Tissue Characterization of Coronary Plaque by Using Fractal Analysis-based Features of IVUS RF-signal

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Abstract—We propose a precise tissue characterization method of coronary plaque by using fractal analysis-based features which are obtained from radiofrequency (RF) signal employing intravascular ultrasound (IVUS) method. The IVUS method is used for the diagnosis of the acute coronary syndromes (ACS). In the proposed method, the fact that the RF signal reflects the complexity of the structure of tissue is used. The effectiveness of the proposed method is verified through a series of experiments by using IVUS RF signals obtained from a rabbit and a human patient.

I. INTRODUCTION

Oxygenated blood is carried to whole heart through the coronary arteries. If the coronary is occluded by a blood clot, anoxia-induced serious heart diseases such as acute coronary syndromes (ACS) are caused [1]. It has been considered that the rupture of coronary plaque causes the most cases of ACS. In order to diagnose whether a coronary plaque has chance to rupture or not, and also to implement appropriate measures for ACS, medical analysis for structural components of coronary plaque is very important [2].

An intravascular ultrasound (IVUS) method [3], which is a tomographic imaging technology, is often used for the diagnosis of ACS [4]. The IVUS method gives two-dimensional cross-sectional images of coronary plaques which are called Bmode images. A medical doctor diagnoses the coronary plaque by carefully observing the B-mode image obtained by the IVUS method. The diagnosis is very hard because the B-mode images, which are constructed by radiofrequency (RF) signals containing various noises and/or measuring errors, are very grainy. In the recent diagnosis, the RF signal is thus directly analyzed without using the grainy B-mode image.

The integrated backscatter (IB) analysis [5] is a representative tissue characterization method using RF signal. In the IB analysis, a locally-averaged power of the RF signal called IB value is employed. The IB analysis is not always effective for the tissue characterization because the IB values are substantially affected by the intensity of the backscattered ultrasound.

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Fig. 1. Brief overview of the intravascular ultrasound (IVUS) method.

The intensity of the backscattered ultrasound depends on the measurement conditions such as the distance between the coronary plaque and the ultrasound probe.

In this paper, to realize a precise tissue characterization of coronary plaque, we propose a new method based on the fractal analysis [6]. In the present method, the fact that the RF signal reflects the complexity of the structure of tissue is used. The complexity is evaluated by using the fractal analysis, and then the tissue characterization is performed by the k-nearest neighbor method employing the result of fractal analysis.

The present method is applied to the tissue characterization problem using the real IVUS data, and its performance is verified quantitatively and qualitatively. The validity and the practical effectiveness of the present method in the characterization of coronary plaque have been confirmed by the actual experiments.

II. ACS AND IVUS METHOD

Intravascular ultrasound (IVUS) method [3] is one of the medical imaging techniques. 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 proximal end of the catheter is connected to computerized ultrasound equipment. The ultrasound waves are emitted from the ultrasound probe, which are in the 40MHz range in this



Fig. 2. Examples of an RF signal and a B-mode image obtained by the IVUS method. (a) RF signal. (b) B-mode image.

study. The catheter also receives the reflected signal from the tissue. It is sampled at 200 MHz and stored in the computerized ultrasound equipment.

An example of a sampled radiofrequency (RF) signal is shown in Fig. 2(a). An IVUS image is constructed of the amplitude information of the received RF signals. In order to visualize the inside of a coronary artery, the sampled RF signal shown in Fig. 2(a) is transformed into an 8-bit luminal intensity signal first by taking the absolute value of signal, then by taking enveloping, and finally by taking the logarithmic value.

The luminal intensity signals in all radial directions are then used to obtain a tomographic cross sectional image of a coronary artery as shown in Fig. 2(b). The IVUS image shown in Fig. 2(b) is called a "B-mode image." A B-mode image shows a real time ultrasound cross-sectional image of a thin section of the blood vessel where currently the catheter is rotating.

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 $3.91 \mu m$ /pixel and 1.41° /line, respectively.

III. PROPOSED METHOD

A. Fractal Analysis of RF signal

In order to apply the Grassberger-Procaccia (GP) algorithm of a fractal analysis to the RF signal y(t), an *m*-dimensional time series:

$$\mathbf{v}(t) = (y(t), y(t+\tau), \dots, y(t+(m-1)\tau))$$
 (1)

is first reconstructed by the method of delayed coordinates [6]. In the above equation, v(t) is the time series, m is the embedding dimension, and τ is the time delay.

The correlation integral [6] is then estimated by:

$$C^{m}(r) = \lim_{N \to \infty} \frac{1}{N^{2}} \sum_{i,j=1, i \neq j}^{N} I(r - \| \boldsymbol{v}(i) - \boldsymbol{v}(j) \|), \quad (2)$$

where N is the length of the segmented RF signal of consideration [6], r is the radius of the hypersphere for counting the box-count feature quantity (as shown in Fig. 3), $I(\cdot)$ is the Heaviside unit function defined by:

$$I(t) = \begin{cases} 1 & (t \ge 0) \\ 0 & (t < 0), \end{cases}$$
(3)

and $\|\cdot\|$ is the distance between the *i*-th and the *j*-th samples in the *N*-dimensional state space.

Plotting the derivative:

$$D(m) = \frac{\log C^m(r)}{\log r} \tag{4}$$

versus $\log r$, we obtain a curve with a plateau, the value of which gives the estimate of the correlation exponent ν .

As we usually do not know the proper topological dimension n of the state space of the studied system, we repeat this procedure by increasing the values of m. When m (socalled embedding dimension) is smaller than n, ν should be equal to m. When m exceeds n, ν should saturate for the chaotic systems and converge to some value $\bar{\nu}$. This value is regarded as an estimate of the correlation exponent of the studied system.

In the fractal analysis, the precision of estimation depends on the length of the time-series. In the real applications, however, the observed time-series is finite. The estimated correlation exponent $\bar{\nu}$ is dependable if the following condition is satisfied.

$$N \ge 10^{D_c/2} \tag{5}$$

B. Proposed Method

In the fractal analysis, a fractal dimension needs to be evaluated definitely as a feature quantity. However, in the real applications, an accurate estimation of the fractal dimension, which is used in the classification, is very difficult to evaluate because of noise.

It is confirmed that the RF signal reflected from the fibrous tissue tends to be complex, on the contrary, the RF signal reflected from the lipid tissue tends to be plain. Furthermore,



Fig. 3. Procedure of GP algorithm.



Fig. 4. Distribution of the feature vectors in the two-dimensional LDA(Linear Discriminant Analysis) space. The gray and the black dots are feature vectors of lipid and fibrous tissues, respectively.

it is also confirmed that the convergence behavior of the correlation exponent is different in the fractal analysis for the RF signals reflected from the fibrous and the lipid tissues. With this knowledge, we employ the convergence behavior of the correlation exponents from the 1st to the 10th dimensions as a 10-dimensional feature vector for the classification.

Fig. 4 shows the distribution of the correlation exponents obtained from the RF signals of fibrous and lipid tissues. It is seen that the two distributions obtained by applying the linear discriminant analysis (LDA) to the two feature vectors are apart enough each other to be used for classification.

The processing procedure of the present method is briefly shown in Fig. 5. An RF signal in the ROI (region of interest) is first decomposed into the segments $y_i(t)$ with N points as shown in the upper part of Fig. 5. The segmented RF signals $y_i(t)$ are analyzed by using the GP algorithm (fractal analysis), then 10-dimensional correlation exponents are obtained as feature vectors. The feature vectors are then classified by the ordinary k-nearest neighbor (kNN) classifier into either fibrous or lipid class.The kNN classifier is a nonlinear and memorybased method, and is easily applicable. Now, let the obtained class be $F(y_i(t))$ as shown in the lower part of Fig. 5. The final



Fig. 5. Brief procedure of the proposed method.

TABLE I ACCURACY RATE OF CLASSIFICATION BY EACH METHOD FOR IVUS IMAGES OBTAINED FROM A RABBIT'S CORONARY ARTERY.

	IB Analysis	Proposed Method
Image 1	85.5%	92.7%
Image 2	76.2%	84.3%
Image 3	63.2%	88.1%
Image 4	61.5%	94.6%

classification result for each part of RF signal at t_k is obtained by the majority decision, taking a count of the number of classes pre-classified by kNN in a longitudinal direction as shown in the bottom of Fig. 5. If the counts of each class are the same at t_k , the final classification result is given to be the same to the result at $t_k - 1$.

IV. EXPERIMENTS AND DISCUSSION

A. Experimental Conditions

The purpose of the experiments is to classify the tissues in the ROI (for example, shown in Fig. 6(a)) into either fibrous or lipid tissue. In the experiments, the images obtained from the rabbit and the human patient coronary arteries are used, respectively. The correct characterization results for each IVUS image are given beforehand by a medical doctor.

In the sampling of data, the carrier and the sampling frequencies of RF signal are 40MHz and 200MHz, respectively. In the fractal analysis of the RF signal, the length of the segmented RF signal is assigned to be N = 150 points by considering the condition of Eq. (5). In the kNN method, k is empirically set to be 9 considering the classification performance and robustness against noise, and 1,000 training vectors are chosen from various IVUS images in total.

 TABLE II

 Accuracy rate of classification by each method for IVUS

 IMAGES OBTAINED FROM A HUMAN PATIENT'S CORONARY ARTERY.

		IB Analysis	Proposed Method
Image 1	Fibrous Tissue	91.5%	96.3%
	Lipid Tissue	58.7%	91.7%
Image 2	Fibrous Tissue	65.0%	78.4%
	Lipid Tissue	90.4%	99.2%
Image 3	Fibrous Tissue	61.7%	84.8%
	Lipid Tissue	95.1%	92.3%



Fig. 6. Tissue characterization results for a rabbit's coronary plaque (IVUS image 2). (a) Desirable characterization result. (b) Result by the IB analysis. (c) Result by the proposed method.

The experimental results by the present method are compared to those by the conventional IB analysis. In the IB analysis, a tissue is classified by using a one-dimensional feature of IB value, which is a locally averaged power of a backscattered RF signal. Here by letting y(t) and $y_0(t)$ be an amplitude of the sampled backscattered RF signal and the smallest signal which can be sensed by the ultrasound probe (reference value), the IB value is calculated as:

$$IBS(t) = 20 \log \left(\frac{\frac{1}{T+1} \sum_{i=t-T/2}^{t+T/2} y(i)^2}{\frac{1}{T+1} \sum_{i=t-T/2}^{t+T/2} y_0(i)^2} \right), \qquad (6)$$

where T is a window size for the calculation of an IB value. In the experiments, the parameters in the IB analysis are set



Fig. 7. Tissue characterization results for a rabbit's coronary plaque (IVUS image 4). (a) Desirable characterization result. (b) Result by the IB analysis. (c) Result by the proposed method.

to be $y_0(\cdot) = 1$ and T = 32. The threshold value of the IB value for the classification of fibrous and lipid tissues is set to be 102. This threshold value is empirically decided for the IB analysis to work best in average for the various kinds of IVUS images.

B. Experimental Results and Discussion

Table I shows the classification accuracy rate by each method for four IVUS images obtained from a rabbit's coronary artery. The images are obtained in vitro analysis. In the case of rabbit's data, plaque tends to accumulate partly on the circumference of the coronary artery. All the results by the present method are much superior to those by the conventional IB analysis. Table II shows the classification accuracy rate by each method for three IVUS images obtained from a human patient's coronary artery. The images are obtained in vivo analysis. In the case of a human patient, plaque tends to accumulate broadly on the entire circumference. Almost all the results by the present method are much better than those by the IB analysis.

Figs. 6 and 7 show the tissue characterization results of IVUS images 2 and 4, respectively, for a rabbit's coronary plaque. Figs. 8 and 9 show the tissue characterization results of IVUS images 1 and 3, respectively, for a human patient's coronary plaque. In all of the results by the IB analysis, it is observed that the areas far from the ultrasound probe are



Fig. 8. Tissue characterization results for a human patient's coronary plaque (IVUS image 1). (a) Desirable characterization result. (b) Result by the IB analysis. (c) Result by the proposed method.



Fig. 9. Tissue characterization results for a human patient's coronary plaque (IVUS image 3). (a) Desirable characterization result. (b) Result by the IB analysis. (c) Result by the proposed method.

misclassified. It is considered that the misclassifications by the IB analysis are caused by the attenuation of RF signal. On the contrary, the present method gives robust characterization results in almost every ROI in spite of signal attenuation.

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

V. CONCLUSION

In this paper, we have proposed a novel tissue characterization method of coronary plaque based on the fractal analysis of RF signal. In the present method, the features acquired by fractal analysis have been used for pre-classification by the ordinary kNN, and then the majority decision of the classification has been performed to obtain the final classification results for each pixel in the ROI. The present method has shown a superior characterization performance compared to the conventional IB method.

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