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Coordinates Encoding Networks: an Image Segmentation Architecture for Side-viewing Catheters

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Abstract: Side-viewing catheter-based medical imaging modalities are used to produce cross-sectional images underneath tissue surfaces. Mainstream side-viewing catheters are based on Optical Coherence Tomography (OCT) or Ultrasound, and they are often applied to the luminal environment. Automatic lumen segmentation is crucial for real-time diagnosis with side-viewing catheters, but it is also providing geometry information for tasks like robotic control and lumen assessment. In this work, we propose a novel semantic segmentation deep neural networks based on explicit coordinates encoding, which is named CE-net. It largely reduces computational consumption and produces clean segmentation by explicitly encoding the boundaries coordinates in one shot. CE-net is based on a parallel encoding and fusion strategy that predicts boundary coordinates at individual endoscopic catheter scanning line (A-line). In the experiment, it achieves a high speed of around 8 ms per frame while maintaining robustness. We propose a data generation method that helps generalize the CE-net, which show considerable performance by just training with 1.6% of annotated images in the dataset. Moreover, the CE-net can be applied to more challenging problems than the lumen segmentation task, since it can be directly adapted to predict multi-layer boundaries without modifying the network architecture.

Key words: Lumen Segmentation, Deep learning, Side-viewing catheter, Real-time Image Processing

Method and Results

Automatic segmentation of tissue contour in side-viewing catheter images is important for real-time diagnosis or off-line image analysis in the case of both Optical Coherence Tomography (OCT) or Ultrasound. State-of-the-art deep learning methods for segmentation are mainly pixel-wise segmentation based on U-net, which is not efficient for the lumen or tissue boundary segmentation task of side-viewing helical scanning images.

We tailor Deep Neural Networks (DNN) for the side-viewing catheter in luminal tissue. To improve the efficiency of lumen contour segmentation and to directly provide the relative distance between luminal tissue and scanning center, we propose a novel DNN architecture based on explicit coordinates encoding networks (CE-net). The proposed CE-net directly encodes the polar domain OCT image into a coordinates vector representing the position of object contour, without detection networks or pix-wise segmentation nets.

To utilize the advantage of Generative Adversarial Networks (GAN) in the usage of conditional information, we additionally train discriminator by an encoding transformation, which transforms the coordinates encoding segmentation into a pix-wise one-hot encoding segmentation. The discriminator uses the original image and the pix-wise segregation as a pair to evaluate segmentation based on a special loss function designed for coordinates encoding.

We propose a data generation method for side-viewing catheter images that help generalize the CE-net. The generation method enriches the dataset with annotations and changes the geometry distribution of the training set. By doing so, the trained networks achieve good performance in different luminal situations. The proposed pipeline shows considerable performance by just training with 50 images from each subset (1.6% labeled images for most challenging train-validation dividing). With Dell 7540 precision laptop, CE-net achieves good robustness and speed trade-off with an interference time of 8ms. Moreover, the CE-net shows potential for a layer segmentation task besides the lumen segmentation task, since it can be directly adapted to predict multi-layer boundaries without modifying the network architecture.

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