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# Tissue Characterization of Coronary Plaque by Subspace Method with Consideration to Neighborhood Information of Target Tissue

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***Abstract*—Tissue characterization of coronary plaque is essential for a diagnosis of acute coronary syndromes. The radio frequency (RF) signals obtained by the intravascular ultrasound (IVUS) method have different frequency characteristics according to the kinds of tissue. The frequency characteristics of the RF signals are conventionally used for tissue characterization of coronary plaque. Those methods however have high computing costs, and the parameter settings are complicated and difficult. In this paper, tissue characterization of coronary plaque by subspace method considering the neighborhood information around the target tissue to be classified is proposed. The proposed method realizes a low cost computing and easy parameter settings. The effectiveness of the proposed method has been verified by the application to the actual tissue characterization problem of the human coronary plaque.**

***Index Terms*—intravascular ultrasound, tissue characterization, subspace method, neighborhood information.**

## I. Introduction

RUPTURE of plaque piled up in the coronary arteries causes acute coronary syndromes. Plaque is classified into stable plaque and unstable plaque according to the structure of plaque. Therefore, for the diagnosis of the acute coronary syndromes, tissue characterization of coronary plaque with high accuracy is essential.

Intravascular ultrasound (IVUS) [1] method is a representative examination method for the diagnosis of plaque. IVUS obtains radio frequency (RF) signals by irradiating ultrasound to the vascular wall from the catheter with the ultrasonic probe loaded, which is inserted in the coronary artery.

It can visualize a section of the coronary artery by converting the RF signals into luminosity values. It however is difficult to characterize the structure of the plaque from only the image due to noise and other reasons to make the image unclear.

Many methods to characterize the plaque structure by analyzing the RF signals had been proposed so far. Those are the discrimination methods using the integrated backscatter (IB) values and the methods using the frequency characteristics of RF signals.

In the discrimination methods using the IB values, it however is difficult to characterize with high accuracy because the IB values change big according to the measurement conditions. Moreover, in the discrimination methods using the frequency characteristics, there are problems that the computing cost is high and the settings of the parameters in the algorithm are complicated and difficult.

In this paper, the tissue characterization of coronary plaque by the subspace method considering the neighborhood target tissue information is proposed. The subspace method [2] classifies the target vector by comparing similarity between the target vector and the vectors for each class. The representative similarity is defined by an orthographic projection of target vector on the subspace.

The present method is based on the hypothesis that the adjacent tissue is likely to be the same tissue. That is, the present method discriminates tissue by means of a new similarity measure under consideration of the neighborhood information around the target tissue to be classified. Furthermore, the present discrimination method calculates in low cost and the parameter settings are easy.

After applying the present method to the actual tissue characterization problem using the RF signals obtained from a human coronary plaque, good experimental results were obtained.

## II. Conventional Discrimination Method Using Frequency Characteristics

k-nearest neighbor algorithm (kNN) [3] is one of the conventional classification methods using frequency characteristics of RF signals. kNN chooses k learning vectors which makes the k smallest distances between a target vector and the learning vectors. Subsequently, the target vector is classified in the major class of those learning vectors.

In kNN, however, computing cost increases in proportion to the number of the learning vectors due to the calculation of all distances between the target vector and the learning vectors.

## III. Tissue Characterization by Subspace Method

The present method classifies the target vector into the appropriate class by subspaces obtained from each class. The target vector reflecting the feature of the coronary plaque tissue of concern is classified with consideration to the neighborhood information around the target vector.

### A. Subspace Method

Each subspace has to include the feature of its class to classify the target vector. Suppose the target vector is being classified into one of the c classes $\omega_1, \omega_2, \cdots, \omega_c$.

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When $d$-dimensional feature vector belonging to class $\omega_i$ ($i = 1, \cdots, c$) is given, the autocorrelation matrix becomes as follows:

$$\boldsymbol{R}_i = \frac{1}{n_i} \sum_{\boldsymbol{y} \in \mathcal{Y}_i} \boldsymbol{y}\boldsymbol{y}^t, \tag{1}$$

where $t$ means a transpose operation, $\mathcal{Y}_i$ means a set of vectors belonging to class $\omega_i$, and $\boldsymbol{y}$ is an element of $\mathcal{Y}_i$. The $d_i (< d)$-dimensional subspace of class $\omega_i$ is constructed by the orthonormal vectors from $\boldsymbol{u}_{i1}$ to $\boldsymbol{u}_{id_i}$, where $\boldsymbol{u}_{ij}$ ($j = 1, \cdots, d$) is the eigenvector of $\boldsymbol{R}_i$ corresponding to $\lambda_{ij}$, which is the $j$th eigenvalue of $\boldsymbol{R}_i$ arranged in descending order.

The target vector $\boldsymbol{x}$ is classified by comparing the similarities $S_i(\boldsymbol{x})$ between the target vector and the learning vectors of each class. Following is a discrimination rule of the subspace method using this similarity:

$$\max_{i=1,\cdots,c} \{S_i(\boldsymbol{x})\} = S_k(\boldsymbol{x}) \quad \Longrightarrow \quad \boldsymbol{x} \in \omega_k. \tag{2}$$

### B. Representative Similarities

Among the representative subspace methods, there are a simple similarity method, a multiple similarity method, and a compound similarity method. The similarities used in those methods are described in the following.

*1) Simple Similarity Method:* The following is a similarity employed in a simple similarity method:

$$S_i^{\text{Simple}}(\boldsymbol{x}) = \sum_{j=1}^{d_i} \left(\boldsymbol{x}^t \boldsymbol{u}_{ij}\right)^2. \tag{3}$$

This is a distance between the origin and the projection of the target vector in the subspace. A simple similarity method classifies the target vector into the class which has the closest feature with the target vector.

*2) Multiple Similarity Method:* Similarity in a multiple similarity method is given by:

$$S_i^{\text{Multiple}}(\boldsymbol{x}) = \sum_{j=1}^{d_i} \frac{\lambda_{ij} \left(\boldsymbol{x}^t \boldsymbol{u}_{ij}\right)^2}{\lambda_{i1} \boldsymbol{x}^t \boldsymbol{x}}. \tag{4}$$

Comparing with the similarity of a simple similarity method (3), each eigenvector is weighted by $\lambda_{ij}/\lambda_{i1}$. Moreover, the denominator of this equation $\boldsymbol{x}^t\boldsymbol{x}$ is a coefficient to normalize the multiple similarity.

*3) Compound Similarity Method:* A compound similarity method is a method to evaluate the similarity emphasizing the difference between the class $\omega_i$ and the comparison class $\omega_k$.

Similarity in the compound similarity method is given as follows:

$$S_i^{\text{Compound}}(\boldsymbol{x}) = \sum_{j=1}^{d_i} \frac{\frac{\lambda_{ij}}{\lambda_{i1}} \left(\boldsymbol{x}^t \boldsymbol{u}_{ij}\right)^2 - \mu \left(\boldsymbol{x}^t \boldsymbol{v}_i\right)^2}{\boldsymbol{x}^t \boldsymbol{x}}, \tag{5}$$

where $\boldsymbol{v}_i$ is a unit vector defined by:

$$\boldsymbol{v}_i = \frac{\boldsymbol{m}_k - \sum_{j=1}^{d_i} \boldsymbol{m}_k^t \boldsymbol{u}_{ij} \boldsymbol{u}_{ij}}{\sqrt{\boldsymbol{m}_k^t \boldsymbol{m}_k - \sum_{j=1}^{d_i} \left(\boldsymbol{m}_k^t \boldsymbol{u}_{ij}\right)^2}}. \tag{6}$$

$\boldsymbol{m}_k$ is a mean vector of comparison class $\omega_k$. $\boldsymbol{v}_i$ shows a difference between the $\boldsymbol{m}_k$ and the projection of $\omega_k$ in the subspace of class $\omega_i$.

Moreover, $\mu$ of the equation (5) is a parameter to adjust the weight of differences between classes.

### C. Similarity Considering Neighborhood Information

In general the discrimination accuracy decreases when the feature vectors of each class overlap each other. Discrimination method considering the information other than the feature vectors is necessary for a high accuracy tissue characterization, because the feature vectors of fibrous, fatty, and fibrofatty tissues constituting coronary plaque are widely overlapped.

The new similarity measure, based on the assumption that the neighborhood tissues are likely to be in the same class, is proposed in this paper.

When it is applied to the simple similarity method, the similarity becomes as:

$$\hat{S}_i^{\text{Simple}}(\boldsymbol{x}) = \sum_{j=1}^{d_i} \left(\boldsymbol{w}^t \boldsymbol{u}_{ij}\right)^2, \tag{7}$$

where $\boldsymbol{w}$ is defined by:

$$\boldsymbol{w} = \frac{1}{l} \sum_{\boldsymbol{x}_a \in \mathcal{A}_x} \boldsymbol{x}_a. \tag{8}$$

$\mathcal{A}_x$ is a set of the feature vectors for the target tissue and for the neighborhood tissues, and $\boldsymbol{x}_a$ is an element of $\mathcal{A}_x$. $l$ is the number of the elements $\boldsymbol{x}_a$ included in $\mathcal{A}_x$, which is the number of feature vectors for neighborhood tissues considered.

Conventional subspace method measures similarity between the target feature vector and the feature vector of each class by projecting the target vector into the subspace of each class. In contrast to this, the proposed method measures the similarity by projecting the mean vector of the feature vectors for the neighborhood tissues into the subspace of each class.

Likewise, when it is applied to the multiple similarity method and to the compound similarity method, the similarities become as:

$$\hat{S}_i^{\text{Multiple}}(\boldsymbol{x}) = \sum_{j=1}^{d_i} \frac{\lambda_{ij} \left(\boldsymbol{w}^t \boldsymbol{u}_{ij}\right)^2}{\lambda_{i1} \boldsymbol{w}^t \boldsymbol{w}} \tag{9}$$

and

$$\hat{S}_i^{\text{Compound}}(\boldsymbol{x}) = \sum_{j=1}^{d_i} \frac{\frac{\lambda_{ij}}{\lambda_{i1}} \left(\boldsymbol{w}^t \boldsymbol{u}_{ij}\right)^2 - \mu \left(\boldsymbol{w}^t \boldsymbol{v}_i\right)^2}{\boldsymbol{w}^t \boldsymbol{w}}. \tag{10}$$

## IV. Experiments

The similarity measure considering the neighborhood information is applied to the tissue characterization of coronary plaque. kNN and the subspace methods without considering the neighborhood information are compared with the proposed method.

Parameters in the experiments are set as $k$=9, $d_i$=5, $\mu$=$\lambda_{i1}/\lambda_{ij}$, and $l$=9. The neighborhood tissues are defined as eight tissues neighboring the target tissue in all directions.

Computing cost of each method is evaluated by the computational time required for characterizing the unknown tissue. CPU used here is Intel ® Core™ i7-2600K 3.40GHz, and memory is 16GB. OS is Windows7 and MATLAB was used for programming.

Shown in Fig.1 are the results by each method for the learning feature vectors for the tissues in the cross section of the coronary artery. Table I shows an accuracy rate and a computational time for each method.

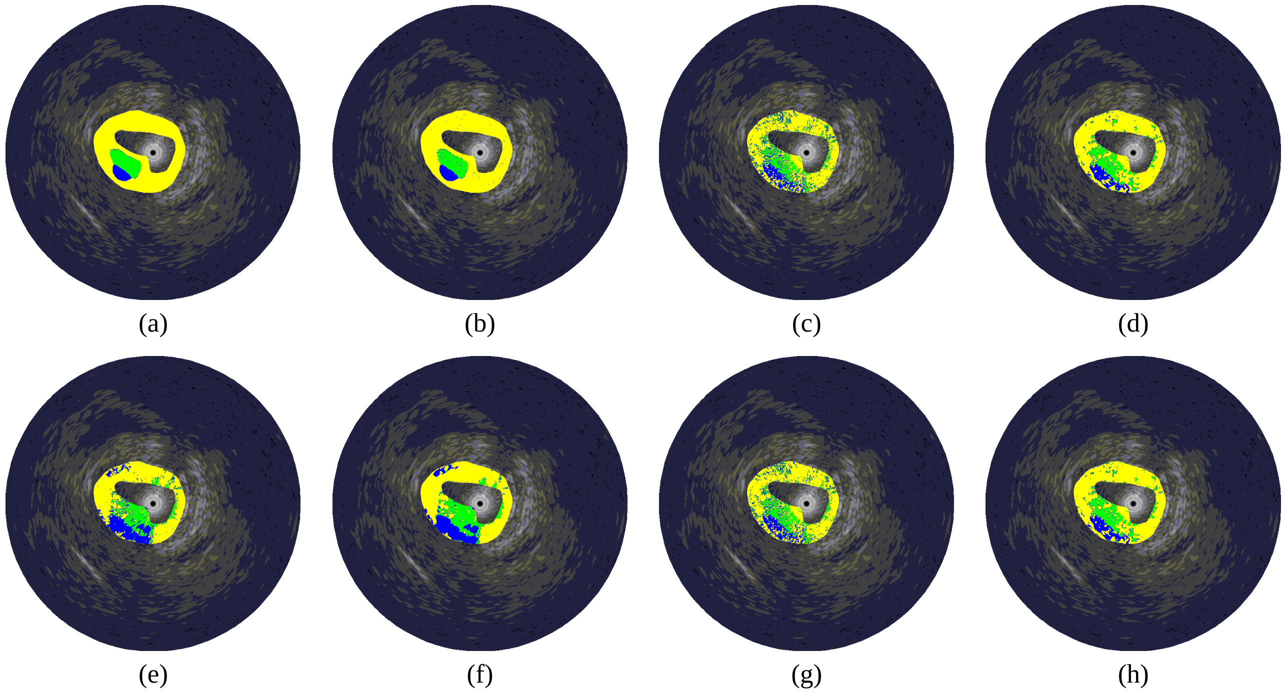

Fig. 1. Tissue characterization results by each method for the learning data. (a) Medical doctor's findings. (b) kNN. (c) Simple similarity method. (d) Simple similarity method considering neighborhood information (Proposed Method 1). (e) Multiple similarity method. (f) Multiple similarity method considering neighborhood information (Proposed Method 2). (g) Compound similarity method. (h) Compound similarity method considering neighborhood information (Proposed Method 3). White shows fibrous tissue, gray shows fibrofatty tissue, and black shows fatty tissue.

TABLE I
TISSUE CHARACTERIZATION ACCURACY RATE (%) AND COMPUTATION TIME (S) FOR THE LEARNING DATA.

| | kNN Method | Simple Similarity Method | Proposed Method 1 | Multiple Similarity Method | Proposed Method 2 | Compound Similarity Method | Proposed Method 3 |
|---|---|---|---|---|---|---|---|
| Fibrous | 99.4 | 72.8 | 82.6 | 65.3 | 65.8 | 73.7 | 82.6 |
| Fatty | 97.2 | 79.7 | 84.4 | 92.5 | 94.0 | 78.8 | 84.4 |
| Fibrofatty | 93.9 | 69.3 | 74.5 | 68.9 | 77.8 | 70.0 | 75.8 |
| Average | 96.9 | 73.9 | 80.5 | 75.6 | 79.2 | 74.1 | 80.9 |
| Computational Time | 553.46 | 1.02 | 1.38 | 1.59 | 1.79 | 1.85 | 2.44 |

Fig.2 shows the results by each method for the test data, i.e., the tissue in another cross section of the coronary artery are classified by the classifier learned at a different cross section. Table II shows an accuracy rate and a computational time for each method.

The results in Fig.1 show that the kNN method has the best result of all the methods for the learning data.The results in Fig.2 show that the multiple similarity method (e), the proposed methods 1(d), 2(f), and 3(h) have comparatively clear tissue boundaries in comparison to other methods.

From Table II, we can see that kNN has the best accuracy rate for fibrous tissue. It however has the worst accuracy rates for fatty and fibrofatty tissues, and accordingly has the worst average accuracy rate for the test data.

In contrast, the accuracy rate of the subspace method is mostly good regardless of the kind of tissue. As for the proposed methods (the subspace methods with consideration of the neighborhood information), the average accuracy rates of the proposed methods are exceeding those of the corresponding conventional subspace methods.

Moreover, in computing cost, kNN has obviously the longest computational time. In contrast the subspace methods and the proposed methods have short computational time.

## V. CONCLUSIONS

In this paper, tissues of coronary plaque have been successfully classified into three categories of fibrous, fatty, and fibrofatty tissues. The method used is the subspace method with consideration of the neighborhood information around the target tissue to be classified.

Future works are to find the best weights for the feature vectors for neighboring tissues, and to find more adequate subspace for better discrimination accuracy of tissue of coronary plaque.

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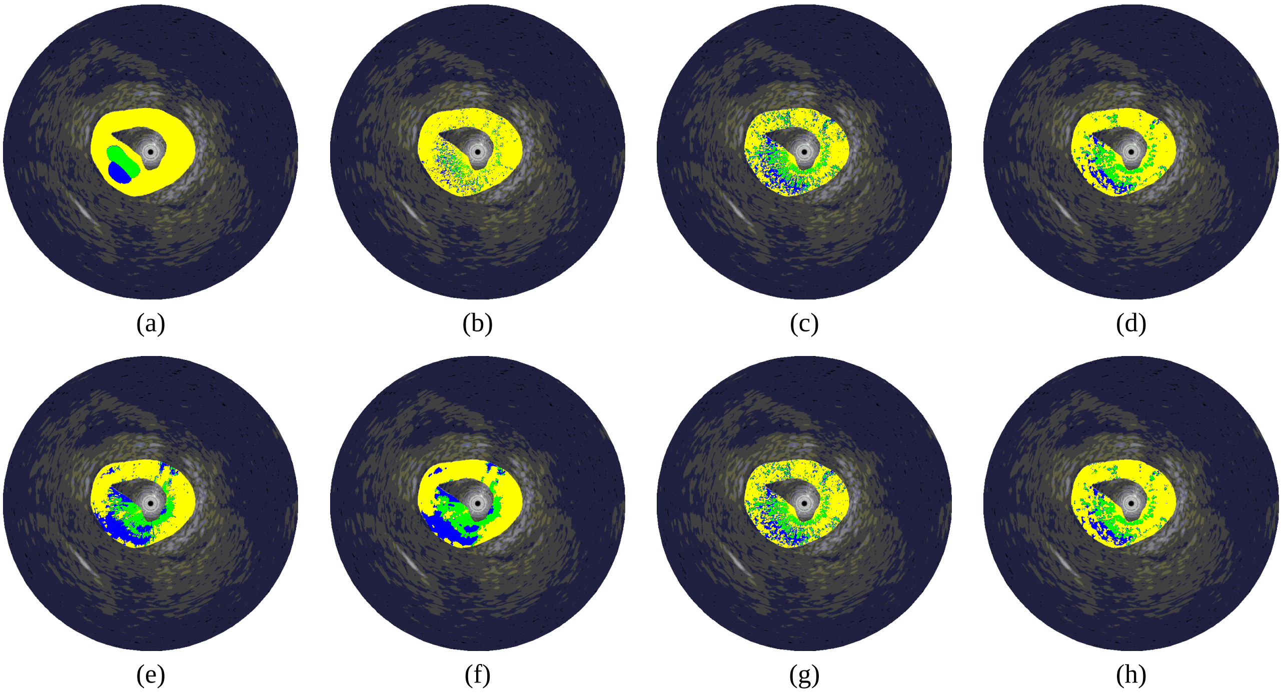


Fig. 2. Tissue characterization results by each method for the test data. (a) Medical doctor's findings. (b) kNN. (c) Simple similarity method. (d) Simple similarity method considering neighborhood information (Proposed Method 1). (e) Multiple similarity method. (f) Multiple similarity method considering neighborhood information (Proposed Method 2). (g) Compound similarity method. (h) Compound similarity method considering neighborhood information (Proposed Method 3). White shows fibrous tissue, gray shows fibrofatty tissue, and black shows fatty tissue.

TABLE II
TISSUE CHARACTERIZATION ACCURACY RATE (%) AND COMPUTATION TIME (S) FOR THE TEST DATA.

| | kNN Method | Simple Similarity Method | Proposed Method 1 | Multiple Similarity Method | Proposed Method 2 | Compound Similarity Method | Proposed Method 3 |
|---|---|---|---|---|---|---|---|
| Fibrous | 90.0 | 70.2 | 78.9 | 61.9 | 62.0 | 71.1 | 79.1 |
| Fatty | 27.5 | 52.4 | 49.7 | 78.0 | 80.1 | 52.7 | 52.2 |
| Fibrofatty | 37.1 | 56.8 | 56.5 | 65.8 | 75.2 | 56.4 | 55.5 |
| Average | 51.5 | 59.8 | 61.7 | 68.5 | 72.4 | 60.1 | 62.2 |
| Computational Time | 723.43 | 1.22 | 2.11 | 1.65 | 2.57 | 2.14 | 3.07 |

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