3D convolutional network for automated prostate segmentation on MR images

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Abstract

Prostate segmentation is a challenging task because of the large variations of shapes and texture of the organ. We proposed a method based on a 3D deep neural network. The segmentation is performed by a fully convolutional network, in one forward pass.

1 Introduction

Accurate segmentation of prostate from MR exams would be a great help in the diagnosis of diseases as for instance prostate cancer. In the following will be given a dry description of our methods, a more complete comparison with the state of the art is ongoing.

2 Methods

2.1 Data preprocessing

The following preprocessing steps are applied before giving a volume to the network:

- Resolution normalization
- Intensity distribution normalization
- Cropping if the volume above a maximum size (for memory issues)

2.2 Network architecture

The network used is the variation of the volumetric ConvNets with mixed residual connections (cf [6]), without the intermediary predictions and with a smaller number of filters. We used 4 layers (*id est* 3 max pooling layers), with 32 filters on the first layer. Convolutional filters were 3*3*3.

2.3 Training

We kept 20% of the training set as for the validation. We trained the network on full preprocessed volumes, one at each iteration (for memory issues), without augmentation.

3 Results

We obtained a mean Dice of 85.9 on the testing set, compared to 92.0 on the training set.

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