Efficient and Robust CT Image Segmentation with a Level Set Network

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Introduction

Medical image segmentation remains a difficult task: liver segmentation from abdominal CT scans is often done by hand, requiring too much time to use to treat hepatocellular carcinoma. Previously, image segmentation was done by solving the level set equation, a partial differential equation (PDE) describing how a boundary curve evolves given an image[1]. Level set methods succesfully capture clear edges and are robust to perturbation, due to the underlying structure of the PDE. In contrast, deep convolutional neural networks (DCNN) are susceptible to large changes in output given small perturbations of input[2]. Despite this drawback, DCNNs are increasingly popular for liver segmentation.

Approach and Methods

We unrolled an iterative method for solving the level set equation, creating a *level set network*. In this framework, each iteration becomes a layer in a DCNN. The correct curve evolution is then 'learned' by the neural network. By definition, the output of this network solves the level set equation, and is therefore robust to perturbation. To test this method, we employed three segmentation methods on the MICCAI 2017 LiTS Challenge dataset[3], consisting of 131 abdominal contrast-enhanced CT image stacks. These methods were: UNet[4], a type of DCNN; ITK-SNAP[5], a segmentation application using the level set equation; and our level set network (LSN). For UNet and LSN, we performed a 5-fold cross validation. In each fold, the selected LiTS data were split into training (90% of 4 remaining folds) and testing (10%). These networks trained via the Adadelta optimizer until saturation (40 epochs for UNet, 20 for LSN), with the Dice Similarity Coefficient (DSC) as the loss function. For ITK-SNAP, which allows users to hand-tune a few parameters, we allotted 10 min for a user to alter these parameters to achieve the best segmentation, after which ITK-SNAP solved the level set equation until DSC no longer improved.

Results

After performing the described methods, we obtained the following DSC scores.

Method	UNet	ITK-SNAP	LSN
# Parameters	32M	3	69K
Avg DSC	0.955	0.745	0.804

Table 1: Parameters and DSC scores from three segmentation methods.

Conclusions

We observed that LSN achieved an average DSC score superior to ITK-SNAP, but below UNet. However, LSN guaranteed robustness to perturbation due to its analytical structure.

References

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