Tissue Boundary Extraction from Ultrasound Image Using Fuzzy Morphology

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To develop a boundary extraction method, and to evaluate an appropriateness of the extracted boundary from ultrasound images are significant problems, because of the complex ultrasound characteristics and the obscurity of tissue boundary image. This paper presents a new method for an automatic tissue extraction from medical ultrasound image, whose extracted edge is optimal from the view point of histogram. We propose a novel method of the automatic tissue boundary extraction by using fuzzy morphology in order to cope with the ambiguous and obscure ultrasound image. Regarding a quantitative evaluation which is considered as the statistical characteristic and the gradient or distribution of level from the original image, proper edges or boundaries are detected using multi structuring elements here. We clarify a relation of boundary with structuring element in connection to fuzzy morphology that is used in the boundary extraction.

Keywords: ultrasound image, fuzzy morphology, structuring element, boundary extraction

1. Introduction

The ultrasonic diagnostic equipments are widely used because it can provide noninvasive diagnostic information. Furthermore, it is excellent in device simplicity and low costs compared with the other diagnostic equipments. However, the quality of ultrasound image is not high and interfered by various factors. Nowadays, the tissue extraction from ultrasound image is not fully automatic and is sometime manually done using the experienced doctors' knowledge and needs much labor. Therefore an automatic tissue extraction is eagerly expected.

Intuitively, the tissue extraction is closely related to edge detection. The edge detection is used in the various fields. Daniel⁽⁵⁾ and Ardeshir⁽⁶⁾ investigated the edge detection aiming a noise reduction and smoothing for NMR images. Sankar Krishnamurthy has examined the method of automatic edge detection in the field of remote sensing for oceanography⁽⁷⁾. Kanemaru⁽⁸⁾ and Hata⁽⁹⁾ used an edge detection for motion picture compression.

There are various methods for detecting the edge. Much of image processing has been based on discrete approximation to differential operators. It is well known that derivatives emphasize high-frequency noise. Canny⁽¹⁰⁾, Masoud⁽¹¹⁾ and Shen⁽¹²⁾ reported an improvement of the conventional method of smoothing in term of noise reduction using Gaussian operator. However, since this Gaussian smoothing that use a complex calculation gave as same result as using a simple average, therefore Gaussian smoothing is less effective in simplicity.

Muragami is concerned with an edge detection method using local gradient operator⁽¹³⁾. The local gradient operator analyzed a 3×3 subimage or receptive field of a large 256×256 or 512×512 image to determine

the strength and orientation of an edge, if any, present at the central pixel of the field. The size of the receptive field being small, the extracted edges may correspond to artifacts and noise.

Furthermore, Nalwa treated an edge detection using a surface fitting⁽¹⁴⁾. Surface fitting by basis functions treated the intensity profile of a larger receptive field (such as 15×15) as a three-dimensional surface. An adaptive algorithm computes the weights multiplying each basis function such that the resulting series is a close match to the three-dimensional surface. The weight values and the derivatives of the basis functions are related to edge strengths and orientations.

However, there is a high possibility that clear edges do not appear in ultrasound images. Since the above edge detection methods cannot be always adopted to every ultrasound images, we propose a novel method of the automatic tissue boundary extraction by using fuzzy morphology in order to cope with the ambiguous and obscure ultrasound image. Regarding a quantitative evaluation which is considered as the statistical characteristic and the gradient or distribution of level from the original image, proper edges or boundaries are detected using multi structuring elements here. Hence, we clarify a relation of boundary with structuring element.

A fuzzy morphologically based approach and its evaluation are presented in this paper. Section 2 discusses the definition of fuzzy morphology. Section 3 describes the algorithm of fuzzy morphological boundary extraction. Section 4 describes the evaluation for the extracted boundary. Section 5 presents and evaluates the experimental results of the algorithm, and suggests areas for further research.

2. Fuzzy Morphology

The theoretical foundations of mathematical morphology and a wide range of its applications were introduced systematically by Haralick⁽¹⁾. Many applications of morphological filters are found in biomedical image processing, metallography, geology, remote sensing and automated industrial inspection. Recently, mathematical morphology has been used for feature extraction, noise suppression, shape analysis, skeletonization and coding^{(3), (4)}. It is particularly useful for a natural image which has contrast level.

The basic idea of mathematical morphology is to probe an image with a template (usually called a structuring element) and to quantify the manner in which the structuring element fits (or does not fit) within the image. By marking the locations at which the structuring element fits within the image, we derive structural information concerning the image. By varying the structuring element, different types of information can be extracted from the image.

The fundamental of morphological operations are erosion and dilation. All other morphological operations are sequences combining erosions and dilations. Opening that one of base on morphology will be expected, since adopting it as a crisp set, even though almost all of structuring element is included by original image, in the case of erosion which is a half of opening, the image will be removed.

Thus, as an effect of erosion, it is not expressed as a crisp set with 'included' or 'not included', but it is expressed as a fuzzy set with 'how much it is included'. Using an introduction of fuzzy into morphology, it is considered that we can extract the feature of the interest from image even though the original image is deteriorated (Fig. 1).

According to Sinha⁽²⁾, fuzzy operation uses an index function $\mathcal{I}$, and is defined as

$$\mathcal{I}(B, A) = \inf_{z \in U} \min[1, \mu_A(z) + 1 - \mu_B(z)] \quad \dots \dots \quad (1)$$

Where A is an image, B is a structuring element, $\mu_{\bullet}(\blacklozenge)$ denotes the degree to which $\blacklozenge$ "belongs" to the set $\bullet$. Therefore, the image A with a fuzzy erosion by structuring element B is

$$\begin{aligned} \mu_{A \ominus B}(x) &= \mathcal{I}(B_x, A) \\ &= \inf_{\substack{z \in U \\ x \in U}} \min[1, \mu_A(z) + 1 - \mu_{B_x}(z)] \quad \dots \dots \quad (2) \end{aligned}$$

Similarity, a fuzzy dilation is defined as

$$\begin{aligned} \mu_{A \oplus B}(x) &= \mathcal{I}(-B_x, A^c) \\ &= \sup_{\substack{z \in U \\ x \in U}} \max[0, \mu_{-B_x}(z) + \mu_A(z) - 1] \quad \dots \quad (3) \end{aligned}$$

Here, fuzzy opening is to dilate the eroded image, and has an effect to smooth an object from inside, while fuzzy closing is to erode the dilated image, and has an

Fig. 1. Illustration of fuzzy morphology

effect to smooth an object from outside.

In Sinha's paper⁽²⁾, no speculation has taken place concerning a post processing in connection to the extraction boundary. Here, we treat a discriminant and least squares criteria to define the boundary⁽¹⁹⁾

3. Fuzzy Morphological Boundary Extraction

3.1 Decision of Structuring Element

It is known that morphology is to scan an image with a structuring element which depends on shape, size and level. Since it is aimed to extract the region smoothly and precisely, we consider a circle as a suitable shape for the structuring element. Then, about the size of structuring element, since it is expected to extract the image with various border, it is better to use a multiple size of the structuring element.

According to⁽²⁾, the degree of the structuring element $\mu_B(z)$ is reasonably large number in $[0, 1]$. Since the structuring element fits inside the image with a relatively high degree of certainty, the level of the structuring element is set to be high level. However, even though it is said that high level is good for the structuring element, it is still an ambiguity. The problem is how to decide a proper level.

For any two images A and B , the property of background color of eroded image is

$$\min[1, \tau + \alpha] \geq \mu_{A \ominus B}(x) \geq \tau, \quad \dots \dots \dots \quad (4)$$

where $\tau = 1 - \sup_{z \in U} \mu_B(z)$ and $\alpha = \sup_{z \in U} \mu_A(z)$.

In other words, when we erode an image with a structuring element which may not be a crisp set (0 or 1), then the background of the eroded image does not necessarily have the value 0, that is, the background's value is τ .

Likewise, for any two images A and B , the property

of background color of dilated image is

$$\max[0, \kappa + \beta - 1] \leq \mu_{A \oplus B}(x) \leq \kappa, \dots\dots\dots (5)$$

where $\kappa = \sup_{z \in U} \mu_B(z)$ and $\beta = \inf_{z \in U} \mu_A(z)$.
Accordingly, when we dilate an image with a structuring element which is not a crisp set, then the highest value of the dilated image is not necessarily 1, that is, the highest value is κ .

However, this phenomenon does not exist if the structuring element has value of 1 at one or more pixels. Hence, this phenomenon does not exist in binary morphology as we are then dealing with crisp structuring elements. It is one of the characteristics of fuzziness.

3.2 Boundary Extraction

For the boundary extraction, we combine the opening and the closing transformation named *open-closing* and *close-opening*. The open-closing has an effect to smooth an object from both of inside and outside. When we open-close an image with a structuring element which is not a crisp set, we have

$$\tau \leq \mu_{A \circ B \bullet B}(x) \leq \kappa, \dots\dots\dots (6)$$

where $\tau = 1 - \sup_{z \in U} \mu_B(z)$ and $\kappa = \sup_{z \in U} \mu_B(z)$.
While, the close-opening has an effect to smooth an object from both of outside and inside. When we close-open an image with a structuring element which is not a crisp set, we have

$$\tau \leq \mu_{A \bullet B \circ B}(x) \leq \kappa, \dots\dots\dots (7)$$

where $\tau = 1 - \sup_{z \in U} \mu_B(z)$ and $\kappa = \sup_{z \in U} \mu_B(z)$.
Fig. 2 shows a flowchart of morphological processing for a boundary extraction. First, open-close or close-open the image using the first n structuring elements of size. Then, for extracting general boundary, take an average of n open-closed or close-opened images. By using discriminant and least squares criteria⁽¹⁷⁾, take a thresholding value to get a binarization. Take the border from the region which is attained from a binarization. Finally, get the boundary by taking separability on the border.

4. Evaluation for Extracted Boundary

To evaluate the extracted boundary accurately, we take the neighborhood of boundary characteristic by using the neighborhood of boundary average with an arbitrary size. It is called separability⁽¹⁸⁾, which has the same meaning of discriminant and least squares criteria⁽¹⁷⁾. Separability S can be calculated by linear discriminant analysis using information from regions 1 and 2 (R_1 and R_2 , see Fig. 3),

$$S_{(x_i, y_j)} = \frac{\sigma_b^2}{\sigma_T^2} \dots\dots\dots (8)$$

$$\sigma_b^2 = \frac{n_1(\bar{P}_1 - \bar{P}_m)^2 + n_2(\bar{P}_2 - \bar{P}_m)^2}{N}$$

$$\sigma_T^2 = \frac{1}{N} \sum_{i=1}^N (P_i - \bar{P}_m)^2$$

$(x_i, y_j) \in$ extracted boundary points

Fig. 2. A flowchart of morphological boundary extraction

(a) Definition of separability

(b) Changes of separability

Fig. 3. Separability

Where $N = n_1 + n_2$, n_1 and n_2 are the number of pixels in investigated R_1 and R_2 , respectively. σ_T^2 is the

variance of the total image features. $\bar{P}_m$ is the average of features. $\bar{P}_1$ and $\bar{P}_2$ are the averages of the image features in investigated R_1 and R_2 , respectively. Here, separability will be $0 < S \leq 1.0$.
 Furthermore, we take an average of separabilities along the boundary, which gives an evaluation of the extracted boundary (E). We define

$$E = \frac{1}{L} \sum_{f=1}^L S_f \dots\dots\dots (9)$$

Where, S_f is separability at a point on the boundary, and L is the number of points.

5. Experiment

In this section we investigate the performance of the discussed boundary extraction method using fuzzy morphology for ultrasound images and compare it with the boundary extraction based on gray scale morphology or a simple mean filter. The extracted boundary with these methods will be evaluated by applying separability described previously. For each point of the extracted boundaries will be computed using mask region with a size 13×13 .

First, we examine the performance of fuzzy morphology to simulated ultrasound image⁽¹⁶⁾. By distributing randomly to a circular region in the background ($128 \times 128 \text{ mm}^2$) (Fig. 4(a)) with scatterers' density 16 point/mm^2 and 2 point/mm^2 , respectively, to get echo signal by irradiating ultrasonic pulse from transducer which is located 50mm from the circular region. Central frequency of pulse and pulse length are set to be the same as the diagnostic equipment with value of 3.5MHz , $0.7\mu\text{s}$, respectively. The velocity is set to 1500 m/s . The simulated image is shown in Fig. 4(b). The extracted boundary using fuzzy morphology and the ideal boundary are shown if Fig. 4 (c) and (d), respectively.

To evaluate the extracted boundary, we define an average of the distance to the each point at the ideal boundary and the extracted boundary as

$$E_{error} = \frac{1}{L} \sum_{i=0}^{L-1} \| a_i - b_i \| \dots\dots\dots (10)$$

where a_i and b_i are ordered pairs of the x and y coordinates of points at the ideal boundary and the extracted boundary, respectively. L is the number of points. The small value of E_{error} is better. Table 1 shows the evaluation of the extracted boundary using open-closing of fuzzy morphology (FM(OC)), close-opening of fuzzy morphology (FM(CO)), open-closing of morphology (M(OC)) and close-opening of morphology (M(CO)) with different size of structuring elements. It is known that both of FM and M using structuring element with size of $r \leq 5$ (that is, $r = 1, 3, 5$) have result with lower value.

Then, we investigate the the performance of the proposed method for ultrasonographic phantom images

Fig. 4. Simulated image

Table 1. An average of the distance to the each point at the ideal boundary and the extracted boundary

SE size	FM(OC)	FM(CO)	M(OC)	M(CO)
$r \leq 1$	1.719	1.730	1.827	2.240
$r \leq 3$	0.816	2.653	1.755	1.775
$r \leq 5$	0.795	3.515	0.811	1.658
$r \leq 7$	0.806	4.163	0.867	7.337
$r \leq 9$	0.995	4.709	0.975	9.944

which are modeled as an organism. The phantom images are made from gelatins that are distributed graphite as scatterers. They are portion of a phased array B-scan sector image, and have 6dB and -6dB display dynamic range, which are named phantom A and phantom B, respectively. Moreover, they are reconstructed by digital processing to be 128×128 , 256 gray level. The phantom images have a light circular region and a dark circular region are shown in Fig. 5 (a) and (b), respectively.

We investigate a relation of structuring element with open-closing (FM(OC)) or close-opening (FM(CO)) process in connection to thresholding value for discriminant and least squares criteria. Fig. 6 depicts the thresholding values on the different sizes and levels of structuring elements. According to Fig. 6, when the levels of structuring elements are low (< 128), they have no thresholding values ($= 0$). For that reason, we can not process FM(OC) or FM(CO) using structuring elements with level less than 0.5 (cf. eq. (6),(7)). In case of FM(OC) processing, larger structuring elements lower the thresholding values. And in the case of FM(CO) processing, larger structuring elements raise the thresholding values. On the other hand, the thresholding val-

Fig. 5. Original image

Fig. 6. Thresholding value vs level

ues on the high level are becoming steady.

Fig. 7 shows the average of separabilities on extracted boundary by using FM(OC) or FM(CO) with different sizes and levels of structuring elements. According to Fig. 7, the average of separabilities on extracted boundary with low levels of structuring elements (great than 128) are not always in the low value, sometimes they are better than the average of separabilities with high levels of structuring elements. Here, we select the structuring elements with size of $r \leq 5$ and level = 205, since they have the average of separabilities in steady and high values.

Fig. 8 shows the separability on the extracted boundary by using FM(OC) or FM(CO) with structuring elements of size $r \leq 5$ and level = 205. According to Fig. 8, phantom A which has a light object will be better if it is processed by FM(OC) ($E = 0.788$), while phantom B which has a dark object will be better if it is processed

Fig. 7. Average of separabilities on extracted boundary

Fig. 8. Separability on extracted boundary

by FM(CO) ($E = 0.821$).

Additionally, as for the robust characteristic, it is necessary to analyze the processed image as a quantitative measure. Here, the measure uses SNR⁽¹⁵⁾ which is given by

Fig. 9. SNR of processed image

$$SNR = \frac{\mu_{i,j}}{\sigma_{i,j}} \dots\dots\dots (11)$$

$$\mu_{i,j} = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} x_{i,j} \dots\dots\dots (12)$$

$$\sigma_{i,j} = \sqrt{\frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (x_{i,j} - \mu_{i,j})^2} \dots\dots (13)$$

where $x_{i,j}$ is the pixel at the location (i, j) , and $M \times N$ is the size of image.

Fig. 9 are shown SNR of the processed image based on fuzzy morphology (FM(OC) or FM(CO)) using different size and level of structuring elements. The results with the structuring elements which use low level have a tendency to lead SNR in a high value.

The extracted boundary based on fuzzy morphology (FM(OC) or FM(CO)) are shown in Fig. 10 (a)-(d). In addition, the extracted boundary based on morphology (M(OC)) or mean filter are shown in Fig. 10 (e)-(h). For each average of separabilities on the extracted boundary and SNR are shown in Table 2 and 3, respectively. Table 2 and 3 also shows the each value on the extracted boundary using structuring element with size $r \leq n$ and $r = n$. It is obvious that, the extracted boundary based on mean filter is almost useless, since it still extracts noise around the object. On the other hand, the extracted boundary based on fuzzy morphology is called to be useful. Here, indeed the boundary extraction based on fuzzy morphology can extract the object.

(a) phantom A by FM(OC)
(b) phantom B by FM(OC)
(c) phantom A by FM(CO)
(d) phantom B by FM(CO)
(e) phantom A by M(OC)
(f) phantom B by M(OC)
(g) phantom A by mean
(h) phantom B by mean

Fig. 10. Extracted boundary

Additionally, Fig. 11 shows the boundary extraction from ultrasound image application named mammary cancer image which is provided by Cancer Research Institute Hospital. The image is reconstructed to be 128×128 , 256 gray level. In this Fig. 11 we can extract the boundary using fuzzy morphology (FM(CO)) pro-

Table 2. An average of separabilities on the extracted boundary

process	phantom A	phantom B
FM(OC)($r \leq 5$)	0.788	0.724
FM(OC)($r = 5$)	0.740	0.720
FM(CO)($r \leq 5$)	0.756	0.821
FM(CO)($r = 5$)	0.745	0.768
M(OC)($r \leq 5$)	0.662	0.735
M(OC)($r = 5$)	0.636	0.723
mean	0.534	0.494

Table 3. SNR of processed image

process	phantom A	phantom B
FM(OC)($r \leq 5$)	5.651	4.659
FM(OC)($r = 5$)	5.167	4.615
FM(CO)($r \leq 5$)	3.623	5.062
FM(CO)($r = 5$)	3.369	4.886
M(OC)($r \leq 5$)	3.158	4.743
M(OC)($r = 5$)	3.091	4.728
mean	3.327	4.639

Fig. 11. Extracted boundary from mammary cancer image

cessing using structuring elements of size $r \leq 5$ and level = 205 with an average of separabilities in 0.752. However, the left upper of the image which has a dark region still can not extract, since the method uses an average of n processed images for extracting general boundary. We consider this problem for the next paper.

6. Conclusion

We have shown the experiment for the edge extraction, in connection with a problem for boundary extraction in the ultrasonic image processing. Using technique on Fuzzy Morphology and evaluation on Statistical Discriminant Method, called Separability,

- Different tissues and their borders can be clearly detected in ultrasound images.
- Detected boundaries are most reliable from the statistical point of view. Thus,
- Segmented regions and borders give useful information for diagnosis as well as for quantitative measurement, and three-dimensional display.

Acknowledgement

We gratefully acknowledge Dr. Atsushi Takemura for his assistance in preparing this paper, Dr. Hiroshi Sakuma of Cancer Research Institute Hospital for providing the cancer image data. This study is supported by the Proposal-Based Immediate-Effect R&D Promotion Program from the New Energy and Industrial Technology Development Organization (NEDO) of Japan.

(Manuscript received June 18, 1999, revised November 24, 1999)

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