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# Hybrid Boundary Detection Method for Image with Application to Coronary Plaque

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## ABSTRACT

This paper proposes a hybrid boundary detection method for image based on a new modified level set method and a fuzzy model. It is applied to a boundary detection problem of coronary plaque. Level set method has been applied widely in image processing. It however does not work well for an intravascular ultrasound (IVUS) image because an image gradient, commonly used for calculating a speed function in the level set method, cannot detect an image boundary well. The level set method and the weighted image separability proposed by the authors in the past were applied for a coronary plaque boundary detection problem. The level set method could not however detect the plaque boundary in several regions. One problem was that the candidates of the plaque boundary detected by the weighted separability were unclear in several regions. The other problem was that the IVUS image often becomes shadowed and it contains no texture information there, which is caused by the presence of the guide wire. To overcome this problem, we propose a new modified level set, and we further propose a hybrid boundary detection method based on the new modified level set and the Takagi Sugeno (T-S) fuzzy model for detecting a coronary plaque boundary. The boundary detection accuracy of the proposed method was significantly better than those of the previous methods we proposed in the past.

## KEYWORDS

Coronary plaque, intravascular ultrasound image, hybrid boundary detection method, new modified level set method, fuzzy model.

## 1 INTRODUCTION

Acute coronary syndrome (ACS) happens when the heart is not getting enough blood. If the coronary arteries are narrowed or blocked by a rupture of vulnerable plaque, which is built up inside the coronary arteries, the heart does not get enough oxygen. This can cause a heart attack.

Intravascular ultrasound (IVUS) method is a medical imaging technique which allows to see the inside of the blood vessel, visualizing the coronary plaque in living individual [1].

IVUS images are employed for a diagnosis of ACS. In the quantitative assessment of the compositions of coronary plaque for a diagnosis of ACS, firstly the luminal boundary (LB) and the adventitial boundary (AB) of the coronary plaque are to be detected and evaluated precisely.

Medical doctors manually detect the plaque boundary and evaluate the area of plaque. Plaque boundary detection is however a very hard and time consuming work for medical doctors. This is not only because the plaque boundary of the IVUS image is difficult to be recognized, but also because the number of IVUS images to be processed by a medical doctor is very large. For those reasons, a method to detect automatically the plaque boundary with high accuracy is strongly required.

The authors have proposed some coronary plaque boundary extraction methods in [2] and [3] to solve this problem. In those methods, the Takagi-Sugeno (T-S) fuzzy model [4] was employed to detect the plaque boundary.

Those methods could significantly reduce the workload of medical doctors. However, those methods needed the seed points to detect the plaque boundary. If the seed points were placed in the wrong position the accuracy of the methods would be reduced drastically.

Boundary detection is one of the tasks in computer vision which has wide applications such as feature extraction, object recognition and image segmentation [5]. The boundary detection is to find the lines separating homogeneous regions.

Active contour models have been applied for detecting image boundaries [6-11]. The active contour models have several advantages over the classical image segmentation methods, e.g., edge detection, thresholding, and region growth.

The first advantage of the active contour models is that they can achieve sub-pixel accuracy of object boundaries [9]. The second advantage is that the active contour models can be easily formulated under a principled energy minimization framework, and allow incorporation of various prior knowledge, such as shape and intensity distribution for robust segmentation [10]. The third advantage is that they can give smooth and closed contours as a segmentation result, which is necessary for many applications.

Active contour models can be classified into two categories, i.e., the classical snakes and the level set method. In this paper, we use the level set method, introduced by Osher and Sethian [12], because it is a highly robust and accurate method for tracking interfaces moving under complex motions, which meets our requirements.

The level set method has been applied successfully in many cases in image segmentation. It has several advantages over other segmentation methods such as the snake method, region growth and thresholding. The advantages of the level set method over the snake method are that the curve may break or merge naturally during an evolution, and its topological changes are thus automatically handled.

The authors have proposed a method for detecting a plaque boundary by using the weighted image separability method and the level set method [13]. An image gradient is commonly used for calculating the speed function in the level set method, but it cannot work well in the IVUS image. Therefore, in [13], the image gradient in the speed function was substituted by the weighted image separability. However it failed to detect the plaque boundary in some regions of the image as shown in Fig 1.

The plaque boundary detection in IVUS image is very difficult because a region of the IVUS image backward the guide wire often becomes shadowed, and then it contains no texture information in the shadow region as shown in Fig 2. Thus it fails to detect the plaque boundary. The other problem is that the candidates of the plaque boundary detected by the weighted image separability are unclear in some regions, which is caused by noise.

The authors also proposed a method for detecting an image boundary by using the modified level set method [14]. In [14], the speed function is modified to make the level set method more successful in boundary detection regardless of noise.

In this paper, we propose a farther modified level set method. We at the same time propose a hybrid boundary detection method based on its modified level set method and the T-S fuzzy model. The speed function in the level set method is further modified based on [14] and [13] to take advantages of each method.

We could successfully detect the plaque boundary in the guide wire shadow region by using the newly proposed hybrid boundary detection method. The effectiveness of the present method was also evaluated by the experiments using the real IVUS images.

## 2 CORONARY PLAQUE BOUNDARY CALCULATIONS IN IVUS IMAGE

The IVUS method is one of the medical imaging techniques. It is an application of the ultrasound technology to a medical area. In the IVUS method, the catheter with an ultrasound probe attached to its end is inserted and rotated in the coronary artery

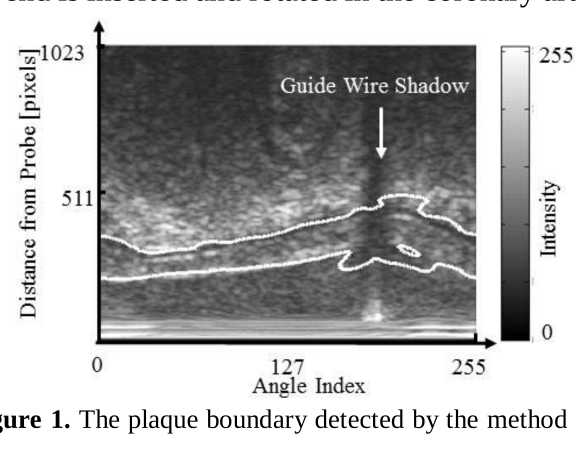
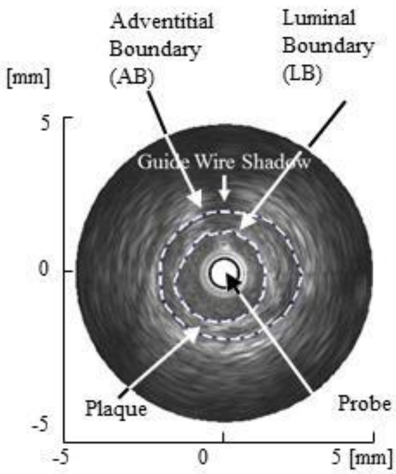
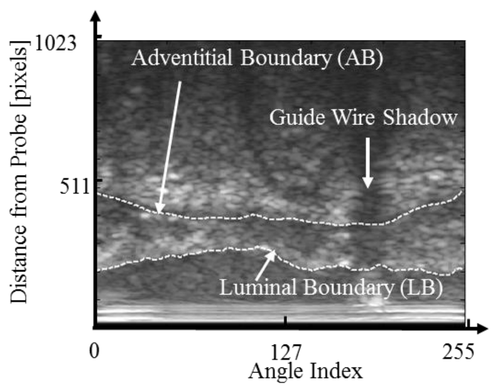



**Figure 1.** The plaque boundary detected by the method [13]

proposed by the authors in the past.




(a)




(b)

**Figure 2.** The guide wire shadow problem of the IVUS image. (a) The guide wire shadow of the IVUS Image in the cartesian coordinate. (b) The guide wire shadow of the IVUS image in the polar coordinate.

to observe the inside of the blood vessel, visualizing the coronary plaque in vivo.

The ultrasound signal is transmitted from the ultrasound probe, and the radio frequency (RF) signal reflected from the tissue is also received by the ultrasound probe. An IVUS B-mode image shown in Fig. 2 is obtained by analyzing the received RF signal.

The IVUS B-mode image is constructed of the amplitude information of the received ultrasound RF signals. That is, the RF signals are transformed into intensities, and the intensities in all radial directions are used to form a tomographic cross-sectional image of a coronary artery to get the B-mode image of Fig. 2.

The plaque boundaries are necessary to be detected for characterizing the coronary plaque. Those are a luminal boundary (LB) and an adventitial boundary (AB) shown in Fig. 2.

### 2.1 Anisotropic Diffusion Filter

The Perona Malik diffusion (PMD) filter [7] is one of the methods for noise filtering. It has two advantages, i.e., one is to preserve the edges of an image, and the other is to reduce speckle noise. The PMD filter is defined by:

$$\begin{aligned} I_t = \frac{\partial I}{\partial t} &= div(c(x,y,t)\nabla I) \\ &= c(x,y,t)\Delta I + \nabla c(x,y,t)\nabla I, \end{aligned} \quad (1)$$

where

$$c(x,y,t) = g(\|\nabla I(x,y,t)\|) \quad (2)$$

denotes a diffusion coefficient. $\nabla I$ represents a gradient of an image. $g(\cdot)$ refers to an edge stopping function, which is defined 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. The initial condition is given by:

$$I(x,y,0) = I_0(x,y). \quad (4)$$

The PMD in discrete version is given by:

$$I_s^{(n+1)} = I_s^{(n)} + \frac{\lambda}{|\phi_s|}\sum g(\nabla I_{s,p}^{(n)}) I_{s,p}^{(n)}, \quad (5)$$

where $s = (x,y)$ is the coordinates of the pixel of concern. $p$ and $I_s^{(n)}$ represent the neighboring pixels of $s$ and an intensity at $I_s^{(n)}$ with an iteration count $n$, respectively. The discretization of image gradient is given by:

$$\nabla I_{s,p}^{(n)} = I_p^{(n)} - I_s^{(n)}, \quad (6)$$

where $\phi_s$ and $|\phi_s|$ represent the diffusion directions and the number of pixels in the neighboring area, respectively. $\lambda$ is a parameter.

$g(\cdot)$ takes a large value at the regions where the intensity gradients are low. It takes a small value at the regions where the intensity gradients are high.

### 2.2 Image Separability

The candidates of the plaque boundaries in IVUS image are given by using a statistical discriminant measure of the image separability [16]. The advantages of the image separability are:

1) Insensitive to noisy and blurred edges,
2) Able to differentiate the edges between texture regions.

The weighted separability is modified by considering the conditions peculiar of IVUS image. The weighted image separability for pixel ***h*** in Fig. 3 is calculated by the difference of the two regions as follows:

$$\eta_{\boldsymbol{h}}^{w} = \eta_{\boldsymbol{h}} \left( \frac{I_{\max} - \bar{I}_A}{I_{\max}} \times \frac{\bar{I}_B}{I_{\max}} \right)^2, \tag{7}$$

where $\bar{I}_A$ and $\bar{I}_B$ are the averages of intensities in the regions of *A* and *B*. $I_{\max}$ is the maximum intensity of the whole IVUS image.

$\eta_{\boldsymbol{h}}$ represents the original image separability which is defined by:

$$\eta_{\boldsymbol{h}} = \frac{n_A(\bar{I}_A - \bar{I})^2 + n_B(\bar{I}_B - \bar{I})^2}{\sum_{k=1}^{S}(I_k - \bar{I})^2}, \tag{8}$$

where $n_A$ and $n_B$ are the numbers of the pixels in the regions of *A* and *B*, respectively. $\bar{I}$ is the average of the intensities in the combined regions of *A* and *B*. *S* and $I_k$ are the number of the pixels and the level of intensity of the *k*-th pixel in the combined region of *A* and *B*.

$\eta_{\boldsymbol{h}}^{w}$ satisfies $0 \le \eta_{\boldsymbol{h}}^{w} \le 1$, and it takes a large value when two regions are separated from each other [17].

## 3 PROPOSED METHOD

We present in this paper a hybrid boundary detection method based on the new modified level set and the T-S fuzzy model for detecting a plaque boundary in the coronary artery.

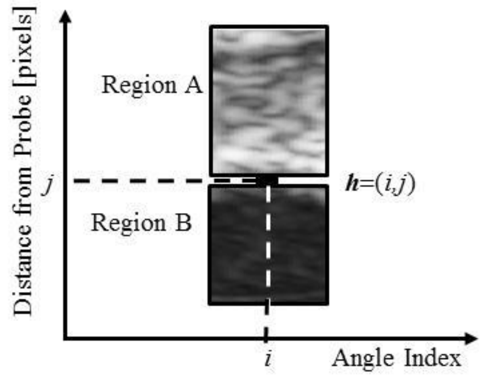



**Figure 3.** Calculation of the image separability.

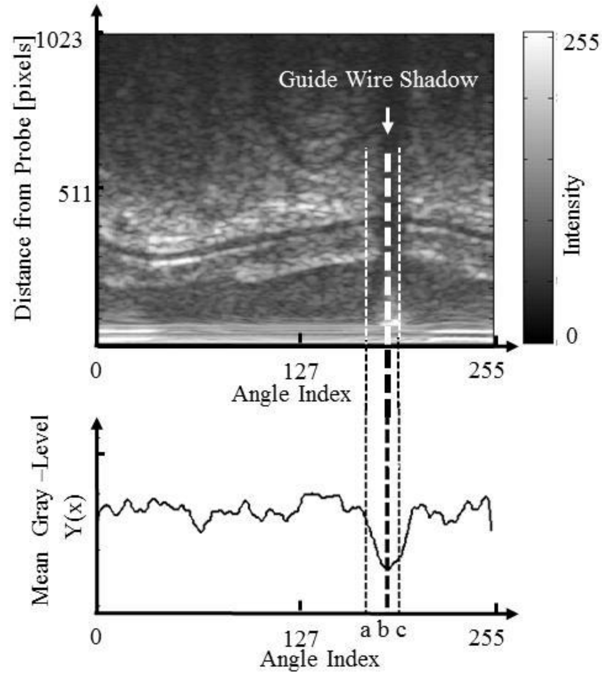



**Figure 4.** Guide wire shadow detection.

This chapter is divided into three sections. Those are: (i) guide wire shadow detection, (ii) plaque boundary detection by using the new modified level set method, and (iii) inference of plaque boundary in the guide wire shadow region by using the T-S fuzzy model.

### 3.1 Guide Wire Shadow Detection

IVUS image has a guide wire shadow and it does not contain any texture information there. Thus the level set method fails to detect the plaque boundary in that region.

To overcome this problem, the plaque boundary in the guide wire shadow region is inferred using the plaque boundary information on the left and on the right hand side of the guide wire shadow region.

In the first step of the present hybrid boundary detection method, the guide wire shadow region is detected. Its procedure is as follows:

1) Convert the B-mode image of Fig. 2(a) in the cartesian coordinate system to the polar coordinate system of Fig. 2(b).
2) Detect the position of the guide wire shadow. From Fig. 2 it can be seen that the guide wire shadow is located in the small gray-level area. The mean gray-level of every column of the polar coordinate system is calculated to determine the guide wire shadow. The mean gray-level of every column is given by:

$$Y(x) = \frac{\sum_{y=1}^{N} I(x,y)}{N}, \; x = 0,1,2,...,255, \tag{9}$$

where $N$ is the number of pixels in one column. The mean gray-level of (9) for Fig. 2(b) is shown in Fig. 4.

It is observed that the shadow area around the guide wire has a small value of the mean gray-level as shown in Fig. 4. We can predict roughly the location of the guide wire shadow region by this mean gray-level of (9).

### 3.2 Plaque Boundary Detection by Using Newly Modified Level Set Method

The level set method has been applied in many areas, especially for detecting the image boundary. In the level set method, the contour is represented by the zero level set of a higher dimensional function. This is called a level set function, and it formulates the motion of the contour based on the evolution of the level set function.

The curve evolution of a parametric contour $C(x(s,t), y(s,t))$, is given by:

$$\partial C / \partial t = FN, \tag{10}$$

where $t$ and $s$ are a set point in time and a curve parameter, respectively. $N$ and $F$ denote the inward normal vector to the curve $C$, and the speed function. The speed function $F$ controls the motion of the contour.

The curve evolution of (10) can be converted to a level set formulation by embedding the dynamic contour $C$ as the zero level set of a time dependent level set function $\phi(x, y, t)$.

We assume that the level set function $\phi$ gets the positive values outside the zero level contour, and the negative values inside. The inward normal vector can be expressed as $N = -\nabla\phi / |\nabla\phi|$, where $\nabla$ is a gradient operator.

The curve evolution of (10) is converted to:

$$\partial\phi / \partial t = F|\nabla\phi|, \tag{11}$$

which is referred to as a level set evolution equation. In this paper, we use the level set $\phi(x)$

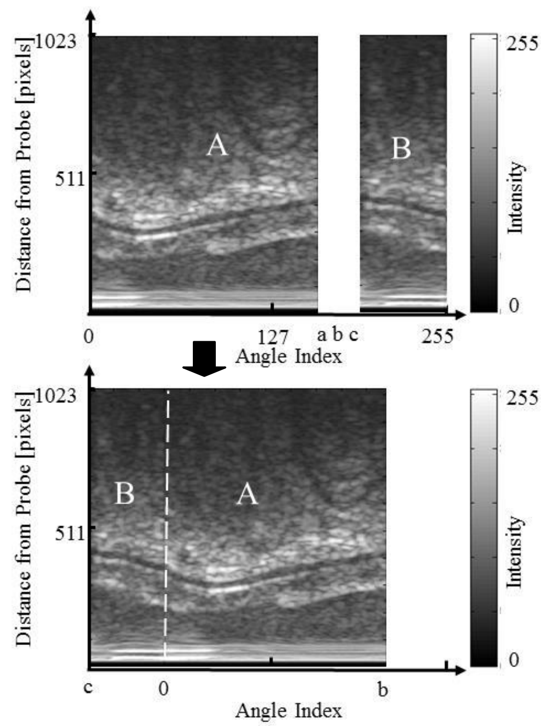



**Figure 5.** IVUS image after ignoring the guide wire shadow.

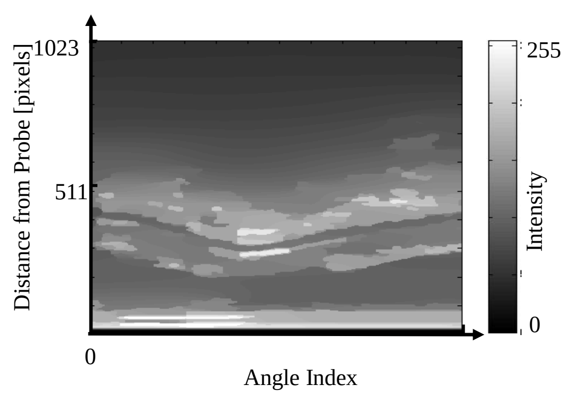



**Figure 6.** IVUS image after applying the PMD filter to Fig. 5.

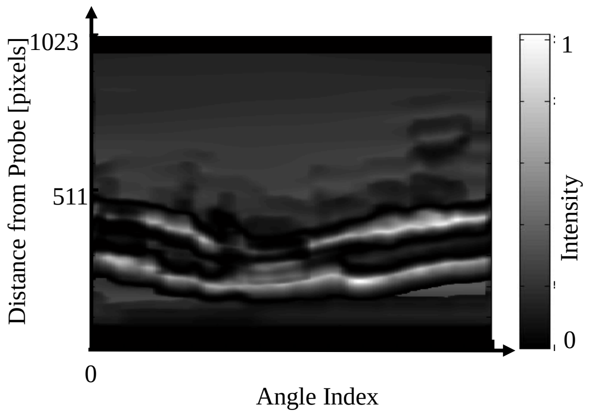



**Figure 7.** Weighted image separability of Fig. 6.

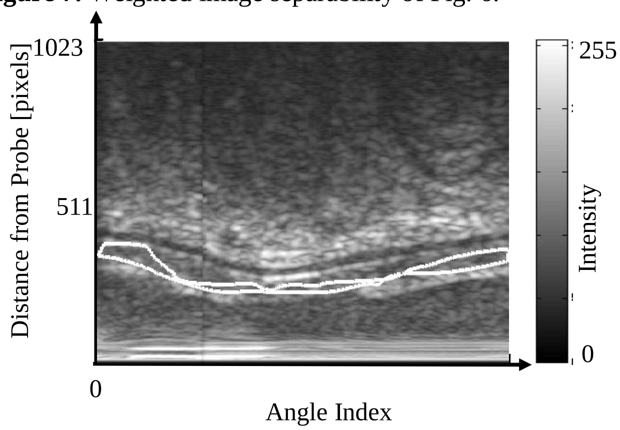



**Figure 8.** Initial contour of the new modified level set.

defined by:

$$\partial\phi/\partial t = \mu div(d_p(|\nabla\phi|)\nabla\phi) + \lambda\delta_\varepsilon(\phi)div(g\nabla\phi/|\nabla\phi|) + \alpha g\delta_\varepsilon(\phi), \tag{12}$$

where $\delta_\varepsilon$ is a dirac delta function, *div* is a divergence operator, and $g$ is a speed function, which is given by:

$$g = 1/(1+|\nabla(G_\sigma * I|), \tag{13}$$

where $G_\sigma$ is the Gaussian filter and $I$ is the image to be processed[8].

In this paper, we propose a new speed function defined by:

$$g = \left(\frac{1}{1+\eta_h^w}\right)^m. \tag{14}$$

The following steps are the procedure of the proposed plaque boundary detection:

1) Detect the guide wire shadow region (angle index between a and c) shown in Fig. 4. The positions of a and c are determined by analyzing the real IVUS images which are used for the experiments. Examining the many IVUS images, a and c are set to be b-14 and b+8, respectively. b is a point where the mean-gray level becomes minimum.
2) Merge areas c to 255 (region B) and 0 to b (region A) by placing the latter on the right side as shown in Fig. 5.
3) Reduce the speckle noise by applying the PMD filter to Fig. 5. The filtering result is shown in Fig. 6.
4) Calculate the weighted image separability to obtain Fig. 7.
5) Calculate the new modified speed function of (14).
6) Give the initial contour of the level set, e.g., as shown in Fig. 8.
7) Calculate the contour evolution by using (12).
8) Calculate the new contour.
9) Repeat steps 7) and 8) until it converges or the maximum number of iterations is reached.

The plaque boundary detected by using the present modified level set is shown in Fig. 9.

## 3.3 Inference of Plaque Boundary in the Guide Wire Shadow Region by Using T-S Fuzzy Model

The plaque boundary in the guide wire shadow region is inferred by the T-S fuzzy model [4]. The plaque boundary is interpolated by the information which is taken from the plaque boundary on the

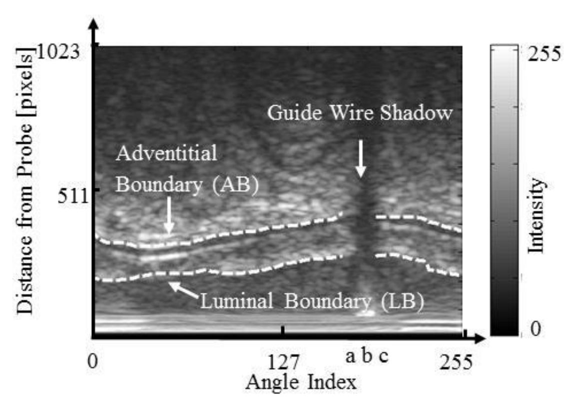



**Figure 9.** Plaque boundary detection results by using the present modified level set method.

left and on the right of hand side the guide wire shadow region as shown in Fig. 10.

The plaque boundary is inferred by the series of the following fuzzy rules:

$$\text{If } x_i \text{ is } A_u \text{ then } f_u(x_i) = a_u x_i + b_u, \tag{15}$$

where $A_u$ is a fuzzy set with the membership function (MSF) $\mu_u(x_i)$, $x_i$ corresponds to the angle index, and $f_u(x_i)$ is a linear function.

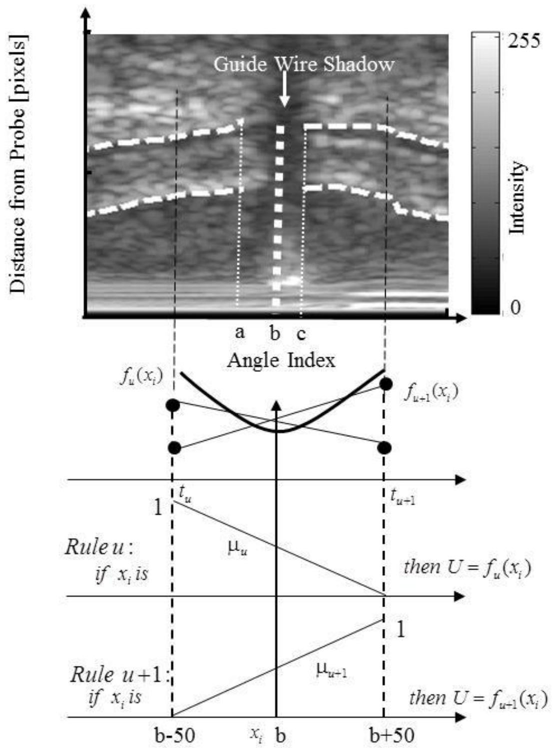



**Figure 10.** Membership functions of the T-S fuzzy model in the guide wire shadow region.

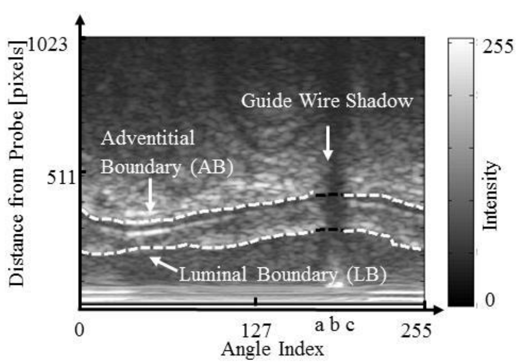



**Figure 11.** Plaque boundary detection results by a hybrid of the newly modified level set method and the T-S fuzzy model.

Fig. 10 shows the complementary linear MSFs which are allocated to infer the plaque boundary. The *u*-th rule is used for approximating the plaque boundary by a linear function in the interval $[b-50, b+50]$. The plaque boundary is inferred by:

$$\hat{y}(x_i) = \mu_u(x_i) f_u(x_i) + \mu_{u+1}(x_i) f_{u+1}(x_i). \tag{16}$$

The optimum coefficients in the consequent part of the fuzzy rule are determined by using the least square method. It minimizes the following error criterion:

$$E = \sum_i (y_i - \hat{y}_i(x_i))^2, \tag{17}$$

where $y_i$ is a plaque boundary that is detected by the newly modified level set method on angle index *i*.

The black dotted lines on the angle interval [*a*, *c*] in Fig. 11 show the plaque boundary inferred by the T-S fuzzy model.

## 4 EXPERIMENTAL RESULTS

Three IVUS images were used for evaluating the performance of the proposed method. The proposed hybrid boundary detection method was compared with the methods by using only the T-S

**Table 1.** RMSEs of boundary detection results for image 1.

($\mu m$)

| Method | LB | AB |
|---|---|---|
| Hybrid Boundary Detection Method (1st Experiment) | 9.1 | 20.4 |
| Hybrid Boundary Detection Method (2nd Experiment) | 9.3 | 20.0 |
| Hybrid Boundary Detection Method (3rd Experiment) | 9.2 | 20.1 |
| Hybrid Boundary Detection Method (4th Experiment) | 9.3 | 19.9 |
| Hybrid Boundary Detection Method (5th Experiment) | 9.3 | 20.1 |
| Hybrid Boundary Detection Method (Average) | **9.2** | **20.1** |
| T-S Fuzzy Model [2] | 13.7 | 28.4 |
| T-S Fuzzy Model Optimized by Particle Swarm Optimization [3] | 12.2 | 28.5 |

fuzzy model [2], and the T-S fuzzy model optimized by particle swarm optimization (PSO) [3].

If the initial contour of the level set is different, the proposed method will produce a different plaque boundary. Therefore the experiment for each image was repeated 5 times with different initial contours. The desired boundaries (correct boundaries) were decided by expert by using the difference between the image brightness.

**Table 2.** RMSEs of boundary detection results for image 2.

($\mu m$)

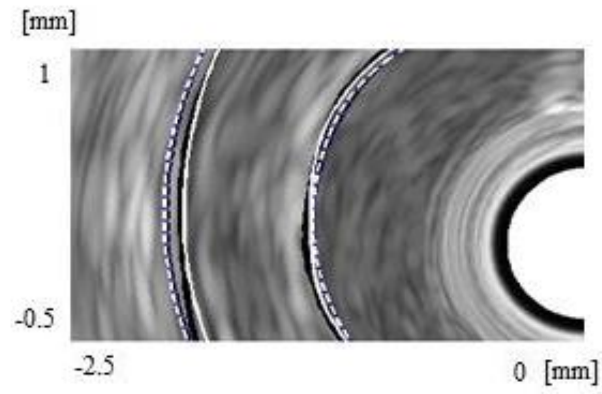
| Method | LB | AB |
|---|---|---|
| Hybrid Boundary Detection Method (1st Experiment) | 11.8 | 24.9 |
| Hybrid Boundary Detection Method (2nd Experiment) | 12.8 | 17.3 |
| Hybrid Boundary Detection Method (3rd Experiment) | 12.7 | 17.6 |
| Hybrid Boundary Detection Method (4th Experiment) | 12.6 | 17.2 |
| Hybrid Boundary Detection Method (5th Experiment) | 12.7 | 17.5 |
| Hybrid Boundary Detection Method (Average) | **12.5** | **18.9** |
| T-S Fuzzy Model [2] | 28.0 | 35.4 |
| T-S Fuzzy Model Optimized by Particle Swarm Optimization [3] | 23.8 | 33.2 |

**Table 3.** RMSEs of boundary detection results for image 3.

($\mu m$)

| Method | LB | AB |
|---|---|---|
| Hybrid Boundary Detection Method (1st Experiment) | 15.3 | 12.0 |
| Hybrid Boundary Detection Method (2nd Experiment) | 15.6 | 13.1 |
| Hybrid Boundary Detection Method (3rd Experiment) | 15.5 | 21.8 |
| Hybrid Boundary Detection Method (4th Experiment) | 15.9 | 12.5 |
| Hybrid Boundary Detection Method (5th Experiment) | 15.7 | 12.3 |
| Hybrid Boundary Detection Method (Average) | **15.6** | **14.3** |
| T-S Fuzzy Model [2] | 20.0 | 30.2 |
| T-S Fuzzy Model Optimized by Particle Swarm Optimization [3] | 19.9 | 40.1 |


(a)




(b)

**Figure 12.** Comparisons of the plaque boundary detection methods. (a) The IVUS image to be processed. (b) The plaque boundary detection results. The solid white lines show the desired (correct) boundaries and the solid black lines show the boundaries detected by the proposed method. The dashed black lines and the dashed white lines show the boundaries detected by the T-S Fuzzy model [2] and the T-S Fuzzy model optimized by particle swarm optimization [3], respectively.

The root mean square errors (RMSEs) between the desired (correct) boundaries and the boundaries detected by the proposed hybrid boundary detection method are shown in Tables 1, 2 and 3. The RMSEs of the proposed method are significantly better than those of the previous methods [2], [3] for all images.

Fig. 12(a) shows the IVUS image to be processed, and Fig. 12(b) shows one of the plaque boundary detection results by the proposed method. The solid white lines show the desired (correct) boundaries and the solid black lines show the boundaries detected by the proposed method. The dashed black lines and the dashed white lines show the boundaries detected by the T-S fuzzy model [2] and the T-S fuzzy model optimized by particle swarm optimization (PSO) [3], respectively.

It can be observed from Fig. 12(b) that the boundaries detected by the proposed method are closer to the desired (correct) boundaries than those by the previous methods [2], [3].

## 5 CONCLUSIONS

We have proposed a hybrid boundary detection method for detecting a coronary plaque in an IVUS image. It incorporates a newly modified level set method with the Takagi-Sugeno fuzzy model. The present method was compared with the previous methods [2], [3], and the boundary detection accuracy of the present method was significantly better.

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