# A Novel Edge Enhancement Method for Ultrasound Imaging

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***Abstract* — One of the most important problems in ultrasound image processing is to find the edges of structures and enhance weak borders between different organs. In this paper, we propose an algorithm that detects and enhances edges adaptively based on local histogram distribution. From the local histogram distribution we can get the "local histogram range image (LHRI)". On the basis of this image we apply an adaptive edge enhancement method to process ultrasound image. We find that the detection technique performs well, edges and borders are then enhanced by the enhance algorithm according to LHRI.**

***Keywords – Edge detection; adaptive enhancement; local histogram processing; segmentation; ultrasound image.***

## I. INTRODUCTION

Ultrasound images are widely used now by doctors to diagnose diseases of patients. Due to the nature of ultrasound imaging such as speckle, the edges and borders on the images are not clear as doctors expect. Finding appropriate ways to enhance ultrasound image resolution to help the doctor's diagnosis is a hot area for researchers in medical image processing. One way is to reduce the speckle; many literatures [1-3] discuss this problem. However, speckle is not genuine noise in a traditional engineering sense because its texture often carries certain information about the image being viewed. So, our purpose is to find and enhance the edges and organ borders, and leave the speckle area unchanged. Some researchers [4-5] have done edge detection on ultrasound images but did not focus on edge enhancement under the speckle environment. Moreover, the enhancement of weak borders due to steering beams (i.e., the beamline is not perpendicular to the orientation of the local border/edge) is another challenge in ultrasound image processing.

In this paper, an algorithm of edge detection based on proposed "local histogram range image" LHRI was presented using the range of local histogram gray values to accurately locate both strong and weak edges in ultrasound images. After this processing, we use an enhancement method to adaptively enhance the areas of the detected edges/borders and leave speckle areas unchanged.

This paper is organized as follows: Part A of Section II introduces the analysis of ultrasound image which gives the foundation of our method. In Part B of Section II, we present LHRI method followed by the enhancement method, Part C of Section II. Testing results from *in vivo* images are shown in Section III. Conclusions and future directions are given in Section IV.

## II. METHOD

### A. Ultrasound image analysis

The purpose of this paper is to present a new edge enhancement algorithm on ultrasound envelope data (i.e., before the scan conversion but after the log compression). Because of the presence of speckle in the ultrasound image, it is quite difficult to use the common edge detection method in this problem directly. We only want to find and enhance the edges but not "enhance" the speckle noise. Because of this, we should have a certain level of image segmentation so that only edges or organ borders are enhanced while speckle noises are unchanged or even reduced. Finding the edges or boundaries is a significant part in our problem. Speckle noise also limits the effective application of image processing and analysis methods such as edge detection and segmentation methods.

To detect edges and avoid speckle, we must know the characteristics of the ultrasound signal. Speckle has a random nature as it is formed from signals from randomly located scatterers in the medium under observation. The analysis of this speckle has been a major subject of investigation. Due to the statistical nature of echo signals, many researchers studied it in a statistical approach. Moreover, the modern ultrasound scanner always applies a log compression to the envelope data to bring up the lower signal values (i.e., increase the detectable signal dynamic range) and reduce the amount of data transfer. Because the log compression is non-linear, the statistics of the envelope signal is different before and after this process.

*1) Probability density function of echo signals before log compression:*

Because the scatterers' distribution and density are different in different tissues, researchers have studied the probability density model of ultrasound envelope signal in different cases. In the condition of fully developed speckle (large number of randomly located scatterers with small scatterer spacing compared to the wavelength of ultrasound), the statistics of the image signal shows a Rayleigh distribution [6]. Yet, when either the number of scatterers is low or their spatial locations are not independent, the statistics is likely to deviate from the Rayleigh model. To account for the non-Rayleigh scattering, a

number of distributions have been presented, such as K distribution (to account for deviations from non-uniformity in scatterer distribution) [7], the Rician distribution (to account for "structure" or non-random coherent component to signals) [8], homodyned K distribution [9] which tries to cover above distribution as a general case, the Nakagami distribution which is also a general and flexible model for ultrasound image [10].

Our methods use log-compressed image in which edge and speckle are described by Nakagami and Rayleigh models. In order to detect edges and avoid speckle we will analyze the log-compressed Rayleigh and Nakagami distributions in the next part.

*2) Probability density function of echo signals after log compression:*

Ultrasound scanners employ logarithmic compression to increase the dynamic range of the echo envelope for display and reduce the data amount for transfer. We subject the input signal $Z$ to a scaled and shifted log compression to form a new random variable $Y$:

$$Y = n_1 \ln(Z) + n_2 \tag{1}$$

where $n_1$ and $n_2$ are constant; $n_1$ is associated with the dynamic range of the scanner and $n_2$ with the gain setting.

This nonlinear transformation changes the statistical model of the echo images, and thus the statistical models previously derived can not be directly used on the echo images. Many researchers had tried to derive statistical models of the compressed envelope which can provide better understanding of how compression affects the dependence of statistics parameters on the scatterer parameters.

*a) Probability density function of echo signals in fully developed speckle area after log compression:* Before log compression the fully developed speckle area obeys Rayleigh distribution and it obeys double exponential distribution after the log compression [11]. Thus,

$$f_Y(y) = (1/\beta)\exp[-g - \exp(-g)] \tag{2}$$

where $\beta = n_1/2,\ g = (a-y)/\beta,\ a = [n_1 \ln(2\sigma^2)/2] + n_2$.

We can get the mean and variance as:

$$Mean_{Log-Rayleigh} = \frac{n_1 \ln(2)}{2} + n_1 \ln(\sigma) - \frac{\gamma n_1}{2} + n_2 \tag{3}$$

$$VAR_{Log-Rayleigh} = E[(y-\bar{y})^2] = \frac{(\pi\beta)^2}{6} = \frac{\pi^2 n_1^2}{24} \tag{4}$$

where $\gamma \approx 0.5772$ is the Euler constant.

From this we can see that the log-compressed Rayleigh is now a double exponential and the mean of this distribution will be affected by $\sigma$ of the Rayleigh and $n_1$, $n_2$ of compression coefficients. Its variance, however, depends only on the dynamic range of the system.

*b) Probability density function of other areas in ultrasound image after log compression based on Nakagami model:* Ghofrani [12] derived the distribution of log-compressed envelope signals by using Nakagami model. The variance of log-compressed signal can be obtained as

$$VAR_{Log-Nakagami} = E[(y-\bar{y})^2] = \frac{n_1^2}{4} \cdot \zeta(m) \tag{5}$$

where $\zeta(m)$ is defined as follow:

$$\zeta(m) = \frac{1}{m^2} + \frac{1}{(m+1)^2} + \frac{1}{(m+2)^2} + \cdots\cdots \tag{6}$$

Nakagami distribution tends to Rician when m is 1.5 and the variance of log-compressed Rician distribution is

$$VAR_{Log-Rice} = \frac{\pi^2 n_1^2}{42.23} \tag{7}$$

*B. local histogram range image (LHRI)*

*1) Reasons of using valid range of local gray value histogram:* In the following analysis we use Fig.1 as an example:

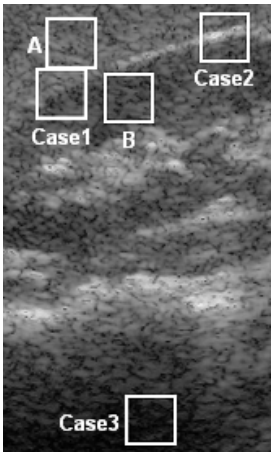


Figure 1. Example image of liver and kidney.

*a) Case 1: Edge between two fully developed speckle areas:*

In this case, the histogram shapes of fully formed speckle areas in liver and kidney are the same in general. It means that the variances of the two histograms are the same. This is the same with the Eqn. (4). But the mean of the two histograms are not the same, Eqn. (3).

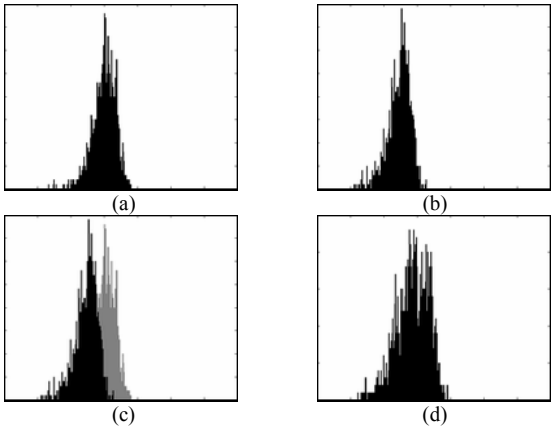


Figure 2. Histograms in different areas as seen in Fig. 1 (a) in the fully formed speckle area of liver which is window A in Fig. 1; (b) in the fully formed speckle area of kidney which is window B in Fig. 1; (c) the overlap of (a) and (b); (d) in the edge between liver and kidney, which is window of Case 1 in Fig. 1, it contains fully developed speckle areas of liver and kidney.

In Fig. 2 (c) it shows that the valid range from two fully formed speckles is the same but their mean values could be different for these two organs. It's clear that, from Fig. 2 (d), the valid range of the border histogram is larger than that from histograms in fully formed speckle areas.

*b) Case 2: edge between speckle area and specular scatterers areas:*

In this analysis, see the edge window in Fig. 1, we know that from [12], the variance of Rician distribution after log compression will be a constant, Eqn. (7), and its value is smaller than the one in Rayleigh distribution. Therefore, if a window contains only specular scatterers, the valid range of the histogram will be not very large. However, the mean value of log-compressed Rician distribution will be larger than the one of log-compressed Rayleigh (or the double exponential) distribution. Moreover, if a window contains both speckle and specular scatterers, the histogram range of this window will be larger than the one of speckle or specular scatterers see Fig. 3.

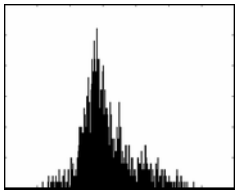

Figure 3. Histogram in the window of case 2 which contains both speckle and specular scatterers.

*c) Case 3: dark area:* It is shown in the bottom of Fig. 1 as a dark area which is echo-free and no information for diagnosis. The variance of any windows in this area is very small. Consequently, on the basis of above analysis, we know that the valid range of local gray value histogram could be an effective factor to discriminate edge/border and other areas. Therefore, we will propose a new method to detect edge/border in ultrasound image.

*2) Definition of Local histogram range image (LHRI):* From the analysis of Part A we know that if a window is large enough to cover an edge, the valid range of the gray value histogram (i.e., the number of bins of the local histogram) will be larger than the one from other areas with different statistics. On the basis of the above analysis, we now define an M×N LHRI as follows:

$$k_{i,j} = \begin{cases} u, & \text{there are } u \text{ different gray values} \\ & \text{in an } a \times b \text{ window,} \\ 0, & \text{gray values of all pixles} \\ & \text{in this window are same.} \end{cases} \quad (8)$$

where $k_{i,j}$ is the pixel value of LHRI at the position (i, j), $a$ and $b$ are the width and height of the moving window, M and N are the width and height of LHRI; they are equal to the ones of original image .

## C. Enhancement method

After the edge/border detection, we use the following equation for image enhancement:

$$f_{i,j} = g_{i,j} + \alpha \cdot k_{i,j}(g_{i,j} - \bar{g}) \quad (9)$$

where $f_{i,j}$ is the updated value, $g_{i,j}$ is the old one, $\bar{g}$ is the mean of the whole image, $k_{i,j}$ is the normalized value of LHRI in pixel $(i, j)$, $\alpha$ is a weighting coefficient which decides how much the current pixel will be enhanced. We can choose a suitable value for different images, but generally, we can set this coefficient to be 0.3 – 1.0.

# III. EXPERIMENTS

To verify our proposed algorithms, we did experiments in phantom and *in vivo* images. We used Saset iMago color ultrasound scanner for data acquisition which is the system we designed in our lab.

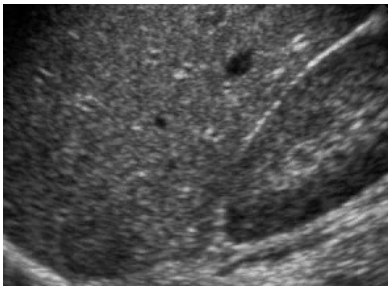

Figure 4. (a) The original liver/kidney image

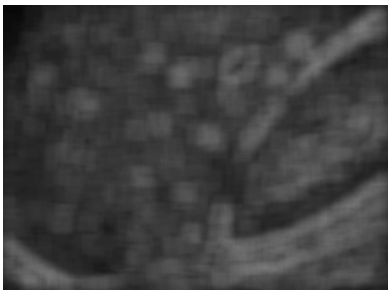

Figure 4. (b) The LHRI for feature detection

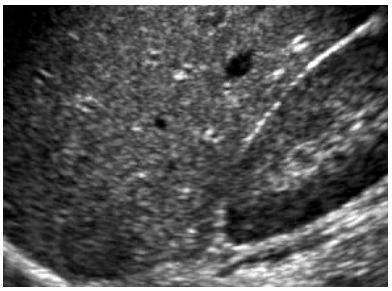

Figure 4. (c) The enhanced image with $\alpha$=0.7

The size of the moving window used in our tests is 15×15. Fig. 4 (a) shows the liver and kidney image. The Fig. 4 (b) displays the result of LHRI where the bright areas correspond to edges, structures, or border which need to be enhanced. In Fig. 4 (c), we see that non-speckle areas are enhanced but speckle areas remain unchanged. Fig. 5 shows similar results where we apply our method to envelop data, i.e., the pre-scan converted images. Fig. 6 shows another set of liver/kidney image with strong edges. Result shows that the edges can be enhanced but speckle can remain unchanged.

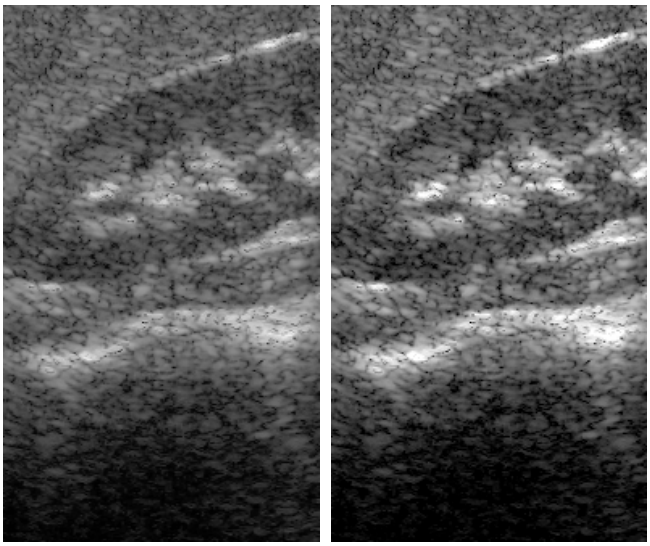

Figure 5. (a) (b) The original and the enhanced image with $\alpha$=0.7

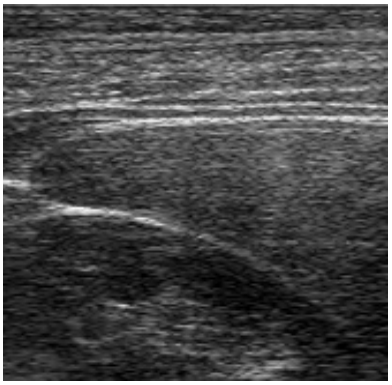

Figure 6. (a) The original image with strong edges

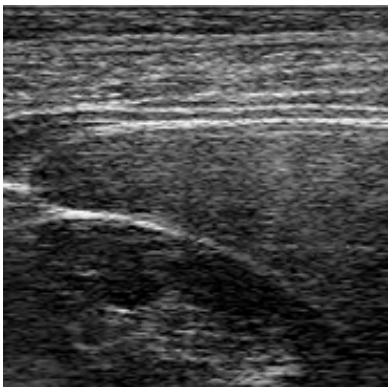

Figure 6. (b) The enhanced image with $\alpha$=0.7

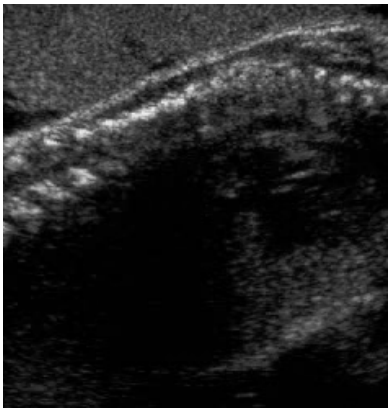

Figure 7. (a) The original OB with lots of echo-free areas

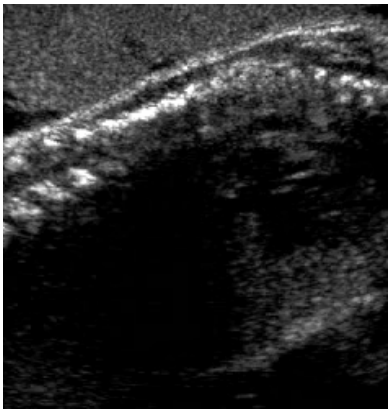

Figure 7. (b) The enhanced image with $\alpha$=0.7

Figure 7. (b) shows results from a set of OB image where big area on the image is echo-free. The enhanced image shows better border and structures but not brings up noise inside the echo-free areas.

## IV. CONCLUSION

In this paper, we propose a new method to detect and enhance the edges and borders in log-compressed ultrasound image. Our theoretical model is based on Nakagami model which contains most of cases of distribution and density of scatterers (including Rayleigh and Rician models). Moreover, this model is easy to use for analyzing the log-compressed distribution of speckle statistics. On the basis of this model, we propose a new method, called LHRI, to detect the edges and borders in ultrasound image. From our experiments in phantom and *in vivo* images, this method can detect the edges, border or tissue structures very well and do enhancement adaptively to these areas but not change (or "enhance") speckle noise areas. In the future, we will do more clinical tests for more robust algorithms and combine them with speckle reduction methods developed in our lab.

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