Basic Study on Optimal Cropping Setting in Convolution Neural Network for Ultrasonic Liver Tumor Diagnosis

超音波肝腫瘤診断 CNN における最適な Cropping 設定に関する 基礎的検討

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1. Introduction

In recent years, research and divelopment on computer-aided diagnosis (CAD) using deep learning method has been actively conducted. It has been reported that high diagnostic accuracy can be obtained in endscopic CAD, fundus camera image CAD, and skin lesion image CAD by using the deep learning method [1-4]. However, a large amount of data is required to improve diagnosis accuracy by using the deep learning. However, there is no large-scale database for ultrasound images. Therefore, the Japan society of ultrasonics in medicine (JSUM) is currently working on the construction of an ultrasound image database for liver tumor, breast tumor, and heart diseases. In this study, we examine the deep learning method for estimating the diagnosis of the lesion from the ultrasound image of the liver tumor.

In deep learning, annotation is as important as the number of learning data. Annotations for deep learning are segmentation and cropping of the target area, and the estimation accuracy depends on the annotation, and is the most laborious work. The annotation in this study is the cropping of ROI images centered on the liver tumor. The problem with this cropping is how much liver tumor ratio should be in the ROI image. In ultrasonic image diagnosis, it is known that not only image features inside a tumor but also image features around tumor are used for diagnosis. For this reason, it is considered that the tumor and its periphery should be cropped. Therefore, in this study, we perform clipping by changing the ratio of tumor in ROI image, and evaluated what ratio is the best.

2. Method

The liver tumor ultrasound data used in this study was collected at Kindai university with the approval of the Ethics Committee in AMED project of the JSUM. This data consists of 159 liver cysts



Fig. 1 Relationship between ROI image size $L \times L$ and maximum tumor diameter *D*.



Fig. 2 Example of ROI image cropped with $\alpha = 0.2, 0.4, 0.6, 0.8, 1.0.$

(338 images), 68 hepatic hemangiomas (279 images), 73 hepatocellular carcinomas (241 images), and 24 metastatic liver cancer (122 images). The total number of this data is 324 cases (980 images).

The deep learning method used in this study is a convolutional neural network (CNN) based on VGG net [5]. In our CNN, the input image size is 64×64 , the network depth is 10 layers, and the output is 4classes (liver cyst, hepatic hemangioma, hepatocellular carcinoma, metastatic liver cancer).

As for annotation, the center coordinates and the maximum diameter of the tumor are recorded manually by using self-made software. Based on

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these, we automatically crop the ROI including the tumor. However, if the ROI size is less than 64×64 , we set the minimum ROI size to 64×64 . When the maximum tumor diameter is *D* and the square ROI size is $L \times L$, the tumor diameter ratio is defined as $\alpha = D/L$ (Fig. 1). We change the value of α from 0.2 to 1.0 and examine the optimal value of the tumor diameter ratio α (Fig. 2).

As data augmentation, we added the horizontally reversed image of the ROI image, the image rotated ± 5 degrees, ± 10 degrees, and its horizontally reversed image to the learning data. All ROI images are resized to 64×64 for input to our CNN.

We randomly divided all data into 10 groups on a case-by-case basis and validated them using the cross-validation method. In addition, we averaged the estimation results of 5 times in each group. Moreover, we evaluated with two estimation accuracies: accuracy in case units and accuracy in image units. In the case-by-case evaluation, we took the average value of the probabilities of the estimation results for each image included in one case, and the one with the highest average probability was taken as the estimation result for that case.

3. Result

The accuracy in case units evaluated by changing the tumor diameter ratio α from 0.2 to 1.0 in increments of 0.2 is shown in Fig. 3, and the accuracy in image units is shown in Fig. 4. From these results, both the accuracy in case units and the accuracy in image units are maximized when α =0.6. That is, it was confirmed that there is an optimum value for the tumor diameter ratio α . We think that if α is too large, the information around the tumor will decrease, and the accuracy will decrease relatively, so the accuracy will decrease.

4. Conclusion

In a CNN that estimates tumor types from ultrasound images of liver tumors, we verified how large a tumor would be in a ROI image to obtain the highest accuracy. We found that the optimal value of the tumor diameter ratio α in the ultrasound image of the liver tumor was $\alpha=0.6$. However, in this time, we could only verify the value of α from 0.2 to 1.0 in increments of 0.2, so in the future we would like to verify in finer icrements.

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Fig. 3 Accuracy in case units for each α .



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