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3D Modeling of Coronary Lumen Structure by IoU Optimization in Deep Neural Network

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1. Introduction

Intravascular Ultrasound (IVUS) is a useful technique to evaluate the detailed vascular structure changed by ischemic heart diseases[1)]. On the other hand, Fractional Flow Reserve (FFR) examination is also used to evaluate the hemodynamics at the narrowed coronary artery[2)]. However, performing both IVUS and FFR requires enormous resources and thus is difficult in the clinical practice[3)]. Therefore, methods to estimate FFR from IVUS-derived anatomical structures have been proposed. To extract the anatomical structure from IVUS data, it is essential to establish to trace the arterial wall in the images, and deep learning models that automatically trace the arterial wall have been reported[4,5)]. In such cases, noise and artifacts may prevent proper segmentation[6)]. In this study, we focused on the imbalance in the number of pixels between the vessel lumen (foreground) and other areas (background) for segmentation of the arterial wall from IVUS images using a deep learning model. When performing segmentation on images with an imbalance in the number of pixels in the foreground and background, the general loss function may not be able to correctly perform optimization for the region of interest. Therefore, in the optimization of neural network models, we adopted an approach that directly optimizes Intersection over Union (IoU), a standard segmentation evaluation metric[7)]. The purpose of this study was to verify the effectiveness of the proposed optimization method for segmenting the vascular lumen from IVUS images and constructing the 3D models of the blood vessels.

2. Materials and Methods

2.1 IoU Optimization in Deep Neural Network

Many image segmentation methods using CNN employed the cross-entropy loss function during training to enable multi-class segmentation[8)]. On the other hand, our study only needed two-class segmentation (i.e., the inside and outside of the vasculature) and thus the accuracy using IoU was important. Therefore, in this study, an IoU loss function was introduced to optimize the neural network to produce the best IoU score for the trained data. The IoU is usually defined as follows,

$$IoU = \frac{TP}{FP + TP + FN} \quad (1),$$

where TP, FP, and FN refer to the number of true positive, false positive, and false negative pixels, respectively[7)]. Since equation (1) is non-differentiable and cannot define its back propagation, we used the IoU approximation method proposed in a previous study[7)]. Let $V = \{1, 2, \ldots, N\}$ be the set of all pixels in all training dataset, X be the output value from the neural network and $Y \in \{0, 1\}^V$ be the ground-truth value of the set V, where 0 represents a background pixel and 1 represents a pixel in the lumen of a blood vessel. Then IoU value was approximated as follows,

$$IoU = \frac{I(X)}{U(X)} \quad (2)$$

$$I(X) = \sum_{v \in V} X_v Y_v \quad (3)$$

$$U(X) = \sum_{v \in V} (X_v + Y_v - X_v Y_v) \quad (4).$$

Finally, the IoU loss function was defined as follows,

$$L_{IoU} = 1 - IoU = 1 - \frac{I(X)}{U(X)} \quad (5).$$

2.2 Experimental Setup

The data used for training and testing the neural network consisted of 3027 IVUS images from 53 subjects. The imaging was performed with a 60 MHz imaging catheter (AltaView for Terumo Corp., Japan) and a mechanical IVUS system (VISICUBE for Ueda Japan Radio Corp., Japan) as a part of the routine examinations at the Gifu Heart Center. The data collection was approved by the local ethics committee. The ground-truth of the arterial wall boundaries in all images was determined manually by a skilled technician. The labeled IVUS images were divided into 2115 images (from 35 subjects) for training and 912 images (from 18 subjects) for testing. The training images were pre-processed by data-augmentation techniques such as rotating and flipping to simulate a six-fold increase in the number of training images. As the CNN model for this study, U-Net[9)], a semantic segmentation model for medical images, was used.

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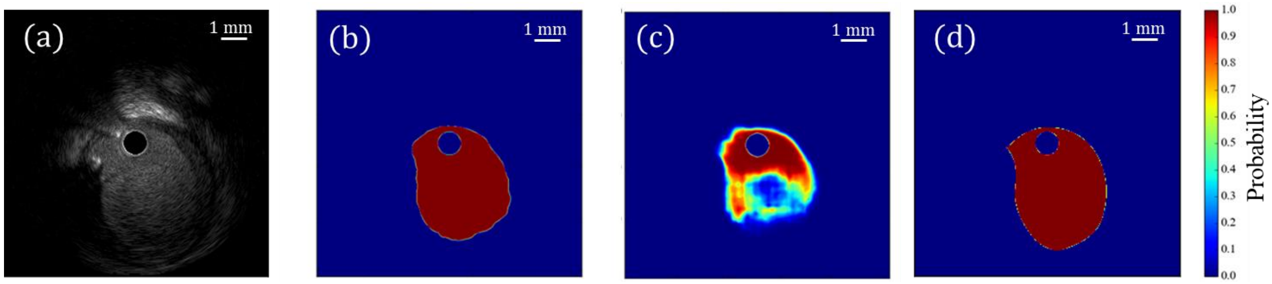

Fig. 1 An example of an image in which the introduction of the IoU loss function improved the segmentation accuracy of the lumen region of a vessel; (a) IVUS image , (b) IoU loss model ($IoU = 0.892$), (c) Binary cross-entropy loss model ($IoU = 0.482$), and (d) Ground truth.

2.3 Evaluation Criteria

To verify the change in segmentation accuracy with the introduction of the IoU loss function, we calculated the IoU scores of the test data when training with the general loss function (binary-cross entropy loss function) and when using the IoU loss function. In addition, to verify the accuracy of the 3D modeling of the lumen structure of the blood vessel, we used Root Mean Square Error (RMSE) to evaluate the error between the modeling results with the binary-cross entropy loss function and with the IoU loss function and the true values using the lumen regions labeled by the technicians.

3. Results and Discussion

The average IoU achieved by the trained model with the IoU loss function was 0.865 ± 0.106. Since the average IoU using the binary-cross entropy loss function was 0.834 ± 0.103, the trained model using the IoU loss function showed improved accuracy in terms of the IoU index. In addition, the model using the IoU loss function specifically produced better classification results for some images than the model using the binary-cross entropy loss function. An example is shown in **Fig. 1**. This result suggests that the introduction of direct estimation of indices for the segmentation problem for IVUS images may lead to more robust segmentation against artifacts present in IVUS images (e.g., guidewires, and motion blurs).

For the 11 cases with more than 50 frames of labeled images in the test data, the RMSE of the reconstructed lumen structures was 118.2 ± 40.5 µm for the trained model using the IoU loss function and 110.6 ± 35.0 µm for the trained model using the binary cross-entropy loss function. **Fig. 2** shows an example of the 3D modeling results of the vessel lumen structure. These results show that the IoU loss function improved the classification accuracy of the IoU index for individual images, but did not improve the RMSE of the 3D reconstructed structures. The reason for the lack of improvement in RMSE despite the improvement in IoU could be that many of the cases that were not reconstructed due to insufficient frames contained images in which the IoU was greatly improved by using the IoU loss function.

4. Conclusion

In this paper, we examined the effect of direct IoU optimization of U-Net model for segmentation the vascular lumen of the blood vessels in the IVUS images. The results suggested that direct optimization of the IoU metric was effective to improve the accuracy and robustness of the segmentation and enabled stable 3D modeling of the lesions in the coronary artery.

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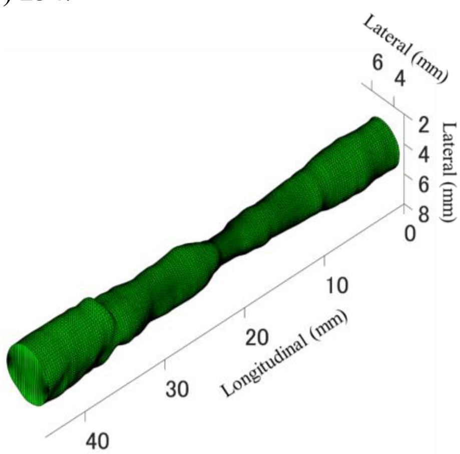

Fig. 2 An example of results of 3D modeling of lumen structures of blood vessels.