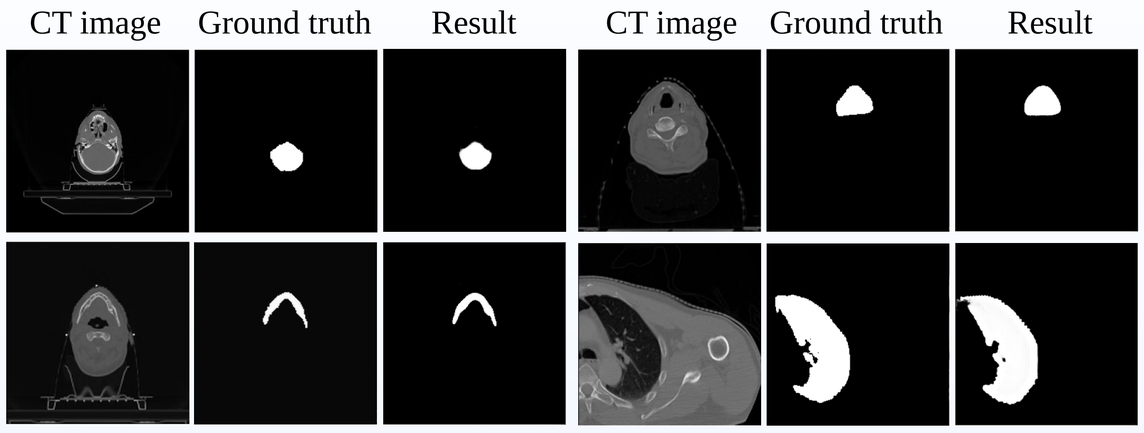

Fig.2 Qualitative illustration of our segmentation results on brain (upper left), larynx (upper right), mandible (lower left) and lung (lower right). The ground truth was created by experts manually.

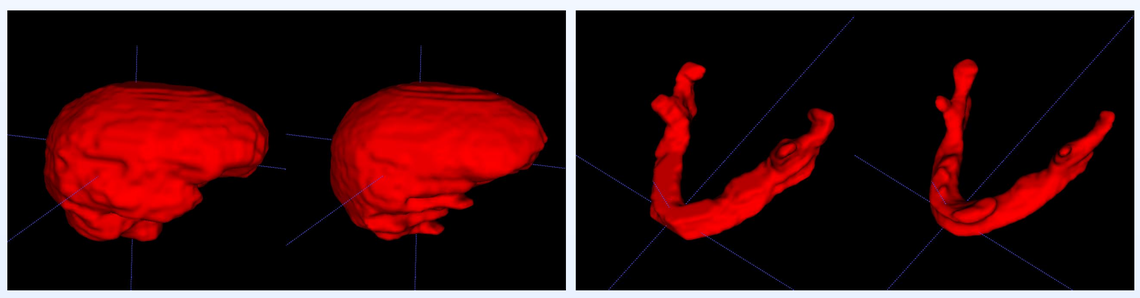

Fig.3 3D illustration of our segmentation results on brain and mandible. In each pair, the left image is ground truth, and the right image is our result.

Organ	Dice	Precision	Recall	Specificity
Brain	93.40%	92.68%	94.13%	99.93%
Left lung	93.29%	92.95%	93.63%	99.82%
Right lung	93.83%	94.60%	93.07%	99.83%
Mandible	79.45%	79.45%	79.44%	99.86%
Left parotid	77.58%	76.43%	78.76%	99.79%
Right parotid	71.44%	71.33%	71.56%	99.75%
Cord	72.07%	81.52%	64.58%	99.97%
Brainstem	68.37%	69.22%	67.53%	99.16%
Pharynx	67.39%	68.13%	66.66%	99.91%
Larynx	87.21%	87.07%	87.35%	99.77%
Left eyeball	86.07%	88.04%	84.18%	99.78%
Right eyeball	82.18%	83.63%	80.77%	99.92%

♦ Conclusion

We presented the first attempt at using cGANs for segmentation of OARs in the head and neck CT images. We observed that cGANs demonstrated qualitatively and quantitatively good performance on segmentation of brain, lungs, mandible, parotids, cord, brainstem, pharynx, larynx, and eyeballs. In the future, experiments on better-labeled datasets will be conducted, and a user interface will be developed.

♦ References

[1] Qazi, A. A., Pekar, V., Kim, J., Xie, J., Breen, S. L., & Jaffray, D. A. (2011). Auto-segmentation of normal and target structures in head and neck CT images: A feature-driven model-based approach. Medical physics, 38(11), 6160-6170.
[2] Isola P, Zhu JY, Zhou T, Efros AA. Image-to-image translation with conditional adversarial networks. Proc-30th IEEE Conf Comput Vis Pattern Recognition, CVPR 2017. 2017;2017-Janua:5967-5976. doi:10.1109/CVPR.2017.632.