Technical Report on Multi-class Segmentation

Jing Zhang

September 2019

1 The work of week

First, I have learned the structure of heart. In this application, the heart has 3 parts: Myocardium, Left atrium and Left ventricle. So in this work, we aim to perform multi-class image segmentation using deep learning method to segment this 3-class image. During the work, I have implemented 4 types of loss functions, Cross entropy loss, Focal loss, Dice loss and Kappa loss, which are little different from binary segmentation. What's more, I figured out some evaluation methods that often come up in some papers. The work is done in Colab because Colab can show the figure and curve immediately while the remote server on Linux can't do that.

In terms of papers. This week I read two papers. First one is AnatomyNet, which they combine Dice loss and Focal loss into one equation [3]. The other is Learning Active Contour Models for Medical Image Segmentation, which they use energy equation in the active contour as loss function in deep learning method [1].

2 Loss functions

- Cross entropy loss

$$CE = -\sum_{c=1}^{M} g_{i,c} \log p_{i,c} \tag{1}$$

- Focal loss

$$FC = -\sum_{c=1}^{M} (1 - p_{i,c})^{\gamma} g_{i,c} \log p_{i,c} \tag{2}$$

- Dice loss

$$Dice = \sum_{c=1}^{M} (1 - \frac{2p_{i,c}g_{i,c}}{p_{i,c} + g_{i,c}}) \tag{3}$$

- Kappa loss

$$Kappa = \sum_{c=1}^{M} (1 - \frac{2\sum_{i=1}^{N} p_{i,c}g_{i,c} - \sum_{i=1}^{N} p_{i,c} \cdot \sum_{i=1}^{N} g_{i,c}/N}{\sum_{i=1}^{N} p_{i,c} + \sum_{i=1}^{N} g_{i,c} - 2\sum_{i=1}^{N} p_{i,c}g_{i,c}/N}) \tag{4}$$

Table 1: Positive and negative predictive values

		True condition	
	Total number	Condition positive	Condition negative
Predicted condition	Predicted condition positive	True positive (TP)	False positive (FP)
	Predicted condition nagative	False negative (FN)	True negative (TN)

3 Evaluation metrics

- Dice coefficient

$$\text{Dice metric} = \frac{2 * |A \cap B|}{A \cup B} \tag{5}$$

- Accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{6}$$

- Specificity

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{7}$$

- Sensitivity

$$\text{Sensitivity(Recall)} = \frac{TP}{TP + FN} \tag{8}$$

- Precision

$$\text{Precision} = \frac{TP}{TP + FP} \tag{9}$$

4 Experiments

4.1 Data set

The data set used in this work is coming from Cardiac Acquisitions for Multi-structure Ultrasound Segmentation (CAMUS) database[2], which is the largest publicly-available and fully-annotated data set for 2D echocardiographic assessment. The CAMUS data set, containing 2D apical four-chamber and two-chamber view sequences acquired from 500 patients.

4.2 Protocol

References

[1] Xu Chen, Bryan M Williams, Srinivasa R Vallabhaneni, Gabriela Czanner, Rachel Williams, and Yalin Zheng. Learning active contour models for medical image segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 11632–11640, 2019.

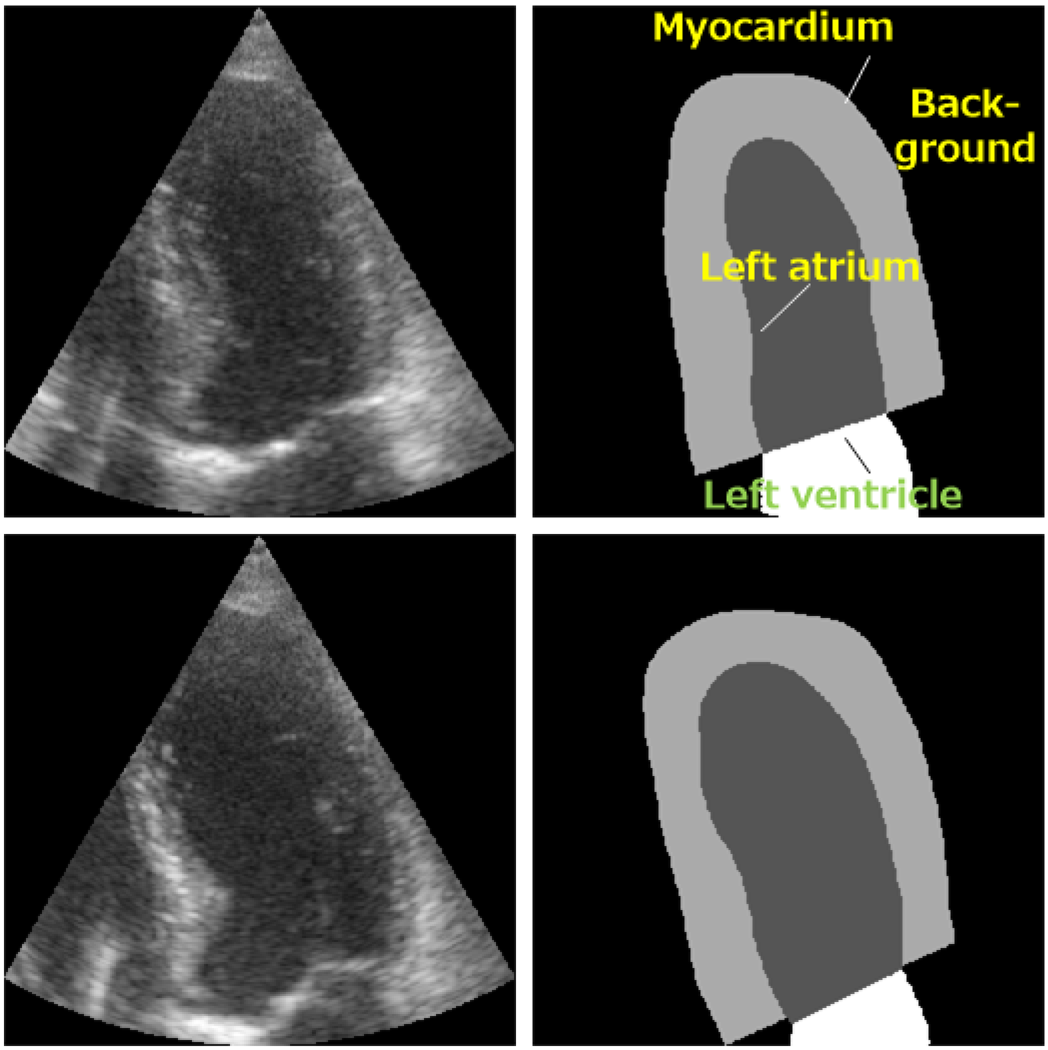

Figure 1: The echocardiographic and its label.This echocardiographic up is the End systole (ES) stage, the down is the End diastole (ED) stage It consists of 3 parts: Myocardium, Left atrium and Left ventricle.

[2] Sarah Leclerc, Erik Smistad, Joao Pedrosa, Andreas Østvik, Frederic Cervenansky, Florian Espinosa, Torvald Espeland, Erik Andreas Rye Berg, Pierre-Marc Jodoin, Thomas Grenier, et al. Deep learning for segmentation using an open large-scale dataset in 2d echocardiography. *IEEE transactions on medical imaging*, 2019.

[3] Wentao Zhu, Yufang Huang, Liang Zeng, Xuming Chen, Yong Liu, Zhen Qian, Nan Du, Wei Fan, and Xiaohui Xie. Anatomynet: Deep learning for fast and fully automated whole-volume segmentation of head and neck anatomy. *Medical physics*, 46(2):576–589, 2019.