Combining PSO and Fuzzy Inference for the Calculation of Coronary Plaque Boundary in IVUS Image

Syaiful ANAM\textsuperscript{a,b}, Eiji UCHINO\textsuperscript{a,c}, Hideaki MISAWA\textsuperscript{d} and Noriaki SUETAKE\textsuperscript{a}

\textsuperscript{a}Graduate School of Science and Engineering, Yamaguchi University, Japan  
\textsuperscript{b}Department of Mathematics, University of Brawijaya, Indonesia  
\textsuperscript{c}Fuzzy Logic Systems Institute, Japan  
\textsuperscript{d}Graduate School of Information Sciences, Hiroshima City University, Japan

Abstract: In this paper, we propose a method for coronary plaque boundary calculation in an Intravascular Ultrasound (IVUS) image by combining Particle Swarm Optimization (PSO) and the Takagi-Sugeno (T-S) fuzzy inference. An IVUS image is commonly used for the diagnosis of Acute Coronary Syndromes (ACS). An IVUS image is very grainy due to a heavy speckle noise. In order to reduce the speckle noise, this study uses the Perona-Malik Diffusion (PMD) filter. Search areas for coronary plaque boundaries are automatically set by using the weighted image separability and a particular set of heuristic rules. The coronary plaque boundaries are interpolated by polynomials inferred by fuzzy rules. PSO tunes the parameters of the membership functions in the antecedent parts of the fuzzy rules. After evaluating the experimental results, we have found that the accuracy of the proposed method is better than that of the conventional methods.

Keywords: Intravascular ultrasound image, Coronary plaque boundary calculation, Weighted image separability, Takagi-Sugeno fuzzy inference, Particle Swarm Optimization.

1. Introduction

Acute Coronary Syndromes (ACS) is one of the leading causes of hospitalization in the world. ACS occurs when the blood supplied to the heart muscle is suddenly blocked. Restricted blood flow, which is caused by atherosclerosis, can damage organs and stop them from functioning properly.

Atherosclerosis occurs when arteries become clogged up by fatty substances called plaque. The plaques build up inside the coronary arteries. ACS is treatable if diagnosed quickly. Intravascular Ultrasound (IVUS) method \cite{1} provides a real time cross-sectional image of a coronary artery \textit{in vivo}. Medical doctors use IVUS images for tissue characterization and plaque volume calculation. For this purpose, the calculation of the inner and outer plaque boundaries is required.

Currently, these boundaries of plaque are manually calculated and the area of that plaque is also evaluated manually by a medical doctor. After that, the volume of the plaque is estimated by integrating the calculated areas. However, the calculation of plaque boundaries is difficult and time consuming. 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 speckle noise. To reduce the workload of a medical doctor, an automatic plaque boundary calculation method with high accuracy is strongly required.

Ruiz et al. have proposed in \cite{2} a probabilistic segmentation for identification of Luminal Boundary (LB) and Gil et al. have also proposed in \cite{3} a statistical strategy for anisotropic adventitial modelling. However, those methods do not automatically work because the method \cite{2} needs an initial area created by a user, and the method \cite{3} needs a set of training data manually segmented by an expert. The shape driven segmentation method proposed

1677-1 Yoshida  
Yamaguchi 753-8512 Japan  
Phone and Fax: +81-83-933-5699  
e-mail: r501wa@yamaguchi-u.ac.jp
by Unal et al. [4] also needs a set of training data which is manually segmented by an expert.

Adame et al. [5] have proposed an automatic segmentation and plaque characterization method, but it is not fully automatic. It still needs a center point in lumen, a seed point somewhere inside the lipid core and a circle that surrounds the vessel, which have to be decided by a user.

For this reason, we have proposed several automatic plaque boundary calculation methods which do not need a set of training data neither any initial area. In our previous works [6-7], the coronary plaque boundaries were calculated by piecewise polynomials approximated via a fuzzy inference-based method, in which the Takagi-Sugeno (T-S) fuzzy inference [8] was used.

Fuzzy inference has several advantages over the conventional methods in the boundary calculation of image, e.g., Sobel’s method, Prewitt’s method, and Robert’s method [8]. The fuzzy inference can handle problems with imprecise, noisy, in-consistent and incomplete data set [9]. Additionally, the T-S fuzzy inference has been successfully applied in many areas. IVUS images have often noise and the plaque boundaries are often missing in several areas. We have employed the T-S fuzzy inference to restore the missing boundaries by inference.

The coefficients of the polynomials were determined by the weighted least square method using the separability of image, which is a kind of statistical measure for the detection of the edge of the image. The candidates for the boundaries are detected by using a statistical discriminant measure (called separability [11]), which is insensitive to noisy and blurred edges and can detect an edge between different texture regions.

In [6], membership functions (MSFs) in the antecedent parts of the fuzzy rules were adaptively allocated by using the information of the seed points given by a medical doctor. In [7], the seed points were automatically determined by the weighted image separability and heuristic rules. In that paper, the Perona Malik Diffusion (PMD) filter [12] was used, because the PMD not only reduces speckle noise but also effectively enhances the edges of plaque tissues in an IVUS image.

In those methods, the accuracy of the plaque boundary calculation is influenced by the parameters of the MSFs. The parameter tuning of the MSFs can be regarded as an optimization problem. However, this optimization was not done in [6].

Particle Swarm Optimization (PSO) is one of the methods of global optimization [13], which is used for function optimization with multiple local solutions. PSO is especially useful when other techniques such as gradient descent or direct analytical discovery are not applicable. In those cases Genetic Algorithm (GA) is another alternative to be applied, but PSO yields faster convergence than GA because of the balance between exploration and exploitation in the search space [14].

In this paper, we propose a method for coronary plaque boundary calculation in an IVUS image by combining PSO and the T-S fuzzy inference.

Fig. 1. An ultrasound probe attached to the distal end of a catheter.

Fig. 2. IVUS B-mode image. (a) B-mode image in the Cartesian coordinates. (b) B-mode image in the polar coordinates.
2. Coronary plaque boundary calculation in IVUS image

2.1. IVUS

The IVUS method is one of the leading medical imaging techniques for the diagnosis of atherosclerosis. It allows the application of ultrasonic technology to observe within the blood vessel all the way through to the surrounding blood column, visualizing the coronary plaque in vivo.

The IVUS image is constructed using the amplitude information from the received ultrasound radiofrequency (RF) signals. 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 the signal. After taking the envelope of this signal, finally we take its logarithmic value.

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). The probe rotates in the arterial lumen in order to receive an IVUS RF Signal reflected from the plaque and the vascular wall.

The RF signal is sampled at 400 MHz. The sampled 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 as shown in Fig. 2. This image is called a “B-mode image.” A B-mode image displays a real time ultrasound cross-sectional image of a thin section of a blood vessel where currently a catheter probe is rotating.

In quantitative assessment of coronary plaque, the following two boundaries are calculated in the IVUS B-mode image. 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. In [6-7], a plaque boundary is approximated by piecewise polynomials inferred by the T-S fuzzy inference based on the given seed points.

2.2. Anisotropic diffusion

The anisotropic diffusion filter was originally proposed by Perona and Malik [12] in order to preserve the edges of an image.

The anisotropic diffusion equation is defined by:

\[
I_t = \frac{\partial I}{\partial t} = \text{div}(c(x,y,t)\nabla I)
\]

\[
= c(x,y,t)\Delta I + \nabla c(x,y,t)\nabla I,
\]

where

\[c(x,y,t) = g(\|\nabla I(x,y,t)\|)\]

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

\[I(x,y,0) = I_0(x,y).\]

The discrete version of PMD process is defined as follows:

\[I_s^{(n+1)} = I_s^{(n)} + \lambda \phi_s \sum g(\nabla I_p^{(n)})I_s^{(n)},\]

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 \(n\). \(\phi_s\) represents the four neighboring pixels in North, West, South and East diffusion directions. \(|\phi_s|\) is the number of pixels in the neighborhood area. \(\lambda\) is a parameter.

A monotonically decreasing function of the gradient of an image is usually adopted as \(g(\cdot)\). The gradient of the image is calculated by:

\[
\nabla I_p^{(n)} = I_p^{(n)} - I_s^{(n)}.
\]

\[g(\cdot) = \frac{1}{1 + \left(\frac{\cdot}{K}\right)}\]

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

The speckle pattern is reduced after the PMD application to an IVUS B-mode image as preprocessing,
and the edges corresponding to plaque boundaries are detected as shown in Fig. 3.

### 2.3. Image separability

In order to distinguish the difference between the plaque boundary and the speckle noise in an IVUS image, the proposed method employs a statistical discriminant measure of image separability [11]. The image separability has the following features:

(i) Insensitive to noisy and blurred edges,

(ii) Able to differentiate the edges between texture regions.

The separability $\eta_k$ for pixel $h$ shown in Fig. 4(a) is defined by:

$$
\eta_k = \frac{n_a (\bar{I}_a - \bar{I})^2 + n_b (\bar{I}_b - \bar{I})^2}{\sum_{i=1}^{S} (I_i - \bar{I})^2},
$$

where $n_a$ and $n_b$ represent the numbers of the pixels in the regions of $A$ and $B$, respectively. $\bar{I}_a$ and $\bar{I}_b$ represent the averages of intensities in the regions of $A$ and $B$. $\bar{I}$ stands for the average of the intensities in the combined region $A$ and $B$. $S$ and $I_i$ represent the number of the pixels and the intensity of the $k$-th pixel in the combined region $A$ and $B$.

The weighted separability, which is a modification of the original separability [11], detects the candidates of the inner and outer boundaries of plaque by considering the conditions peculiar to an IVUS image.

The weighted image separability for pixel $h$ is defined by:

$$
\eta^w_k = \eta_k \left( \frac{I_{\text{max}} - \bar{I}_a \times \bar{I}_b}{I_{\text{max}}} \right)^2,
$$

where $I_{\text{max}}$ is the maximum intensity in the whole of IVUS image. $\eta^w_k$ satisfies $0 \leq \eta^w_k \leq 1$, and it takes a larger value when two regions are separated from each other.

Fig. 4(b) shows the weighted image separability $\eta^w_k$ calculated for each pixel of Fig. 3.

### 3. Particle Swarm Optimization (PSO)

PSO was first introduced by Kennedy and Eberhart in 1995 [13]. It is inspired by swarm intelligence and general theories such as bird flocking, fish schooling and human behavior. Particles in PSO represent the solution candidates and each of which has a position and a velocity represented by $z_i(t)$ and $v_i(t)$, respectively.

The algorithm of PSO consists of two operators. The first operator in PSO is an update of these particle velocities. During each generation each particle is accelerated toward the particles previous best position and the global best position.

At each iteration a new velocity value for each particle is calculated based on its current velocity, the distance from its previous best position, and the distance from the global best position. An update of the general

![Fig. 4. Calculation of image separability. (a) Regions to be used for separability calculation. (b) Weighted separability of IVUS image in Fig. 3.](image)

![Fig. 5. Final seed points that have been automatically placed.](image)
The particle velocity is defined by:

$$v_i(t+1) = w_i v_i(t) + c_1 R_1(t) [Z_i(t) - z_i(t)] + c_2 R_2(t) [\hat{Z}(t) - z_i(t)]$$  \( \ell = 1,2,...,s \),

where \( s \) is the number of particles, \( t \) is an iteration number, \( w \) is an inertia weight, \( c_1 \) and \( c_2 \) are acceleration coefficients, and \( R_1(t) \) and \( R_2(t) \) are uniformly distributed random variables.

Each particle remembers its own best position which is called “personal best position” \( Z_i(t) \) defined by:

$$Z_i(t+1) = \begin{cases} z_i(t+1), & \text{if } f(z_i(t+1)) < f(Z_i(t)) \\ Z_i(t), & \text{otherwise.} \end{cases}$$  

The best position among the particles which is called “global best” is calculated by:

$$\hat{Z}(t) = \arg \min_{Z \in G} f(Z), \ G = \{ Z_1(t),...,Z_s(t) \},$$  

where \( f(\cdot) \) is an objective function.

The second operator in PSO is an update of particle position given by:

$$z_i(t+1) = z_i(t) + v_i(t+1).$$

4. Proposed method

In this chapter, we explain how to tune the parameters of PSO. This chapter is divided into two sections, which are the boundary calculation procedure and MSF parameter tuning by using PSO.

4.1. Boundary calculation procedure

The boundary calculation procedure is briefly summarized as follows:

(i) Seed points are roughly placed automatically on the B-mode image as shown in Fig. 5 to get search areas described in [6].

(ii) The plaque boundary is inferred by using the T-S fuzzy inference. The boundary is piecewise ap

**Tab. 1. Values of objective function of Luminal Boundary (LB) calculation results.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Conventional Method</th>
<th>Gradient Descent Method</th>
<th>Proposed Method</th>
<th>Averaged</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Image 1</td>
<td>45.63</td>
<td>36.82</td>
<td>36.80</td>
</tr>
<tr>
<td></td>
<td>Image 2</td>
<td>44.91</td>
<td>41.69</td>
<td>47.07</td>
</tr>
<tr>
<td></td>
<td>Image 3</td>
<td>47.78</td>
<td>44.48</td>
<td>44.30</td>
</tr>
</tbody>
</table>

**Tab. 2. Values of objective function of Adventitial Boundary (AB) calculation results.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Conventional Method</th>
<th>Gradient Descent Method</th>
<th>Proposed Method</th>
<th>Averaged</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Image 1</td>
<td>49.06</td>
<td>47.40</td>
<td>47.35</td>
</tr>
<tr>
<td></td>
<td>Image 2</td>
<td>46.76</td>
<td>47.09</td>
<td>47.07</td>
</tr>
<tr>
<td></td>
<td>Image 3</td>
<td>41.73</td>
<td>51.40</td>
<td>51.30</td>
</tr>
</tbody>
</table>

Fig. 7. Two solutions of the locations of the MSFs for LB and the boundaries calculated by PSO.
proximated by the following series of fuzzy rules:

\[
\text{IF } x_i \text{ is } A_u \text{ THEN } f_u(x_i) = a_u x_i + b_u,
\]

where \( A_u \) is a fuzzy set with the MSF \( \mu_u(x_i) \), \( x_i \) corresponds to the angle index, and \( f_u(x_i) \) is a linear function. In the antecedent part of the fuzzy rule, the complementary triangular MSFs are used. The \( u \)-th rule thus stands for a piecewise approximation of the plaque boundary in the interval \([z_{u-1}, z_{u+1}]\) where \( z_{u-1} \) and \( z_{u+1} \) are MSFs locations. The inferred boundary is given by:

\[
\hat{y}(x_i) = \mu_u(x_i) f_u(x_i) + \mu_{u+1}(x_i) f_{u+1}(x_i).
\]

(iii) The optimum coefficients in the consequent part of the fuzzy rule are determined by using the Weighted Least Square Method (WLSM) so as to minimize the following weighted error criterion:

\[
E = \sum_{j=0}^{J} \sum_{i=0}^{I} \eta_{h}^{v}(y_j - \hat{y}_j(x_i))^2,
\]

where \( \eta_{h}^{v} \) is a weighted image separability of pixel \( h = (i, j) \). In this method, \( \eta_{h}^{v} \) inside the search areas (see Fig 6.) are used as the weights for WLSM.

4.2. MSF parameter tuning by using PSO

PSO is used for tuning the parameters of MSFs. The positions of MSFs are decided by PSO based on the evaluation of the objective function of equation (16).

The tuning procedure of the MSFs using PSO is briefly summarized as follows:

(i) Generate the initial positions of the particles \( z_i(0) = (z_{i1}(0), z_{i2}(0), \ldots, z_{ip}(0)) \), where \( p \) is the number of MSFs.

**Fig. 8.** Boundary calculation results by the proposed method for image 1. The white and black lines indicate the calculated boundaries and the desired boundaries, respectively. (a) IVUS image to be processed. (b) Boundary calculation results.

**Fig. 9.** Boundary calculation results by the proposed method for image 2. The white and black lines indicate the calculated boundaries and the desired boundaries, respectively. (a) IVUS image to be processed. (b) Boundary calculation results.
(ii) Determine the consequence parameters $a_u$ and $b_u$ of the T-S fuzzy inference of equation (13).

(iii) Evaluate the values of the following objective function:

$$E(z_i(t)) = \frac{\sum_{j=0}^{l-1} \sum_{r=0}^{l-1} \eta^r_j (y_j - \tilde{y}_j, (x_i; z_i(t)))^2}{\sum_{j=0}^{l-1} \sum_{r=0}^{l-1} \eta^r_j}, \quad (16)$$

and then calculate the personal best position for each particle, and the overall global best position of all the particles.

(iv) Update the velocity and position of the particle using equations (9) and (12), respectively.

(v) If the global best position does not change during the fixed number of iterations, then the worst 10% particles are replaced with the new particles randomly selected.

(vi) Check the terminal conditions. If one of the terminal conditions is satisfied, then go to step (vii), otherwise go to step (ii).

(vii) Finish the search.

5. Experimental results and discussions

In the experiments, we used three IVUS images. The proposed method uses PSO to tune the parameters of MSFs. To evaluate the performance of the proposed method, we compared it with the conventional method [6], [16] and the gradient descent tuning method.

The seed points are automatically placed by the method [7]. The parameters of PSO of equation (9) are assigned as $s=10$, $w=0.7298$, and $c_1=c_2=1.49618$ accordingly to [15]. In this experiment, the maximum iteration is set to 100. If the improvement of the global best position is less than 0.0001 during 20 iterations, then the search is terminated.

PSO is based on a stochastic method, and so the processing for each image was repeated 5 times (5 runs). The desired boundaries were decided based on the difference of image brightness.

Tables 1 and 2 show the values of the objective function of equation (16) for LB and AB, respectively. Good performance of the proposed method can be seen.

In the proposed method, the different solutions (the locations of the MSF locations) were obtained in different runs. This indicates that the objective function has local minima. Fig. 7 shows the two solutions of the locations of MSFs for LB.

The proposed method may get stuck at a local minimum, but the values of the objective function of the proposed method are better than those of the conventional method [6], [16] and the gradient descent method.

Figs. 8, 9 and 10 show the calculation results by the proposed method for each image. It is observed from Figs. 8, 9 and 10 that the calculated boundaries (white) by the proposed method are close to the desired boundaries (black). These results show that the proposed method works well.

The Root Mean Square Errors (RMSEs) of the proposed method is $1.863 \times 10^{-2} \text{ mm}$ for LB and $3.392 \times 10^{-2} \text{ mm}$ for AB. Taking into account that the diameter of the coronary artery is around 5 mm, the above RMSEs can be considered to be very small, and then we can conclude that the accuracy of the proposed method is enough. Additionally, the proposed method works automatically which does not need any set of training data, seed points,
neither initial areas which were given manually in the conventional methods.

6. Conclusions

We have proposed a method for coronary plaque boundary calculation in an IVUS image by combining PSO and the T-S fuzzy inference.

The proposed method gives better performance than our previous works [6], [16] and the gradient descent method in terms of the calculation accuracy.

The proposed method has more advantages over the methods in [2], [3] and [4]. It works automatically which does not need any set of training data, seed points, neither initial areas which were given manually in the conventional methods.

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References


Syaiful ANAM
He is a Lecturer at Mathematics Department, University of Brawijaya, Indonesia. He is a PhD student at the Graduate School of Science and Engineering, Yamaguchi University, Japan since 2011. His present research interests include numerical optimization, image processing and intelligent system. He is a member of the Indonesian Mathematical Society (IndoMS) and a member of the Institute of Electrical and Electronics Engineering (IEEE).

Eiji UCHINO
He is presently a Professor of the Graduate School of Science and Engineering at Yamaguchi University, Japan. He is also a Chairman of the Board of Directors at the Fuzzy Logic Systems Institute (FLSI). His research interests include adaptive system modeling, intelligent signal and image processing, and human brain based information processing system. He is an Honorary Member of the Ukrainian Academy of Sciences since 2002. He is also a Member of the Institute of Electronics, Information and Communication Engineers (IEICE), the Society of Instrument and Control Engineers (SICE), the Acoustical Society of Japan (ASJ), Japan Society for Fuzzy Theory and Intelligent Informatics (SOFT), Japan Ergonomics Society (JES), etc.

Hideaki MISAWA
He is presently a Specially Appointed Assistant Professor of the Graduate School of Information Sciences at Hiroshima City University, Japan. His research interests include soft computing techniques and their application to the biomedical field. He is a Member of the Institute of Electronics, Information and Communication Engineers (IEICE) and the Institute of Electrical and Electronics Engineers (IEEE).

Noriaki SUETAKE
He is presently an Associate Professor of the Graduate School of Science and Engineering, Yamaguchi University, Japan. His research interests include digital signal processing, image processing and intelligent systems. He is a Member of the Institute of Electronics, Information and Communication Engineers (IEICE), the Institute of Electrical and Electronics Engineers (IEEE), Signal Processing Society, and the Optical Society of America (OSA).