

Automated Boundary Extraction and Visualization System for Coronary Plaque in IVUS Image by Using Fuzzy Inference-based Method

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Abstract—We propose a fully automatic plaque boundary extraction system for an intravascular ultrasound (IVUS) image aiming at practical use in clinic. The IVUS image, which is commonly used for a diagnosis of acute coronary syndromes (ACS) in the field of cardiology, has coarse-grained texture due to heavy speckle noise. A medical doctor's interpretation of the IVUS image is disturbed frequently by the heavy speckle noise. In the proposed system, the heavy speckle noise is reduced firstly by using an anisotropic diffusion filter. Secondly, the plaque boundary is extracted by using the Takagi-Sugeno (T-S) type fuzzy inference with a weighted separability measure and some heuristic rules. Extraction of plaque boundary is achieved fully automatically. The proposed system substantially reduces the workload of medical doctors. The effectiveness of the proposed system has been verified by the experiments using the real IVUS images.

Index Terms—Acute coronary syndromes, IVUS image, plaque boundary extraction, fuzzy inference.

I. INTRODUCTION

Intravascular ultrasound (IVUS) method [1], [2] is a real-time computed tomographic imaging method for the visualization of coronary atherosclerotic plaque. It provides thousands of cross-sectional images of a coronary artery in vivo, and is employed especially for a diagnosis of the acute coronary syndromes (ACS) caused by a rupture of vulnerable plaque [3], [4]. For quantitative assessment of plaque [5], precise boundary extraction of plaque is strongly required in the interpretation of the tomographic images produced by the IVUS method. In particular, the inner and outer boundaries of the plaque and the cross-sectional area of the plaque are to be extracted and evaluated precisely in order to monitor the effect of medical treatment.

Frequently, medical doctors manually trace the boundaries of the plaque and then evaluate the area of that plaque for many IVUS images. After that, the volume of the plaque is estimated by integrating the extracted area. However, the boundary extraction task of plaque is tough and time-consuming for a medical doctor. This is not only because a large number

of the IVUS images must be processed, but also because recognizing the boundaries of plaque is very hard due to a heavy blood speckle noise. A computer-aided full-automatic precise boundary extraction of plaque is thus strongly desired.

So far, in the representative boundary extraction methods [6], e.g., curve interpolation method such as spline interpolation is used, where seed points are given manually by a medical doctor. Those methods and tools can reduce somewhat the workload of the tracing task on a medical doctor. However, the accuracy of the plaque boundary extraction by the curve interpolation is considerably affected by the number of the seed points and/or the positions of those points.

On the other hand, the methods based on automatic search algorithms, e.g., an active contour (snake) model [7], genetic algorithm [8], and so on, have been proposed to date. However, those methods involve some iterative processes for optimizing evaluation function and take plenty of computing time. To meet with a demand for a practical use, a quick and fully automatic boundary extraction of plaque is definitely required.

In the past, to cope with this problem, the authors proposed some fundamental techniques for the plaque boundary extraction such as speckle noise reduction by using a modified anisotropic diffusion filter [9], [10] with a statistical discriminant measure (being called separability) [11], an automatic searching algorithm for the boundary extraction area based on some heuristic rules [12], boundary extraction method by using Takagi-Sugeno (T-S) type fuzzy inference [13], and so on. Then the authors furthermore advanced the method by employing an adaptive allocation rule of membership functions in the T-S fuzzy inference engine, and some of the performance of the proposed method has been presented in [14]. The fuzzy inference-based method realizes a fast, precise, robust, and automatic extraction of the boundary of plaque.

In this paper, we introduce an automatic boundary extraction system which combines all the above-mentioned fundamental techniques. The proposed system is implemented as

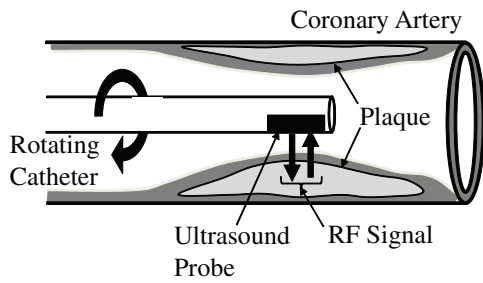


Fig. 1. Overview image of the intravascular ultrasound (IVUS) method.

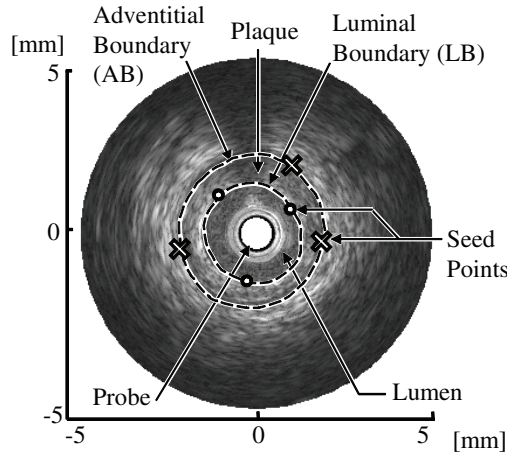


Fig. 2. An example of B-mode image obtained by the IVUS method. In the image, 4mm corresponds to 2,048 pixels.

a software with easy-to-use graphical user interface (GUI) aiming at the real practical use in clinic and at the research use.

In the proposed system, the plaque boundary extraction area is automatically searched and is found by an edge-preserved smoothing filter using anisotropic diffusion, weighted separability, the heuristic rules, and T-S type fuzzy inference. This system also has a semi-automatic boundary extraction function using the seed points allocated by the user, for the IVUS images with very complicated boundary of coronary plaque.

The validity and the effectiveness of the system are briefly reviewed by applying it to the practical problem of plaque boundary extraction in clinic. Finally, it is shown that a 3-dimensional image of the coronary plaque can be reconstructed.

II. INTRAVASCULAR ULTRASOUND (IVUS) METHOD

Intravascular ultrasound (IVUS) method [1], [2] is one of the medical imaging techniques. It allows the application of ultrasound technology to observe from inside the blood vessels out through the surrounding blood column, visualizing the coronary plaque in vivo.

In the IVUS method, a specially designed thin catheter with the ultimately-miniaturized ultrasound probe attached to

its distal end is used (see Fig. 1). To visualize the coronary arteries and plaques in vivo, angiographic techniques are used. A medical doctor steers the guidewire with very thin diameter from outside the body through angiography catheters into the coronary artery to be visualized. The ultrasound catheter tip is slid in over the guidewire and positioned, using angiography techniques so that the tip is at the farthest away position to be visualized. The guidewire is kept stationary and the ultrasound catheter tip is slid backwards, usually under motorized control.

The proximal end of the catheter is connected to a computerized ultrasound equipment. The ultrasound waves are emitted from the ultrasound probe, which are in the 40MHz range in this study, and the catheter also receives the reflected signal from the plaque tissue. It is sampled at 400 MHz and stored in the computerized ultrasound equipment.

An IVUS image is constructed of the amplitude information of the received radiofrequency (RF) signal. In order to visualize the inside of a coronary artery, the sampled RF signal is first transformed into an 8-bit luminal intensity signal by taking the absolute value of a signal, then by taking the envelope of a signal, and finally by taking its logarithmic value.

The luminal intensity signals in all radial directions are then formed to obtain a tomographic cross sectional image of a coronary artery as shown in Fig. 2. The IVUS image of Fig. 2 is called "B-mode image." A B-mode image displays a real time ultrasound cross-sectional image of a thin section of a blood vessel currently surrounding a catheter probe.

In this study, the B-mode image is constructed with 2,048 pixels in depth, and 256 lines in radial direction. Hence, the resolution of distance and angle are $1.95\mu\text{m}/\text{pixel}$ and $1.41^\circ/\text{line}$, respectively.

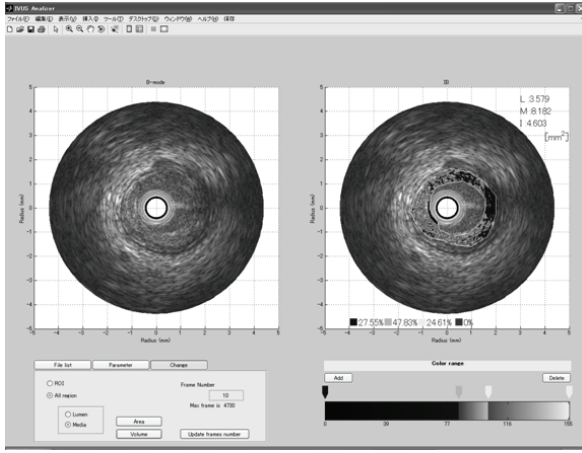
In the quantitative assessment of coronary plaque, the following two boundaries are extracted in the IVUS B-mode image as shown in Fig. 2. One is a luminal boundary (LB) between the lumen and the plaque, and the other is an adventitial boundary (AB) between the plaque and the vascular wall.

III. PROPOSED SYSTEM

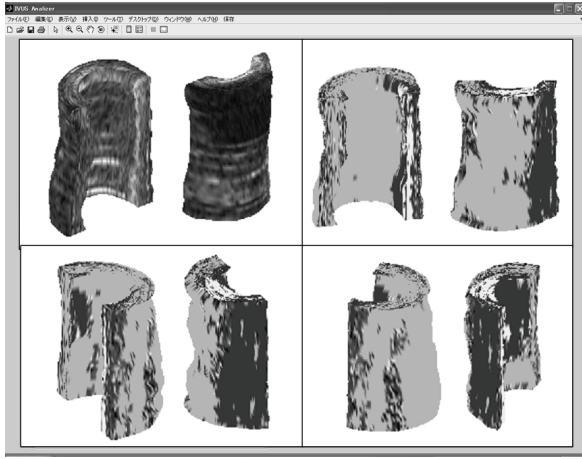
Figs. 3(a) and 3(b) show the overviews of the proposed diagnosis system. By applying a set of IVUS data obtained by IVUS instrument, the software extracts the boundaries of plaque by the full-automatic extraction algorithm and reconstructs the 3-D classified tissue structure of the plaque as shown in Fig. 3(b). In this section, we firstly describe the full-automatic search method for the area of boundary extraction without using any seed points and giving any initial boundary. Then semi-automatic (interactive) boundary extraction method, which is used for IVUS images with very complicated boundaries of plaque, is described.

A. Fully automatic plaque boundary extraction

In the present method, at first, an IVUS image is transformed from the polar coordinate system into the orthogonal coordinate system as shown in Fig. 4(a). Then the edge-preserved smoothing using anisotropic diffusion is performed



(a)



(b)

Fig. 3. Overview of the proposed diagnosis system. (a) Overview of main GUI. (b) 3-D viewing of the extracted plaque.

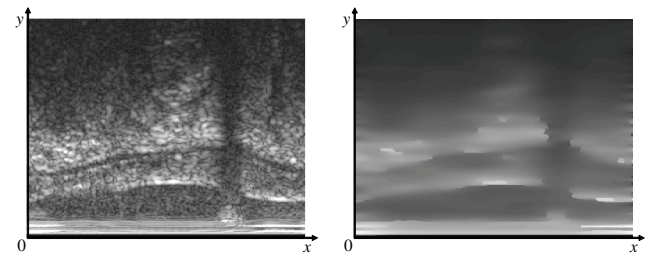
on the input image as shown in Fig. 4(b). An anisotropic diffusion filter is known as an effective edge-preserved smoothing method, and it is broadly used.

Then image processing using some heuristic rules are applied to find out the boundary extraction areas. Finally in the found areas, the objective boundaries are extracted by T-S type fuzzy inference with the weighted separability measure. The weighted separability is a modification of a separability measure with special consideration to an IVUS image.

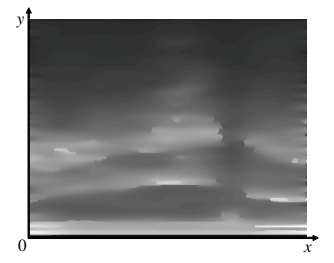
1) *Speckle Noise Reduction by Perona-Malik's anisotropic diffusion (PMD)*: The anisotropic diffusion filter proposed by Perona and Malik [9] is employed to realize an edge-preserved smoothing for an IVUS B-mode image. The discrete version of PMD is given as follows:

$$I_s^{(n+1)} = I_s^{(n)} + \frac{\lambda}{|\phi_s|} \sum_{p \in \phi_s} g(\nabla I_{s,p}^{(n)}) \cdot \nabla I_{s,p}^{(n)}, \quad (1)$$

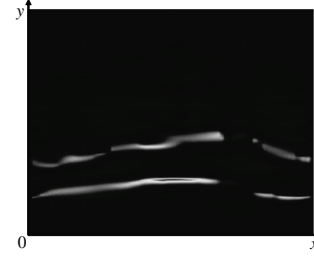
where $s=(x,y)$ and p are the coordinates of the pixel of concern and its neighboring pixels, respectively. $I_s^{(n)}$ is an intensity at s with an iteration count n . ϕ_s represents the four neighboring pixels in North, West, South and East diffusion



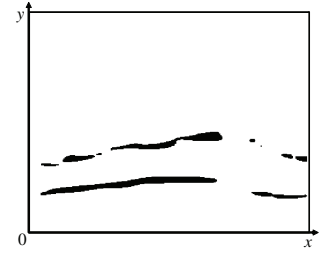
(a)



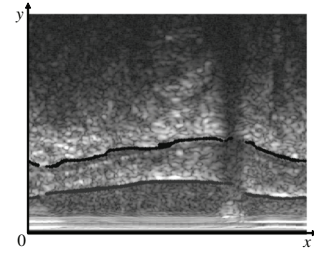
(b)



(c)



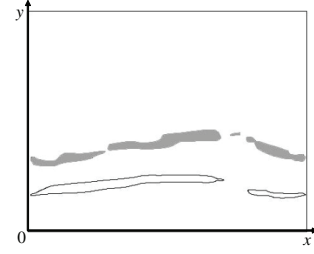
(d)



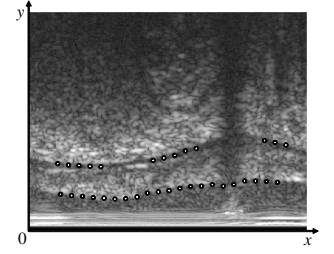
(e)



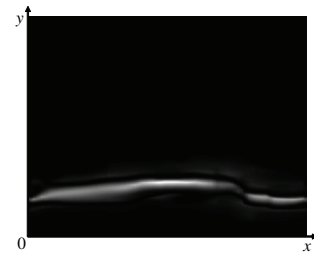
(f)



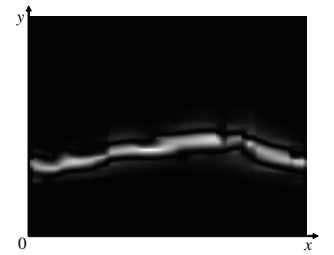
(g)



(h)



(i)



(j)

Fig. 4. Automatic placement of seed points and automatic partitioning of boundary extraction area. (a) Input image. (b) Edge-preserved and smoothed image by PMD. (c) Discriminant image of (b) by weighted separability. (d) Binary image obtained by threshold processing for (c). (e) Candidates of the seed points. (f) Regions for getting the final seed points. (g) Classified regions of (f) for LB or AB. (h) Final seed points automatically placed. (i) The plaque boundary extraction area for luminal boundary (LB). (j) The plaque boundary extraction area for adventitial boundary (AB).

directions. $|\phi_s|$ is a number of the pixels in the neighborhood area, which is then $|\phi_s| = 4$ in this study. λ is a parameter. $g(\cdot)$ is called an edge stopping function. A monotonically decreasing function of the gradient of an image is usually adopted as $g(\cdot)$. The gradient of the image is calculated by:

$$\nabla I_{s,p}^{(n)} = I_p^{(n)} - I_s^{(n)}. \quad (2)$$

In PMD, the edge stopping function is given by:

$$g(z) = \frac{1}{1 + \left(\frac{z}{K}\right)^2}, \quad (3)$$

where K is a parameter which controls the strength of diffusion. $g(\cdot)$ takes large values at the regions where the intensity gradients are small. On the contrary, it takes small values at the regions where the intensity gradients are large.

By applying the PMD to an IVUS B-mode image as a pre-processing, the speckle patterns are reduced enough, and the edges corresponding to the luminal boundary and the adventitial boundary of plaque are preserved enough as shown in Fig. 4(b).

2) *Detection of boundary extraction area by weighted separability measure:* In order to distinguish the edge of plaque and that of the speckle pattern in an IVUS image, the proposed method employs a statistical discriminant measure of image separability [11]. Evaluation of image separability is very simple, and it has the following features:

- i) Robust to noisy and blurred edge,
- ii) Sensitive to an edge between different texture regions.

Separability is calculated by a linear discriminant analysis using the information of the two local regions. The separability η_s for the pixel $s=(x,y)$ is calculated by:

$$\eta_s = \frac{\sum_{k=1}^{k=L} \sigma_{bk}^2}{\sum_{k=1}^{k=L} \sigma_{Tk}^2}, \quad (4)$$

$$\sigma_{bk}^2 = n_1(\bar{I}_{k1} - \bar{I}_k)^2 + n_2(\bar{I}_{k2} - \bar{I}_k)^2, \quad (5)$$

and

$$\sigma_{Tk}^2 = \sum_{i=1}^{n_1+n_2} (I_{ki} - \bar{I}_k)^2, \quad (6)$$

where $\bar{I}_{k1}$ and $\bar{I}_{k2}$ are the means of the intensities in the regions 1 and 2, respectively. $\bar{I}_k$ is the mean of the intensities in the combined two regions. n_1 and n_2 represent the numbers of the pixels in regions 1 and 2, respectively. η_s is $0 \leq \eta_s \leq 1$, and it takes a large value when two regions are separated with each other in the meaning of separability.

The weighted separability, which is a modification of the original separability [11], detects the candidates of the inner (lower) and the outer (upper) boundaries of plaque by considering the following two conditions peculiar to an IVUS image. Those are: i) intensity in the outside area of a luminal boundary

(LB) tends to be bigger than that in the inside area of LB; ii) intensity in the outside area of an adventitial boundary (AB) tends to be bigger than that in the inside area of AB.

The weighted separability for a pixel $s = (i, j)$ is defined by:

$$\eta_s^w = \eta_s \cdot \left(\frac{\bar{I}_2(I_{Max} - \bar{I}_1)}{I_{Max}} \right)^2, \quad (7)$$

where I_{Max} is a maximum intensity on the whole IVUS image. $\bar{I}_1$ and $\bar{I}_2$ are the means of the intensities in the two discriminative regions 1 and 2, respectively [14].

Fig. 4(c) shows a discriminant image of Fig. 4(b) by using η_s^w . Each pixel of the image represents the weighted separability η_s^w . When η_s^w is large, high brightness is assigned to its corresponding pixel.

The weighted separability takes a large value around the regional edge of the IVUS image. That is, a chain of white pixels with high brightness can then be a candidate of a boundary of plaque.

Fig. 4(c) shows vividly the two candidates of plaque boundary. Furthermore, it is observed that the weighted separability in the area where the blood speckle noise exists (in the lumen area) is suppressed.

3) *Automatic partitioning of boundary extraction area and placement of seed points by heuristic rules:* Here, the candidates of boundaries of plaque shown in Fig. 4(c) are partitioned to the candidate for LB and that for AB. The following are the concrete processes of each step shown in Figs. 4(d)-(h).

Fig. 4(d) shows a binary image obtained by the threshold processing for the image of Fig. 4(c). Here, let the threshold value of the weighted separability be ζ . By changing the value of ζ from ζ_{low} to ζ_{high} at regular intervals, a binary image with each threshold value of ζ , such as Fig. 4(d), is obtained.

The points on the central line of each black-colored region of Fig. 4(d) are regarded as candidates of the seed points. The candidates are detected by line scanning in parallel to the x-axis. When two regions are detected by the line scanning, the centers of regions are regarded as the candidates. The candidates of the seed points for all the binary images are superimposed on Fig. 4(e).

The optimum threshold value of ζ has to be set to obtain the best binary image of Fig. 4(d) for detecting the final seed points. In this process, the binary images are evaluated by using the following score S :

$$G_1 = \begin{cases} \frac{1}{N_{r1}} \cdot n_r & 0 \leq n_r < N_{r1} \\ -\frac{1}{N_{r2}-N_{r1}} \cdot n_r + \frac{N_{r2}}{N_{r2}-N_{r1}} & N_{r1} \leq n_r < N_{r2} \\ 0 & N_{r2} \leq n_r, \end{cases} \quad (8)$$

$$G_2 = \begin{cases} 0 & 0 \leq n_p < N_{p1} \\ \frac{1}{N_{p2}-N_{p1}} \cdot n_p - \frac{N_{p1}}{N_{p2}-N_{p1}} & N_{p1} \leq n_p < N_{p2} \\ -\frac{1}{N_{p3}-N_{p2}} \cdot n_p + \frac{N_{p3}}{N_{p3}-N_{p2}} & N_{p2} \leq n_p < N_{p3} \\ 0 & N_{p3} \leq n_p, \end{cases} \quad (9)$$

$$G_3 = \begin{cases} 0 & 0 \leq l_r < L_{r1} \\ \frac{1}{L_{r2}-L_{r1}} \cdot l_r - \frac{L_{r1}}{L_{r2}-L_{r1}} & L_{r1} \leq l_r < L_{r2} \\ -\frac{1}{L_{r3}-L_{r2}} \cdot l_r + \frac{L_{r3}}{L_{r3}-L_{r2}} & L_{r2} \leq l_r < L_{r3} \\ 0 & L_{r3} \leq l_r, \end{cases} \quad (10)$$

$$S = G_1 \cdot G_2 \cdot G_3, \quad (11)$$

where G_1 , G_2 and G_3 are concerned with the membership functions for the number of regions n_r , the number of pixels n_p , and the total length of regions l_r , respectively.

The sets of parameters $\{N_{r1}, N_{r2}\}$, $\{N_{p1}, N_{p2}, N_{p3}\}$, $\{L_{r1}, L_{r2}, L_{r3}\}$ define the figure of each membership function. Those functions are empirically determined by analyzing hundreds of real IVUS images. The image with the maximum score of S is selected to obtain Fig. 4(f).

The color-coded regions in Fig. 4(f) are then classified either to the region for LB or that for AB as shown in Fig. 4(g) by majority decision by using the class information of the candidates of the seed points.

Finally, the points on the central line of each region of Fig. 4(g) are regarded as the final seed points to get Fig. 4(h). The selected seed points are linearly interpolated, and the boundary extraction areas are allocated around this linearly interpolated curve with weights of the following Gaussian kernel function:

$$f(y) = \exp\left(-\frac{(y - y(i))^2}{2\sigma^2}\right), \quad (12)$$

$$\sigma = (y_{out}(i) - y_{in}(i))/3, \quad (13)$$

where $y_{in}(i)$ and $y_{out}(i)$ are lines obtained by the interpolation for LB and AB, respectively. The allocated areas for the boundary extraction are shown in Fig. 4(i) and 4(j).

4) *Plaque boundary extraction by T-S type fuzzy inference:* By using the images obtained by the above-mentioned procedures shown in Figs. 4(i) and 4(j), the objective true boundaries of coronary plaque are extracted by T-S type fuzzy model [13] as shown in Figs. 5(a) and 5(b).

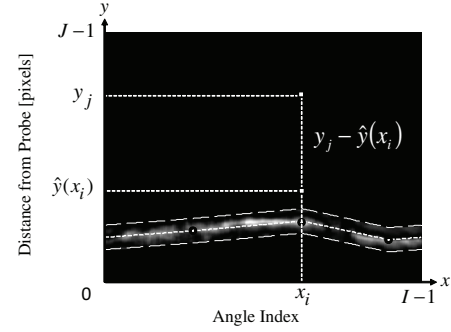
Concretely, the boundary is piecewise approximated by the polynomials in the orthogonal coordinates by a series of the following fuzzy if-then rules [15]:

$$\text{IF } x_i \text{ is } A_\ell \text{ THEN } f_\ell(x_i) = a_\ell x_i + b_\ell,$$

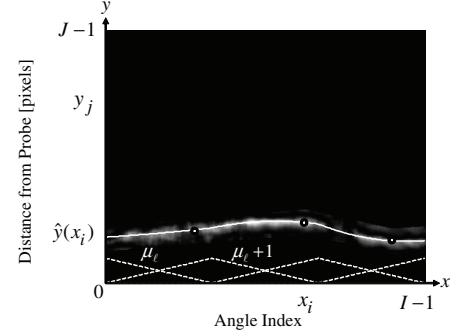
where A_ℓ is a fuzzy set with the membership function (MSF) μ_ℓ as shown in Fig. 5(b). Usually, four complementary triangular MSFs are uniformly allocated over the interval of concern. x_i corresponds to an angle index, and $f_\ell(x_i)$ is a linear function. The ℓ -th rule thus stands for a piecewise approximation of a plaque boundary by a linear function in the interval $[t_{\ell-1}, t_{\ell+1}]$. The inferred boundary $\hat{y}(x_i)$ is given by:

$$\hat{y}(x_i) = \mu_\ell(x_i) f_\ell(x_i) + \mu_{\ell+1}(x_i) f_{\ell+1}(x_i). \quad (14)$$

The optimum coefficients a_ℓ^* and b_ℓ^* of the ℓ -th fuzzy if-then rule are determined with use of the weighted least square



(a)



(b)

Fig. 5. Plaque boundary extraction scheme by the T-S type fuzzy inference. (a) A primitive boundary and a specified search area, which is within the two thin dotted lines. (b) The extracted luminal boundary (LB) by T-S type fuzzy inference.

method (WLSM) so as to minimize the following weighted error criterion:

$$E = \sum_{j=0}^{J-1} \sum_{i=0}^{I-1} \eta_{ij}^2 \{y_j - \hat{y}(x_i)\}^2, \quad (15)$$

where η_{ij} is a separability of pixel $s = (i, j)$ [11].

In this method η_{ij} which lies in the specified boundary search area, i.e., within the thin dotted lines in Fig. 5(a), are used as the weights of WLSM.

B. Semi-automatic (interactive) plaque boundary extraction with adaptive allocation of membership functions

At first, Seed points are placed on the B-mode image by a medical doctor. The image is then transformed from the polar coordinates into the orthogonal coordinates.

The seed points are first linearly interpolated on the orthogonal coordinates to obtain a primitive boundary (the bold dotted line shown in Fig. 6). The true boundary is then searched by starting from this primitive boundary. The weighted separability is calculated for this image and the search area is restricted around this primitive boundary.

Let θ_n ($n=1, \dots, N$) be a specified angle at the n -th seed point as shown in Fig. 6. If all θ_n are obtuse angles, four complementary triangular MSFs are uniformly allocated over the interval of concern. A plaque boundary is then extracted by

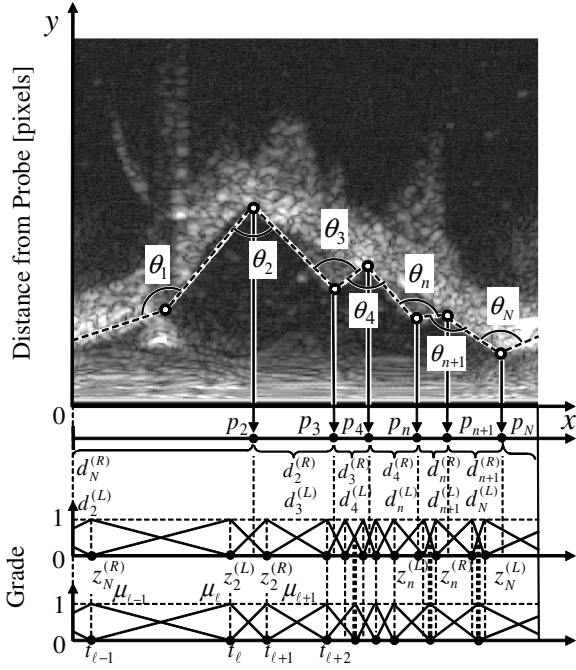


Fig. 6. Procedure of adaptive allocation of membership functions. Some θ_i angles look like to be obtuse, but they are acute. This is because of the length and width ratio of the Cartesian coordinates of the figure.

the T-S fuzzy model. In that case, a smooth plaque boundary is depicted along the obtuse seed points with a small number of MSFs.

In other cases, e.g., acute and obtuse angles coexist in the interval of concern, the following procedures are applied for the seed points with acute angles. The seed points with obtuse angles are left unprocessed.

- i) Let p_n be an angle index of the n -th seed point, and $d_n^{(R)}$ and $d_n^{(L)}$ be the length between p_n and p_{n+1} , and between p_{n-1} and p_n , respectively. Note that the right-hand side edge and the left-hand side edge of the plaque boundary in Fig. 6 are linked.
- ii) Two complementary and triangular MSFs are allocated on either side of each seed point. Let $z_n^{(R)}$ and $z_n^{(L)}$ be the tentative peak positions of the MSFs on the right-hand side and the left-hand side of p_n , which are given as:

$$\begin{cases} z_n^{(R)} = p_n + (1 - \rho_n) [d_n^{(R)} / \{2 + \beta(d_n^{(R)})\}] \\ z_n^{(L)} = p_n - (1 - \rho_n) [d_n^{(L)} / \{2 + \beta(d_n^{(L)})\}], \end{cases} \quad (16)$$

where ρ_n is a sharpness of the angle θ_n defined by:

$$\rho_n = \begin{cases} 1 - \theta_n / T & \theta_n < T \\ 0 & \theta_n \geq T. \end{cases} \quad (17)$$

T is a constant value. The function $\beta(\cdot)$ compensates the peak position of $d_n^{(\cdot)}$ when it is extremely large, and is defined by:

$$\beta(d_n^{(\cdot)}) = 1 / [1 + \exp\{-a(d_n^{(\cdot)} - c)\}], \quad (18)$$

TABLE I
QUANTITATIVE EVALUATION FOR THE PLAQUE BOUNDARY EXTRACTION RESULTS.

	Spline Function		Previous Method		Present Method	
	LB	AB	LB	AB	LB	AB
RMSE	14.5	16.9	36.5	52.1	37.5	63.2
SD	14.3	16.5	34.5	31.1	34.9	33.3

where a and c are parameters to fix the shape of $\beta(\cdot)$. Eq. (16) specifies that when θ_n is small, the MSFs are allocated close to the n -th seed point. This means that the MSFs around p_n are allocated densely, because when θ_n is small, the plaque boundary is complex. The MSFs' allocation map at the upper row in Fig. 6 is thus obtained.

- iii) The tentatively allocated MSFs above are merged if the following three conditions are satisfied at the same time; (a) the seed point position p_n and the peak position of its right-hand side MSF $z_n^{(R)}$ are apart enough each other; (b) the seed point position p_{n+1} and the peak position of its left-hand side MSF $z_{n+1}^{(L)}$ are apart enough each other; (c) the positions of the peaks $z_n^{(R)}$ and $z_{n+1}^{(L)}$ are close each other.

We now define the following criterion to reflect the above three merging conditions:

$$f_1 = 2 \|p_n - z_n^{(R)}\| / d_n^{(R)}, \quad (19)$$

$$f_2 = 2 \|p_{n+1} - z_{n+1}^{(L)}\| / d_n^{(R)}, \quad (20)$$

$$f_3 = \max(1 - 2 \|z_n^{(R)} - z_{n+1}^{(L)}\| / d_n^{(R)}, 0), \quad (21)$$

$$S_{merge} = f_1 \cdot f_2 \cdot f_3. \quad (22)$$

If S_{merge} is greater than 0.5, the peaks $z_n^{(R)}$ and $z_{n+1}^{(L)}$ are merged. An example of merging is shown in the MSFs' allocation map at the bottom row of Fig. 6.

IV. EXPERIMENTAL RESULTS

In this section, experimental results of the full-automatic boundary extraction and of the semi-automatic boundary extraction are shown.

A. Fully automatic plaque boundary extraction

The proposed method is applied to real IVUS B-mode images. Extraction results are compared to those by spline function method and by our previous method. In those experiments, the threshold values of ζ_{Low} and ζ_{High} are set to be 0.1 and 0.2, respectively. The binary images are generated by changing ζ at 0.02 intervals. The other settings are the same as those in our previous paper [14].

The parameters of Eqs. (9)-(11) which define the figures of each membership function, are empirically set to be $\{N_{r1}, N_{r2}\} = \{4, 20\}$, $\{N_{p1}, N_{p2}, N_{p3}\} = \{5000, 15000, 25000\}$, $\{L_{r1}, L_{r2}, L_{r3}\} = \{256, 512, 640\}$.

Figs. 7(a)-7(d) show the plaque boundary extraction results for the IVUS image. The results show that the proposed

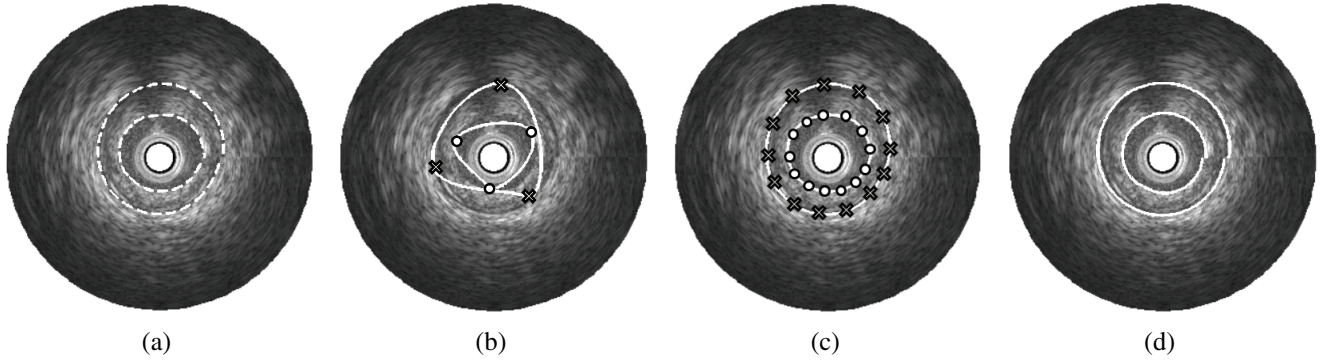


Fig. 7. Plaque boundary extraction results. $\times$: Given seed points for AB (Adventitial Boundary). $\circ$: Given seed points for LB (Luminal Boundary). (a) B-mode image and objective true boundaries to be extracted. (b) Extracted boundaries by spline function method with a few seed points. (c) Extracted boundaries by spline function with many seed points. (d) Extracted boundaries by the proposed method without using any seed points (fully automatic boundary extraction).

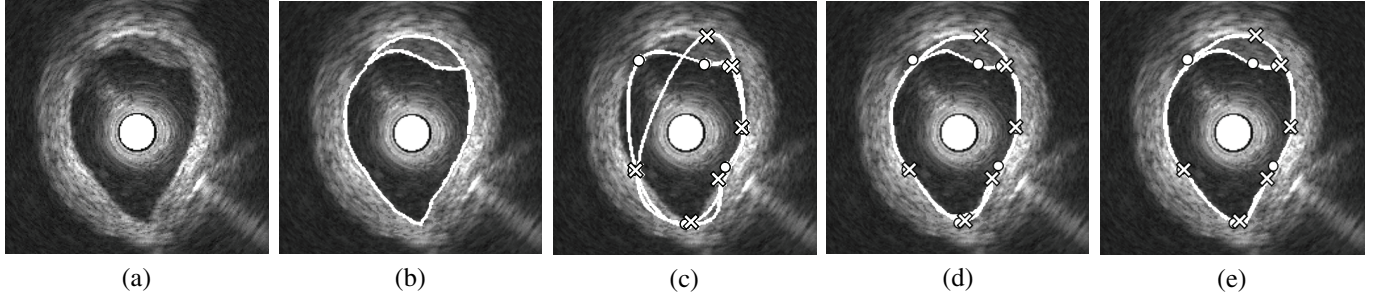


Fig. 8. Boundary extraction results. $\times$: Given seed points for AB (Adventitial Boundary). $\circ$: Given seed points for LB (Luminal Boundary). (a) B-mode image 4. (b) Objective true boundaries to be extracted. (c) Extracted boundaries by spline function method with a few seed points. (d) Extracted boundaries by the proposed method with the fixed membership functions uniformly allocated. (e) Extracted boundary by the proposed method with the membership functions adaptively allocated.

method works very well compared to the conventional methods, even if without using any seed points. Particularly, the spline function method requires many seed points though the accuracy of boundary extraction is good.

The root mean square errors (RMSEs) between the true boundary $y^*(x_i)$ and the extracted one $\hat{y}(x_i)$, and the standard deviations (SDs) calculated from 60 IVUS images are shown in Table I. The true boundary is calculated by a parametric spline-interpolation with a lot of seed points. It is observed that the proposed method, fully automatic, gives nearly equal extraction results to the previous method which uses some seed points given by a medical doctor.

With those results, the effectiveness of the proposed method has been verified.

B. Semi-automatic (interactive) plaque boundary extraction with user's assistance

The proposed method is applied to four IVUS B-mode images (Image 1 through Image 4). Extraction results are compared to those by the conventional method with fixed MSFs allocated at even intervals. In the experiments, the parameters in Eqs. (17) and (18) are empirically assigned to be $T=45$, $a=0.05$ and $c=150$.

The parameter T must be tuned by considering the figures of the boundaries of the objective IVUS images. In this experiment, $T=45$ is employed. On the other hand, the parameters a and c in Eq. (18) are not so sensitive for the extraction of

TABLE II
COMPARISON OF RMSEs OF BOUNDARY EXTRACTION RESULTS UNDER THE SAME NUMBER OF MSFs.

	Img. 1		Img. 2		Img. 3		Img. 4	
	LB	AB	LB	AB	LB	AB	LB	AB
No. of MSFs	4	3	10	4	12	9	9	6
Proposed Method	33.2	27.3	44.5	46.4	30.6	34.5	72.7	29.4
Fixed MSFs	33.2	43.3	49.3	68.3	38.0	41.9	89.9	78.8

plaque boundaries. This is because a function $\beta(\cdot)$ is used only for a compensation of a peak position of the MFS.

Fig. 8 shows the boundary extraction results for Image 4, one of the four IVUS images employed for the experiments. The results show that the proposed method works very well compared to the conventional method with the fixed MSFs uniformly allocated.

The root mean square errors (RMSEs) between the objective boundary $y^*(x_i)$ and the extracted one $\hat{y}(x_i)$ are shown in Table II. The objective boundary is calculated by a parametric spline-interpolation using a lot of seed points given. It is observed that the proposed method gives better extraction results than the conventional methods with the fixed MSFs uniformly allocated. Table II shows the RMSEs of boundary extraction results in case of using the same number of MSFs in comparison with the method with the fixed MSFs and the

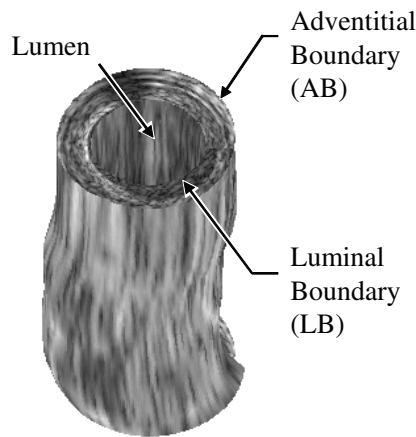


Fig. 9. 3-dimensional viewing of coronary plaque.

method with MSFs adaptively allocated (the proposed method). This implies that the position of each MSF is important for an accurate boundary extraction.

With those results the effectiveness of the proposed method has been verified.

C. 3-dimensional viewing of coronary plaque

Fig. 9 shows a 3-dimensional viewing of a coronary plaque which is reconstructed by interpolating the extracted boundary of 20 frames of B-mode image. By using the automatic plaque boundary extraction function of the proposed system, the 3-dimensional view is easily obtained. This 3-dimensional viewing is very useful and indispensable for analyzing the structure of coronary plaque. Particularly, the assessment of the objective response to therapeutic interventions by measuring the volume of plaque can be achieved by using this 3-D view of coronary plaque.

V. CONCLUSIONS

We have proposed fully automatic and semi-automatic plaque boundary extraction techniques for an IVUS image, and have implemented them as a software diagnosis system. In the present system, the plaque boundary extraction area is automatically found by using anisotropic diffusion, weighted separability, and some heuristic rules. T-S type fuzzy inference is used to extract the plaque boundary in that area.

The fully automatic present system has shown a nearly equal extraction performance to the previous method using seed points placed by a medical doctor, and thus the workload of a medical doctor is substantially reduced. After the boundary extraction, the proposed system can produce the 3-D view of coronary plaque which can be used for assessment of objective response to therapeutic interventions.

Future works are automatic adjustment of parameters and further speed up of each calculation process.

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