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Effect of amplitude-envelope statistics of ultrasonic image on CNN classification of liver fibrosis stages

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1. Introduction

The progression of liver fibrosis in diffuse liver disease is the most important indicator which determines life prognosis. Quantitative diagnosis of liver fibrosis is performed by liver biopsy or ultrasound shear-wave elastography. However, the invasiveness of biopsy and the effect of steatosis and inflammation on elastography remain challenges. In this study, we have investigated ultrasound image analysis using a convolutional neural network (CNN) for non-invasive and more accurate quantitative diagnosis. In the previous work, we have proposed CNN classification of liver fibrosis stages based on the transfer learning of the pretrained network[1]. Then, CNN classification using ultrasound images colorized by their echo-amplitude-envelope statistics have studied to improve the classification accuracy. In this report, the effect of colorization for the classification accuracy is discussed.

2. Method

2.1 Clinical echo data

Dataset with hepatitis B virus and hepatitis C virus infections were provided from Chang Gung Memorial Hospital, Taiwan. The clinical ultrasound scanner equipped with the convex array probe (Model3000 / Model5C2A, Terason) was used to acquire raw echo data. The center frequency of the transmitted ultrasound and the sampling frequency of echo data were 3.5 and 30 MHz, respectively. The liver fibrosis stage is assessed by liver biopsy; normal (F0), early to severe fibrosis (F1-F3), and cirrhosis (F4). Because there were not enough cases for F0, 20 cases each from F1 to F4 (80 cases in total) were used. The ratio of intracellular fatty deposition in each case ranged from 0 to 30%, as assessed by liver biopsy.

2.2 Creation of input image

First, the ultrasound image reconstructed (scan converted) from raw echo data is normalized to remove the effects of focuses and gains during transmission and reception. For the normalization of each pixel, the 2nd-order moment of echo amplitudes in the region around the pixel was used. The region is centering on the pixel and 16 (4×4) times the spatial resolution (1.9 mm×2.4 mm) of the ultrasound image. The size of the region of interest (ROI) was 15 mm in depth and lateral, and ROIs were extracted by sliding more than 1 mm from the normalized ultrasound image. All ROIs are rotated so that each vertical direction follows the scan line. The 1st-order and 3rd-order moments were calculated in each ROI for colorization of the ultrasound image (ROI). For the 1st-order moment M_1, we normalized the value corresponding to the Rayleigh distribution (and above) to 1 and the value corresponding to the multi-Rayleigh model with the fibrotic variance of 4 and the fibrotic mixture rate of 20% (and below) to 0. The 3rd-order moment M_3 was similarly normalized from 0 for the Rayleigh distribution to 1 for the multi-Rayleigh model. Then, the echo amplitudes of all pixels $\mathrm{I}_{i,j}$ in the ROI are modulated as

$$\mathrm{I}_{i,j(n)} = \mathrm{I}_{i,j} * \alpha^{2*(M_n - 0.5)}, \qquad (1)$$

where n is the order of moments and α is the modulation coefficient. The colorized image input to the CNN was created by using the original image ($\mathrm{I}_{i,j}$) and the modulated images ($\mathrm{I}_{i,j(1)}$, $\mathrm{I}_{i,j(3)}$) as pixels in the blue, red and green layers, respectively.

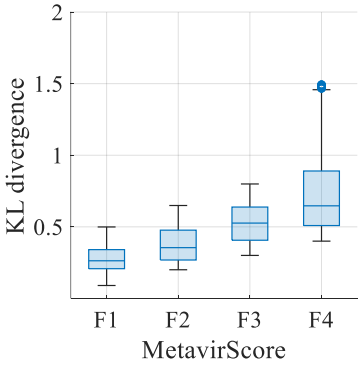

Fig. 1: Kullback-Leibler divergences of probability density distributions of the selected ROIs between the Rayleigh distribution.

2.3 Selection of the ROI

From a single ultrasound image (case), about 100 to 500 ROIs can be extracted. Therefore, in order to select ROIs thought to reflect the changes in tissue structure (acoustic properties) due to liver fibrosis, we calculated the Kullback-Leibler divergence (KLD), which indicates the similarity between the probability density distribution (PDF) of echo amplitudes and the Rayleigh distribution for each

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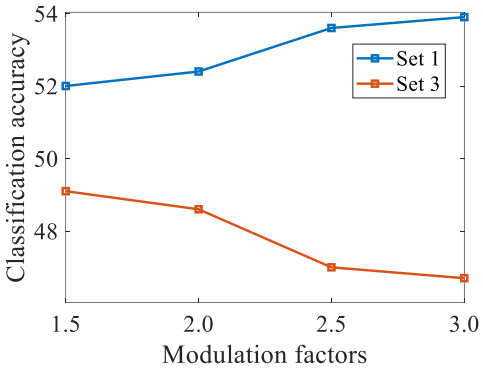

Fig. 2: Relationships between the modulation factors α and classification accuracies in set 1 and set 3.

ROI. As shown in Fig. 1, 2560 ROIs each from F1 to F4 (10240 ROIs in total) were selected, so that KLD increases with the progression of liver fibrosis. If liver fibrosis stages are classified based on KLDs of ROIs, the classification accuracy is 45.6%. Therefore, the accuracy of CNN classification must be larger than this accuracy.

2.4 Learning and validation of networks

The selected ROIs and horizontally flipped ROIs were used for learning and validating the network. In this study, VGG-16 in Deep Learning Toolbox (MATLAB) is trained for CNN classification of liver fibrosis stages. For the transfer learning, the last fully connected layer of VGG-16 was replaced for classification of the Metavir score F0 to F4 (input 4096, output 4). Weights of the replaced layer were initialized with random numbers. In the transfer learning, only 3 fully connected layers and 2 convolutional layers from the output layer were trained by using the stochastic gradient descent with a mini-batch processing of 64 data. Dropout between the fully connected layers were 80 %, the learning rate was 3.5×10^{-5}, and the number of epochs was 2~5. For validation of network, we adopted the fivefold cross-validation, all ROIs were divided into 5 sets, 3 of sets were used to train the network, and the remaining 2 set were used to validate the network, and the combination of these sets was switched and repeated.

3. Results/Discussion

First, to search the suitable modulation factor α, the classification accuracies were estimated in α from 1.5 to 3.0. However, the relationships between the modulation factors α and classification accuracies were different in particular sets. As shown in Fig. 2, the accuracy of set 1 increased by α, and that of set 3 decreased. Therefore, 3rd-order moments of all ROIs in train data and those in validation data were compared between set 1 and set 3. Boxplots of their 3rd-order moments are shown in

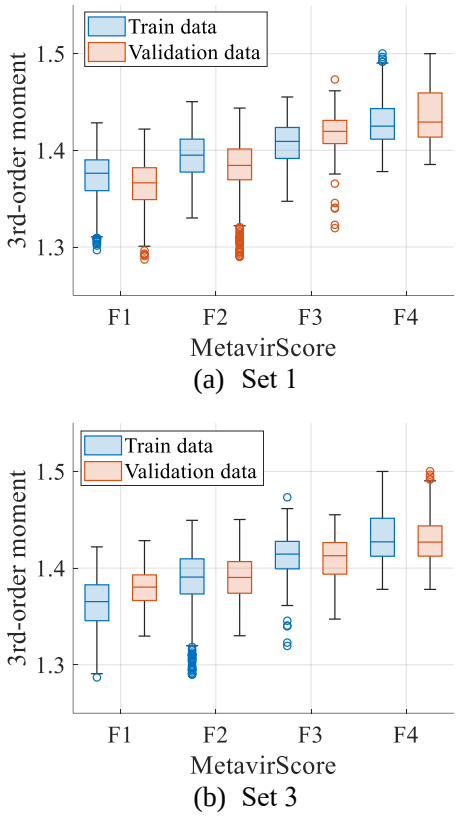

Fig. 3: 3rd-order moments in training and validation data from F1 to F4 in set 1 and set 3.

Fig. 3. In Set 1, the distribution of 3rd-order moments of validation data is wider than that of train data. The classification emphasis on the moments seems to be made easier. On the other hand, in Set 3, the distribution of validation data is narrower than that of train data. The effect of colorization seems to be suppressed in set 3. However, the classification accuracy is improved from 40.5 % to 49 % by colorization even set 3.

4. Conclusion

To improve the classification accuracy of CNN classification of liver fibrosis stages, the colorization of ultrasound images by echo-amplitude-envelope statistics have been studied. In this study, there are not enough clinical data. Therefore, if there is the bias of echo-amplitude-envelope statistics between train and validation data, the evaluation of the proposed method may become difficult.

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References

1. A. Isshiki *et al.*, Proc. Symp. Ultrason. Electron., 42, 3Pb5-11, 2021.