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Three Dimensional Adaptive Morphological Filters for Preprocessing Ultrasound Images

Masayasu Ito, Hiroshi Inaba
Graduate School of Sciences and Engineering, Tokyo Denki University, Hatoyama-machi, Saitama 350-0394, Japan
ito@re.ccs.dendai.ac.jp

Abstract

This paper proposes an adaptive morphological filter for preprocessing ultrasound images. It smooths and enhances the images at a time by a morphological operation. The necessary parameters are determined statistically for setting the structuring element of a morphological operation. We applied the method to the successively scanned ultrasound images of small blood vessels, from which we extract the contours of the blood vessels and display them in a three dimensional way.

We also evaluate the reduction of speckle noises and edge enhancement statistically and show its usefulness together with some experimental results.

1. Introduction

Preprocessing is indispensable to almost all digital image processing problems, especially when the images are noisy and blurred. Ultrasound images are of low resolution due to their sound properties and noise, called speckle noise. Resulting ultrasound mages are strongly affected by imaging techniques and equipment. They also change from person to person because of sound attenuation in a living body.

Speckle noise always appears in an ultrasound image and it also blurs the edge along the boundary of a tissue. Since it contains high-frequency components, the edge can not be enhanced by a high-pass filter. Speckle noise is also enhanced in this case. Speckle noise forms a small noisy pattern in an ultrasound image and is better to be removed for preprocessing. Thus, the shape-oriented analyses have been proposed rather than a linear filter.

So far, various kinds of smoothing techniques have been reported from linear to nonlinear filters [1, 2, 3, 4]. Morphological filters are useful for ultrasound image preprocessing in many aspects [5, 6].

Among them are such smoothing techniques as median filter, edge preserving smoothing [7], and adaptive morphological filter [8]. These methods may eliminate noise effectively, but the blurred edges still remain. We proposed morphological operations by locally variable structuring elements [9]. We compared and evaluated some conventional techniques with our method using a two dimensional ultrasound image before. Useful results are reported using a morphological filter [5, 6, 9].

Our objective is to develop a three dimensional adaptive preprocessing technique, which becomes independent of ultrasound equipment as much as possible. In ultrasound images, speckle noise blurs the contour of an organ or lesion like a tumor. For small blood vessels of a few hundred micron in diameter, speckle reduction and edge enhancement processing is indispensable, to extract the contour.

Geometrical shape and characterization are more discussed for the diagnostic information in an ultrasound image. Mathematical morphology is a set-theoretical method for image analysis, using a structural element. The structuring element transforms the image by morphological operations: erosion, dilation, opening, and closing. Generally, opening and closing operations smooth an image. They play a role of geometrical or morphological filtering in both binary and gray-scale images. Thus the shape and the value of a structuring element are the most important factors to decide.

The point spread function of an ultrasound image can be assumed to be oval in shape considering the cross section ultrasound imaging and its resolution. Thus the speckle noise often forms a speckle pattern of oval shape or of overlaid ovals. Extending this idea, speckle is assumed to ellipsoidal in 3D space. Its size is determined considering the average speckle pattern.

The proposed adaptive morphological filters can smooth and enhance the image at a time. In this paper we analyze the processed ultrasound blood vessel images statistically in order to evaluate the parameters of the locally variant structuring elements. We demonstrate it becomes easy to extract small and large blood vessels from the images after the three dimensional morphological filters are applied to them.

2. Adaptive morphological operations by locally variant structuring elements

2.1. Locally variant structuring element

Morphological techniques are useful for extracting regions and representation of the shapes in an image. Among them are morphological filters for binary and multi-scale images.

Our adaptive morphological operation is extended from the conventional gray-scale morphological operations in such a way that a structuring element is a function of local image rather than a constant [1]. We use here a three-dimensional structuring element in order to process the successively scanned images, which constitute 128 frames of 512x512x8 bits in size. We treat here a digital ultrasound gray-scale image of 8 bits so that the image intensity or gray level may correspond to the echo intensity of the tissue. We can take advantage of color after this preprocessing in order to display the extracted special region or some characteristics.

The structuring elements are designed here so that their values vary adaptively following the characteristics of the local image. They are defined as in the next paragraph.

Let $f(X)$ and $g(f(X),Z)$ be an ultrasound gray-scale image and a structuring element, respectively. X and Z are coordinates of the image and the structuring element. F and G are domains of f and g, respectively. For practical purpose, G is assumed to be symmetric and contain the origin. We treat a two or three dimensional digital ultrasound image or data and thus, an appropriate variable structuring element $g(f(X),Z)$ is defined as

$$g(f(X),Z) = \alpha \cdot (\sup - \inf) + \beta \cdot \max(\sup - f(X), f(X) - \inf\} \quad (1)$$

, where

$$\sup = \max_{\substack{X+Z\in F\\ Z\in G}} \{f(X+Z)\} \quad (2)$$

$$\inf = \min_{\substack{X+Z\in F\\ Z\in G}} \{f(X+Z)\} \quad (3)$$

The coefficients α and β in (1) are weighting parameters and they must satisfy the conditions $\alpha \geq 0$, $\beta \leq 0$, and $\alpha + (\beta/2) \geq 0$. The structuring element $g(f(X),Z)$ reacts to the intensity difference in the local image. It becomes small if the difference between a maximum value and a minimum one in the local image covered under G is small. On the other hand it becomes large if the difference is large. Such cases occur when $f(X)$ takes either a maximum or a minimum value at X. Generally, it becomes large at the boundary, since a large difference is possibly expected. Since G covers a local image for morphological operation, the size of G is also an important parameter to decide.

2.2. Adaptive morphological operations

Let the operation symbols, Θ, $\oplus$, $\circ$, and $\bullet$ denote erosion, dilation, opening, and closing, respectively. Four fundamental morphological operations are defined as follows.

a. Dilation:

$$D(f,g)(X) = (f \oplus g)(X) = \max_{\substack{X-Z\in F\\ Z\in G}} \{f(X-Z) + g(f(X),Z)\} \quad (4)$$

b. Erosion:

$$E(f,g)(X) = (f \Theta g)(X) = \min_{\substack{X+Z\in F\\ Z\in G}} \{f(X+Z) - g(f(X),Z)\} \quad (5)$$

c. Opening:

$$O(f,g)(X) = D(E(f,g),\bar{g}) = (f \circ g)(X) = \max_{\substack{X-Z'\in F\\ Z'\in G}} \{(f \Theta g)(X-Z') + \bar{g}(f(X),Z')\} \quad (6)$$

, where

$$\bar{g}(f(X),Z') = \min_{\substack{X-Z'\in F\\ Z'\in G}} \{g(f(X-Z')\} \quad (7)$$

d. Closing:

$$C(f,g)(X) = E(D(f,g),\bar{g}) = (f \bullet g)(X) = \min_{\substack{X+Z'\in F\\ Z'\in G}} \{(f \oplus g)(X+Z') - \bar{g}(f(X),Z')\} \quad (8)$$

, where

$$\bar{g}(f(X),Z') = \min_{\substack{X+Z'\in F\\ Z'\in G}} \{g(f(X+Z')\} \quad (9)$$

Note here that the opening and closing operations are slightly different from those by the normal definitions. The newly defined opening and closing smooth and enhance an image, while the conventional opening and closing morphological operations smooth an image but not enhance it simultaneously.

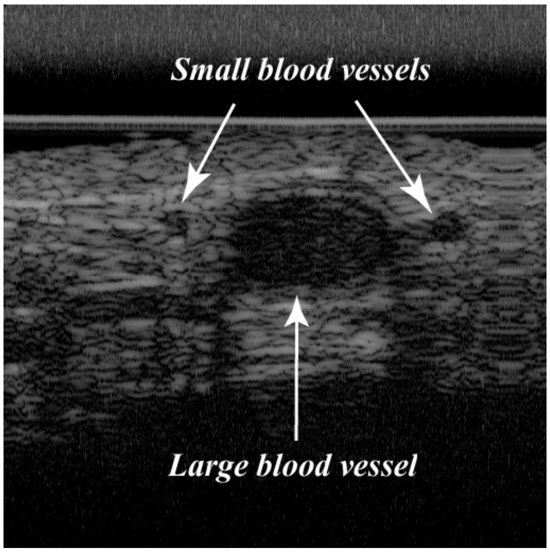


Figure 1 Ultrasound image of blood vessels.

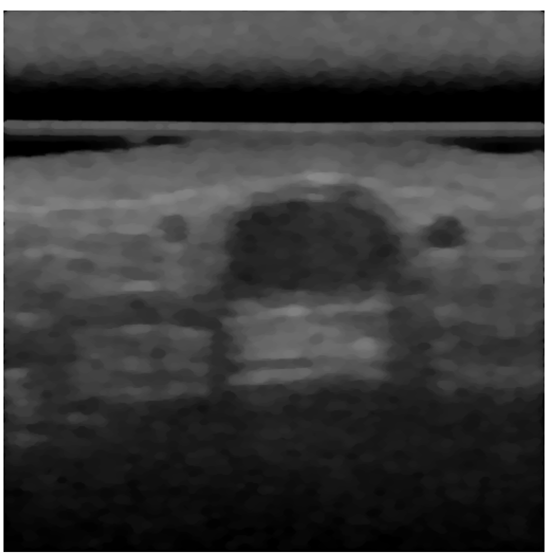


Figure 2 Close-Opened image of Fig. 1.

Fig. 1 is an original ultrasound image of blood vessels. Since the reflected ultrasound echoes from the blood vessels are relatively small, they are displayed as low intensities in the image. Other tissues or areas are hyperechoic and represented as a brighter image.

After the image is processed by opening the closed image with parameters a=3, b=2, c=1, α=10, β=-5, speckle noise is reduced and the contours are enhanced as shown in Fig. 2. For simplicity, we say close-opening for opening the closed image.

3. Parameter evaluation and setting

3.1. Evaluation parameters

Ultrasound diagnostic equipment scans a region of 1[cm] x 1[cm] x 3 [cm] to obtain successive 128 frames of 512x512x8 bit cross-sectional ultrasound image (Fig. 3). Here the x-y plane represents a cross-section and z is a scan direction.

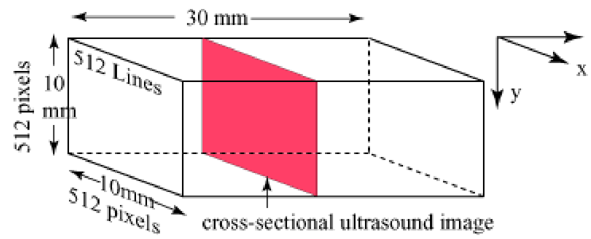


Figure 3 Scanning size.

The locally variable structuring element in (1) has three parameters α , β , and *G.* Fig. 4 is a ellipsoidal structuring element for defining *G*, where a, b, and c are each the radius in x, y, and z direction. For convenience, the five parameters are defined as a quintuplet (a, b, c, α, β).

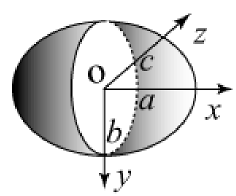


Figure 4 An ellipsoidal structuring element.

3.2. Evaluation functions and resultant values

The most effective values of the parameters mentioned above are determined statistically from the processed images. The functions evaluate the degree of smoothing and enhancement of the processed ultrasound blood vessel images. They include average levels and variances in the inside and outside regions of blood vessels, difference between them, and separability along the contour.

The accessed three dimensional data are processed by close-opening morphological operations, in order to find effective values of five parameters. Sampling regions are selected manually to compute the statistical values by placing a circle successively at appropriate regions in different cross-sections. We repeat this process changing the radius of the circle. The statistic data consist of about 600 to 700 samples for each point in Figures 4 to 8.

Fig. 5 shows the average intensities in the image areas of a large blood vessel, a small blood vessel, and in the area excluding the blood vessels. From this graph, we can observe the average brightness in the three different regions of each processed image. Horizontal axis represents a quintuple (a, b, c, α, β). For example, 3-2-1-10-08 means a=3, b=2, c=1, α=10, β=-8 in the prescribed order.

"Orig" means an unprocessed original ultrasound image. The graph shows that the average intensities of the processed images increase after close-opening operations, but they do not change remarkably with the parameters except the case a=5, b=3, c=1, α=10, and β=-5.

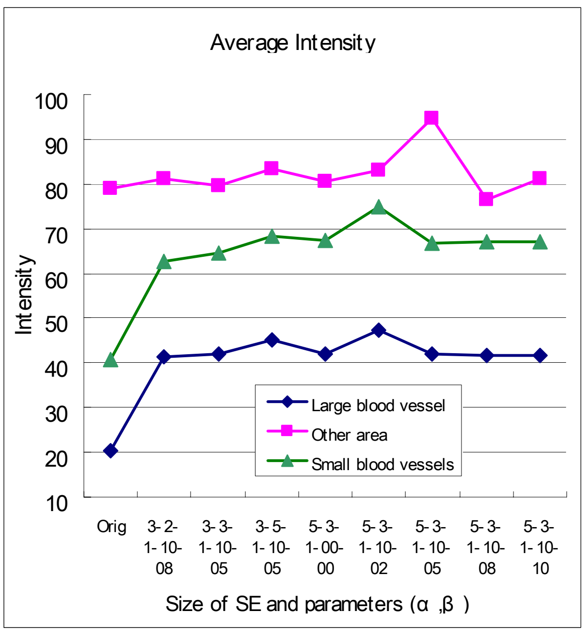


Figure 5 Average intensities in the three areas.

Fig. 6 shows the difference between of the mean (average intensity or brightness) of the blood-vessel images and that of other tissue area. "O-L" denotes the difference between the large blood vessel image and the region excluding the vessels. "O-S" denotes the difference of the means between the small blood-vessel image and the region excluding the vessels. We see there is a tendency that the larger the structuring element, the smaller the difference. In this experiment, the difference becomes largest for parameters a=5, b=3, c=1, α=10, and β=-5.

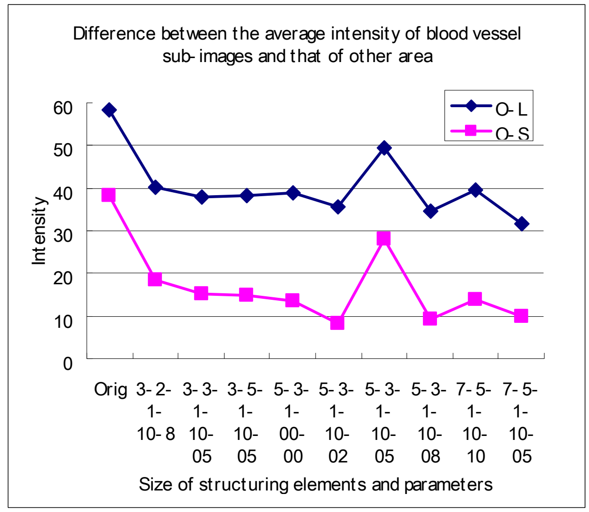


Figure 6 Difference of average intensities between the two areas.

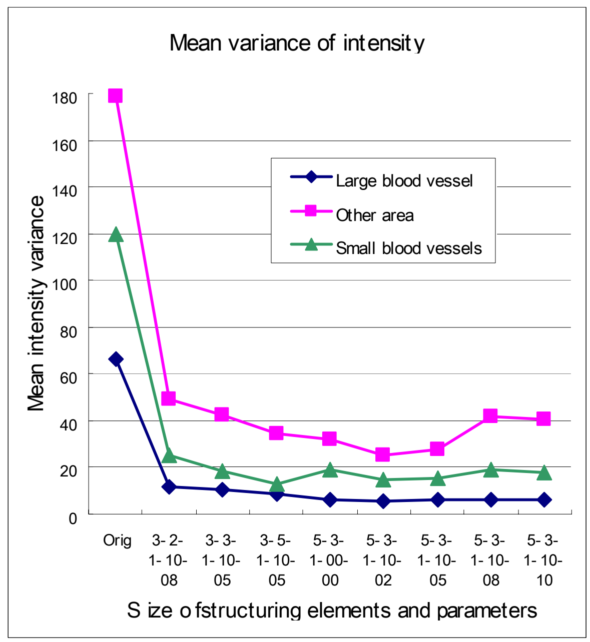


Figure 7 Mean variances in the three areas.

Speckle noise must be reduced for preprocessing. Fig 7 shows the mean variances in three regions, where the variance is computed from the histogram of each sampled small area and all the variances are averaged. Note a small variance shows strong smoothing. The variance is large in every region of the original image, since it contains not only echo signals but also speckle noise.

We can assume here that echo signals are relatively weak in blood vessels and relatively strong in other regions. Thus the contours can be extracted from a binary image, which is obtained from a smoothed image by an optimum threshold. We know that two regions are easily separable when the inter-class variance is large and inner-class variance is small. For this purpose, an evaluation function called separable index or separability, is defined as the ratio of the inter-class variance of the two regions to the variance of the entire region [10].

$$\eta = \frac{\sigma_b^2}{\sigma^2} \tag{10}$$

Here a large number of evaluation samples are collected along the boarder(s) of the blood vessels to average them. The measured data are shown in Figure 8. When $\alpha=\beta=0$, the conventional morphology operation is implemented.
Among these data, the most effective parameter values were a=3, b=2, c=1, $\alpha=10$, $\beta=-5$.
We can conclude that the proposed adaptive morphological filters result in more effective preprocessing than a conventional one.

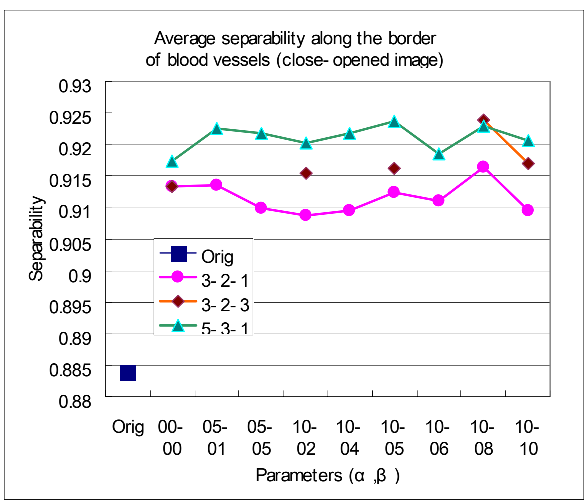


Figure 8 Average separable indices along blood vessel boarder.

4. Experimental results

Now we can obtain a smoothed but edge-enhanced image as shown in Fig 1, from which the blood vessels are to be extracted. Here, binarization is done for small sub images rather than the entire image, since a small region like a small blood vessel is often neglected by a global processing. The smoothed cross sectional image is subdivided into a large number of overlapped local sub images and they are binarized at a statistically optimum threshold level. The resultant binary images are again summed so that the walls of blood vessels are emphasized as shown in Fig. 9. Fig. 9 is again binarized, yielding Fig. 10 (a). Both small and large blood vessels are detected with some noise and extra components. Fig. 10 (b) shows a filtered image processed by binary morphological operation. After comparing neighbor cross sections each other, we obtain blood vessel regions as in Fig. 10 (c).

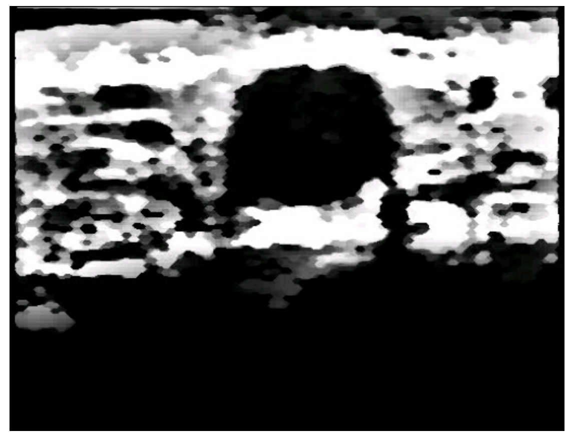
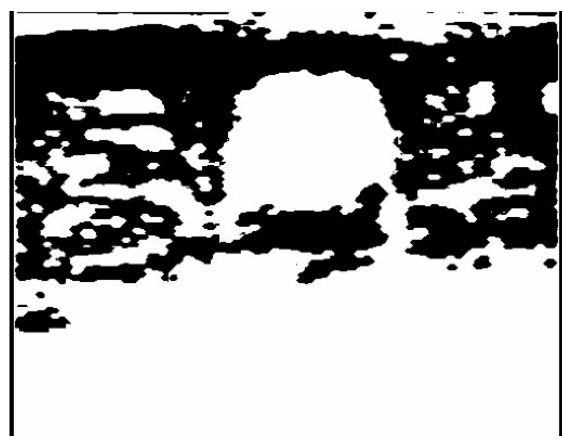


Figure 9 Summation of binarized local images.



(a)

(b)

(c)
Figure 10 Post processing.

6. Conclusions

We proposed a new adaptive three dimensional morphological filter, in which the value of the structuring element changes according to the local image characteristics. The filter can smooth and enhance an image simultaneously. We applied it to the cross section ultrasound images and demonstrated its usefulness statistically in many aspects. But we have to continue this work and develop efficient post processing for medical diagnosis.

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