

## Accuracy evaluation of quantitative estimation for hepatic fibrosis using phantom data

ファントムデータを用いた肝線維化指標の精度検討

Atsushi Koriyama<sup>†</sup>, Sinnosuke Hirata, and Hiroyuki Hachiya (Tokyo Tech.)

郡山 惇之<sup>†</sup>, 平田 慎之介, 蜂屋 弘之 (東工大)

### 1. Introduction

To realize a quantitative diagnosis of liver disease, we have examined the relationship between the change of liver tissue and ultrasound images, and have developed the quantitative estimation method of liver fibrosis[1-3]. In these method, we have assumed that the echo signals of normal liver were Rayleigh distributed. However, actual data of normal liver obtained through diagnostic equipment slightly deviate from the Rayleigh distribution because of nonlinearity in measurement system, and then, estimation errors become larger. In this report, we studied a robust quantitative method that was effective in the situation such that the echo signals of normal liver were not Rayleigh distributed.

### 2. Quantitative diagnosis with amplitude distribution

Echo images of homogeneous tissue with high scatterer density, such as normal liver tissue, have many granular patterns that are called speckle pattern. It is known that the probability density function (PDF)  $p(x)$  of RF signal amplitude  $x$  of the echo images can be approximated by Rayleigh distribution given by

$$p(x) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right), \quad (1)$$

where  $\sigma$  is shape parameter of the distribution.

Focusing on the phenomenon that the PDF of echo signals gradually deviates from Rayleigh distribution with fibrosis progression, we have proposed an amplitude distribution model for liver fibrosis in which the distribution function is modeled by a combination of Rayleigh distributions (eq. (2)).

$$p_{\text{mix}}(x) = (1 - \alpha)p_{\text{low}}(x) + \alpha p_{\text{high}}(x), \quad (2)$$

where  $\sigma_{\text{high}}^2/\sigma_{\text{low}}^2$  is a variance ratio (the degree of fibrosis progression) and  $\alpha$  ( $0 \leq \alpha \leq 1$ ) is a mixture rate (the amount of fibrotic tissue). From the observed statistical properties, we can estimate the variance ratio ( $\sigma_{\text{high}}^2/\sigma_{\text{low}}^2$ ) and the mixture rate ( $\alpha$ ) as an inverse problem.

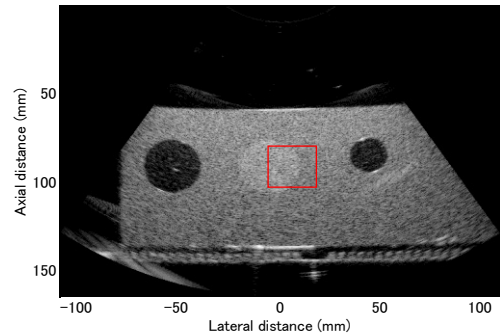


Fig. 1 B-mode image of gray scale phantom.

### 3. Quantitative characteristics of disease progression model

#### 3.1 Conventional method

Since the skewness and the kurtosis are uniquely determined by the variance ratio and the mixture rate, in the conventional quantitative method, we have calculated the skewness and the kurtosis from the obtained data, and have estimated a variance ratio and a mixture rate as an inverse problem. The skewness and the kurtosis, statistical parameters, are moments  $\mu_n^{(c)}$  of the distribution with the parameter  $n = 3, 4$  in the following equation, respectively.

$$E\left(\left(\frac{X - \mu_x}{\sigma_x}\right)^n\right) = \int_{-\infty}^{\infty} p(x) \frac{(x - \mu_x)^n}{\sigma_x^n} dx, \quad (3)$$

where  $E$  is an expectation. In previous report, using the phantom as shown in Fig. 1, we obtained data in which degree of fibrosis progression and amount of fibrotic tissue were controlled arbitrarily, and then, estimated a variance ratio and a mixture rate. The results are shown in Fig. 2. There are large estimation errors at setting mixture rate ranging from 0 to 0.2, which is a region assuming initial lesion. Since skewness and kurtosis have higher order terms of amplitude value in their calculation process (eq. (3)), these errors are thought to result from fluctuations of higher amplitude area as shown in Fig. 3.

#### 3.2 Robust estimation method

There is a problem that higher amplitude area

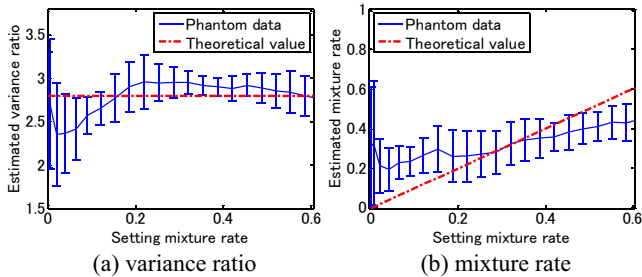


Fig. 2 Estimation of model parameters.

strongly affects the estimation in the conventional method. To solve this problem, we examined to use lower order moments than skewness and kurtosis for estimation and tried to reduce the effect of higher amplitude area.

Moments around the mean were calculated using eq. (3).  $N$ -th power calculation of the value in eq. (3) was carried out while changing  $n$  from 0.75 to 2.95 by 0.05. When  $n$  is not integer, the moment becomes a complex number. From one complex number, we can estimate distribution parameters in eq. (2).

Using the numerical simulation, we theoretically estimated the variance ratio and the mixture rate with  $n$ -th order moments, and evaluated the estimation accuracy. First, we estimated the variance ratio and mixture rate from several random trial data for each moment at setting mixture rate ranging from 0 to 0.2. Residual sum of squares in the estimated variance ratio and mixture rate for the true value at setting mixture rate ranging from 0 to 0.2 are shown in Fig. 4. The smaller value of the residual sums mean that estimation accuracy is high. Conventional method results are shown by the broken line in Fig. 4. Clear improvement is seen in the mixture rate estimation as shown in Fig. 4(b). Figures 5 and 6 show comparisons between the (a) conventional and (b) proposed methods, in which the order of the moment,  $n$ , is 1.6. We found that the mixture rate could be stably estimated at a setting mixture rate ranging from 0 to 0.05.

#### 4. Conclusions

We estimated the model parameters of phantom PDF with a conventional method, and discussed the reason of errors. We proposed a method in which the lower order moment was used, and compared the estimation accuracy using numerical simulation and phantom. We will apply the proposed method to the phantom data with nodule structure and the clinical data.

#### Acknowledgement

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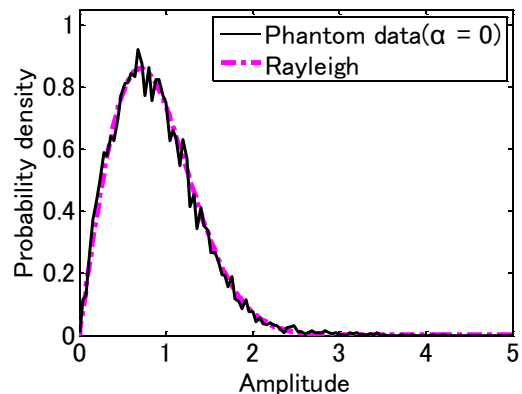


Fig. 3 Probability density function of reflected signal from phantom at setting mixture rate 0.

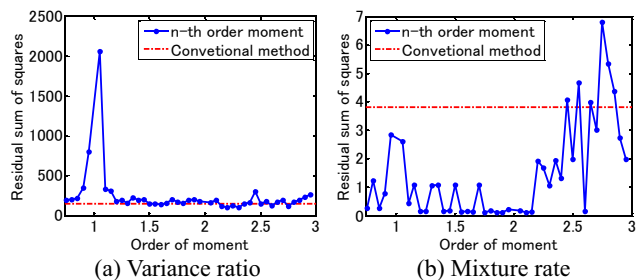


Fig. 4 Estimation accuracy of each moment.

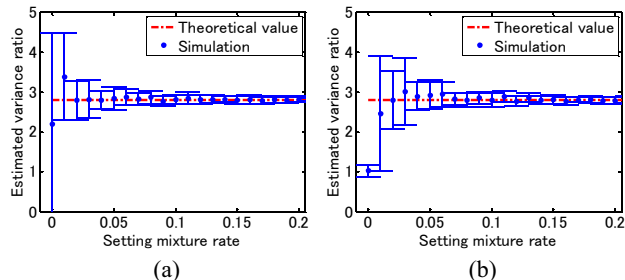


Fig. 5 Estimated variance ratio from (a) skewness and kurtosis, (b)  $n$ -th order moment.

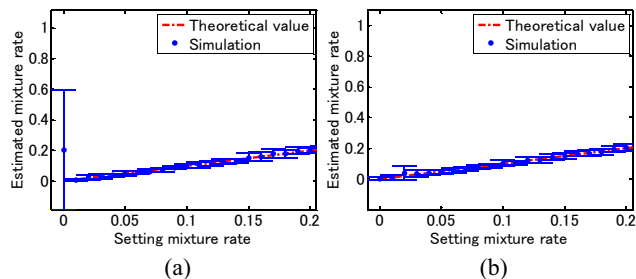


Fig. 6 Estimated mixture rate from (a) skewness and kurtosis, (b)  $n$ -th order moment.

#### References

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