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Basic study about quantitative diagnosis of fatty liver by CNN classification of multidimensional moment heatmaps

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1. Introduction

Metabolic dysfunction-associated fatty liver disease (MAFLD) carries a high risk of progressing to cirrhosis and hepatocellular carcinoma [1]. The estimation of hepatic fat deposition with MRI-PDFF is one of the quantitative diagnoses of MAFLD. As a more cost-effective method, a diagnosis method using ultrasound imaging is also desirable. In this study, therefore, quantitative diagnosis of fatty liver from ultrasound images is investigated.

It is known that the deposition of fat droplets within hepatocytes increases the ultrasonic attenuation. Because the texture of the attenuated ultrasound image becomes a homogeneous speckle, the probability density function of the echo envelopes is close to a Rayleigh distribution. In the previous studies, the diagnosis methods of fatty liver using echo-envelope statistics of ultrasound images have been reported [2]. In this study, we focus on the distribution and variance of echo-envelope statistics and propose a new diagnosis method to analysis the characteristics of echo-envelope statistics using a convolutional neural network (CNN).

In the proposed method, the moments around each pixel are employed as echo-envelope statistics. For analysis of the distribution and variance of echo-envelope statistics as an image, the heatmap of two different moments is formed. The fatty liver grade of the ultrasound image is classified by the CNN classification of the heatmap.

2. Method

2.1 Clinical echo data

Clinical data were provided from Chiba University Hospital, Chiba, Japan. The ultrasound scanner (Aplio a550, Canon Medical Systems) equipped with the convex array probe (PVT-475BT, Canon Medical Systems) was used to acquire ultrasound images. The center frequency of the transmitted ultrasound was 3 MHz. Hepatic fat fractions measured by MRI-PDFF were 1.9-23.8%. The grade of fatty liver was classified into three groups: healthy (<5%), mild (5%-10%), and severe (>10%). The number of cases of each fatty liver grade was 8, 10, and 6, respectively. 4 ultrasound images were used per case. Liver stiffness values were 3.4-46.1 kPa as measured by the transient elastography (FibroScan, Echosens).

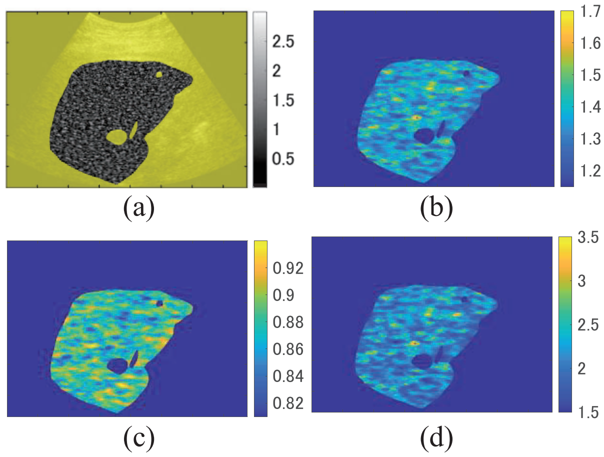

Fig. 1 (a) Normalized ultrasound image and liver region, (b) 1st-order moment map, (c) 3rd-order moment map, (d) 4th-order moment map.

2.2 Multidimensional moment heatmaps

First, the ultrasound image reconstructed from scan line data is normalized to remove the effects of focuses and attenuation. 2nd-order moment in the elliptical region (4.6×10.8 mm) centered on each pixel was calculated as follows,

$$M_n = E[x_i^n] \quad (1)$$

where n is the order of moment and x_i is the pixel brightness in the region. The center pixel was divided by the root of the 2nd-order moment for the normalization. Then, 1st-, 3rd-, and 4th-order moments in the elliptical region (3.0×8.1 mm) were calculated, as illustrated in **Fig. 1**.

To generate the multidimensional moment heatmap, the region of interest (ROI) was extracted from the liver region. The size of ROI was 20 mm in depth and lateral, and ROIs were extracted by sliding more than 1 mm. In the heatmap, the vertical and horizontal axes were set for each moment. The number of pixels whose moments corresponded to the axes was placed in the heatmap, as illustrated in **Fig. 2**. Depending on the combination of moments

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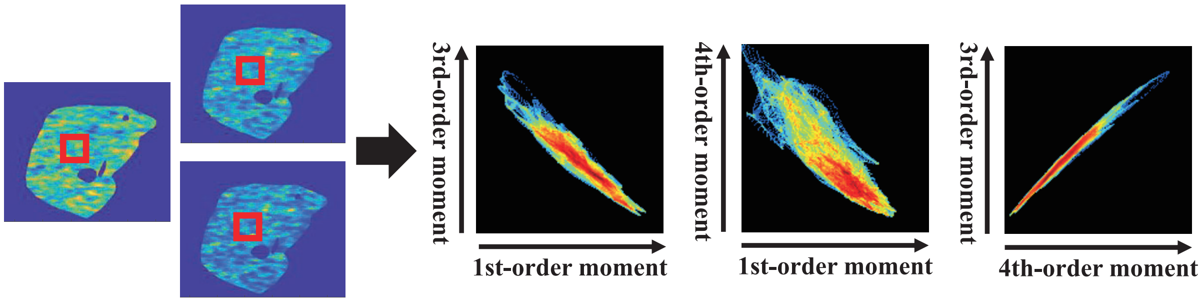
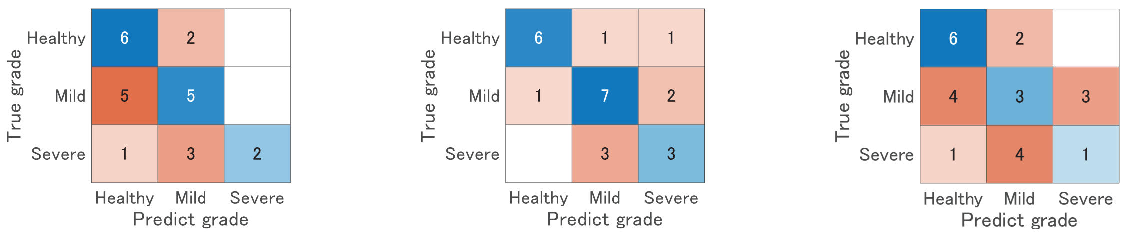


Fig. 2 The created moment maps of three combination.



(a) (b) (c)

Fig. 3 confusion matrix of cases (a) 1st- and 3rd-order moment, (b) 1st- and 4th-order moment, (c) 4th- and

used, three different heatmaps can be generated. The numbers of heatmaps in each combination were 1920, 2000, and 1800 for healthy, mild and severe, respectively.

2.3 Learning and validation of networks

The generated moment heatmaps were used for learning and validating the network. In this study, VGG-16 in Deep Learning Toolbox (MATLAB) is trained for the CNN classification of fatty liver grade. For the transfer learning, the last fully connected layer of VGG-16 was replaced for classification of the fatty liver grades (input 4096, output 3). 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 75 %, the learning rate was 5.0×10^{-5}, and the number of epochs was 5~10. For the four-fold cross-validation, all ROIs were divided into 4 sets, 3 of sets were used to train the network, and the remaining 1 set was used to test the network, and the combination of these sets was switched and repeated.

3. Results and Discussion

Multidimensional moment heatmaps generated with 1st- and 3rd-order moments, 1st- and 4th-order moments, and 4th- and 3rd-order moments, respectively, were used as input to the CNN. The classification accuracy of ROIs by the trained network was 42.5%, 43.5% and 43.6%, respectively. In this study, multiple input images were generated from a single image and classified using the CNN. Therefore, probabilities for each fatty liver grade in each ROI can be summarized. As a result, the fatty liver grade of the case was determined the summarized probabilities. The classification results are shown in **Fig. 3**. The classification accuracy for each case was 54.2%, 66.7%, 41.7%, respectively. In the case of 1st- and 4th-order moments, the distribution of the heatmap was larger, and the classification accuracy was the best for fatty liver classification.

4. Conclusion

In this report, the method to predict fatty liver grade from ultrasound images was proposed. The heatmap of multidimensional moments which change with the progression of fatty liver is used as an input image to the CNN. By using heatmaps with 1st- and 4th-order moments, 16 of the 24 cases could be classified.

Acknowledgment

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References

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