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【Abstract】

We propose a novel framework, multi-path U-Net, that is more suitable to complete the PROMISE 12 challenge. The segmentation method is based on U-Net architecture with incremental training methods, which has successfully segmented all the test data and reached a good accuracy.

【Method】

1. Pre-processing

We employed the MICCAI-PROMISE12 dataset, which totally consists of 80 T2 MRI scans (50 training and 30 testing). This data set obtained from multi-center and multi-vendor studies, which have different acquisition protocols (i.e., different slice thickness, with/without endorectal coil). The first thing we do is to adjust the window width of each data, and then map the gray value and size to the same level. In this way, all the data yield to the same distribution, which is good for training a more robust network.

2. Data Augmentation

On the one hand, we performed online augmented with randomly rotation, flipping, and mirroring. Each data in every training iteration will has a different way of data augment, which can effectively reduce the overfitting phenomenon caused by insufficient numbers. On the other hand, we select the subsampling regions with different locations of the prostate as the training data.

3. Network Structure

According to the existing U-Net architecture, we propose a novel framework, multi-path U-Net, that is more suitable for solving our current problems. Our net employs both short-range and long-range residual connections, which help to avoid overfitting and to achieve good performance.

By deepening the structure of U-net, our final feature map output ends up being 32 times smaller in each spatial dimension than the original image, to learn more deeply features. In the down-sampling path, we repeat max-pooling 5 times with stride2, obtaining features that are roughly 1/2,1/4,1/8,1/16 and 1/32 of the original image size. Likewise, we custom symmetric methods to deal with the up-sampling path.

In order to take full advantage of the features of the middle layers, we add some skip-connections to our network. Specifically, we directly perform transpose convolutions on multi-level features for 4,8,16 and 32 times to get the original size and concatenate together with the last up-sampling path results before last two convolution layers and loss layer. It is these residual connections make our multi-path U-Net method more robust in the face of overfitting.

4. Training

The hyperparameters of our method are depicted in Table I.

Our network is trained by a gradual learning strategy. In this way, we try to use different training sets with corresponding learning rate to control the process of training. In the first phase, we only sample the slices alignment with the prostate position and assign a weighted loss to each pixel, to balance frequency between negative and positive and force the network to learn the border pixels more. In the second phase, we add other position sub-samplings, which also contain the prostate region, into our training data. In the last phase, we replace the frequency balancing and use a lower learning rate (i.e., 10e-6 in our experiments) for training the model. Step by step training alleviates the problem of overly suppressing the negative samples and learn much better results, greatly avoiding the overfitting.

TABLE I

HYPERPARAMETERS OF THE PROPOSED METHOD

Stage	**Hyperparameter**	**Value**
Initialization	bias	0.1
	weights	Xavier

Dropout	p	0.85
Training	v	0.9
	Initial ε	0.001
	Final ε	0.000001
Loss Function	Softmax	

【Evaluation】

We have keep 4 samples(Case 00, 01, 03 and 49) from the training set, to use them as test set. The simple test results are described in Table II. After choosing the parameters and measure the effectiveness of the training, we also add these four examples into the training set to train the final network.

TABLE II

RESULTS OF THE PROPOSED METHOD

DSC	PPV	Sensitivity
0.89±0.02	0.88±0.05	0.90±0.07