Abstract: This paper proposes a tissue characterization method for coronary plaque by using a sparse coding. The sparse coding can efficiently represent a signal by a few basis functions extracted by learning. In the proposed method, the radio frequency (RF) signal obtained by the intravascular ultrasound (IVUS) method is expressed by a linear combination of the basis functions learned by the sparse coding, and the coefficient patterns of the basis functions are used for the tissue characterization. The effectiveness of the proposed method has been verified by comparing it with the conventional integrated backscatter (IB) analysis and frequency analysis.

Key–Words: Sparse coding, Tissue characterization, Coronary plaque, Radio frequency (RF) signal, Intravascular ultrasound (IVUS)

1 Introduction

The rupture of an unstable coronary plaque which is abundant in lipid is a cause of most acute coronary syndromes (ACS). On the other hand, a dense fibrosis plaque tends to be stable in a coronary artery. Therefore, in a diagnosis of ACS, it becomes very important to investigate the compositions of the plaque in order to distinguish accurately between the stable plaque and the unstable one.

The intravascular ultrasound (IVUS) method is a tomographic imaging technique using an ultrasound probe mounted at the tip of a catheter. It provides a tomographic view of the coronary artery by analyzing the radio frequency (RF) signal, which is a backscattered ultrasound signal from tissue.

The IVUS method gives a real-time imaging of the section of the coronary artery. This image is called a B-mode image [1], and is often used for the diagnosis of ACS. However, it is very difficult to perform tissue characterization of coronary plaque only by observing this B-mode image.

The integrated backscatter (IB) analysis is a typical method for the tissue characterization using the IVUS method [2][3]. The IB analysis employs the IB value, which is a locally averaged power of the RF signal, as the feature for the tissue characterization. This is not always useful, because the different tissues sometimes have similar IB values with each other. Also the IB value is strongly affected by the measurement conditions.

The tissue characterization based on the frequency analysis of the RF signal has been proposed [4]. However, a precise tissue classification by this method is not yet achieved, because the frequency characteristics of some tissues are similar to others.

In order to realize the precise tissue classification, this paper proposes a novel method for the tissue characterization of coronary plaque by using the sparse coding [5]-[8], which is a statistical method to esti-
mate the underlying features of the observed signals. In the proposed method, the RF signal is coded by the sparse coding, and the code (coefficient) patterns are used for a classification of the target tissue.

Experiments are performed to classify the tissues of the plaque into the fibrous and lipid tissues using the RF signal obtained from a rabbit coronary artery. The effectiveness of the proposed method has been verified by comparing the classification results by the proposed method with those by the IB analysis and by the frequency analysis.

2 Application of Sparse Coding to Tissue Characterization

2.1 IVUS Method

The IVUS method is one of the medical imaging techniques. In the IVUS method, the catheter with the ultrasound probe is inserted and then rotated in the coronary artery. The ultrasound signal is transmitted from the ultrasound probe, and the RF signal reflected from the tissue is received also by its ultrasound probe. The transmitting frequency of the ultrasound is 40 MHz, and the RF signal is sampled at 400 MHz.

An IVUS B-mode image [9] is obtained by analyzing the received RF signal. This IVUS B-mode image expresses a tomographic image of the section of the coronary artery. This image is constructed with 2,048 points in depth, and 256 lines in radial direction.

2.2 Sparse Coding

The sparse coding was originally proposed to represent an image signal by using a few basis functions extracted from natural image. It is closely related to the independent component analysis (ICA) [10][11], which is well known as a statistical method to estimate the underlying features of the observed signals. We try to apply this high ability of the sparse coding for feature extraction to the tissue characterization using the RF signal.

2.2.1 Representation of RF Signal

A local part of the RF signal is assumed to be represented as a linear combination of the basis functions \( \phi_i \) as follows:

\[
x = \sum_{i=1}^{M} a_i \phi_i,
\]

where \( a_i \) is a coefficient for each basis function \( \phi_i \), and \( M \) is the number of the basis functions. \( x \) and \( \phi_i \) are given by:

\[
x = (x_1, \ldots, x_L)^t,
\]

\[
\phi_i = (\phi_{i1}, \ldots, \phi_{iL})^t,
\]

where \( L \) is the dimension of \( x \) sampled in the short time interval, and \( t \) is a transpose operation.

2.2.2 Cost Function of Sparse Coding

The basis functions \( \phi_i \) and the coefficients \( a_i \) are statistically determined from a set of the local part of the RF signal \( x \), which are cut out randomly from the learning signals obtained from the same tissue. \( \phi_i \) and \( a_i \) are estimated only by using \( x \).

In the sparse coding, the following cost function is employed to determine \( \phi_i \) and \( a_i \) [5][6]:

\[
E = \left( \sum_{j=1}^{L} \left( x_j - \sum_{i=1}^{M} a_i \phi_{ij} \right)^2 + \beta \sum_{i=1}^{M} S \left( \frac{a_i}{\sigma} \right) \right),
\]

where \( \langle \cdot \rangle \) is an averaging operator, and \( \beta \) is a positive constant. \( \sigma \) is a scaling constant. The standard deviation of the learning signals is used as \( \sigma \) here. \( S(y) \) is an arbitrary nonlinear function such as \( \log(1+y^2) \) or \( -e^{-y^2} \), or \( |y| \).

The first term of Eq. (4) indicates the signal reconstruction performance by evaluating the sum of the square error between the input signal \( x_j \) and the reconstructed signal. The second term determines the sparseness of the coefficients \( a_i \).

2.2.3 Learning Algorithm of Sparse Coding

The learning algorithm of the sparse coding is obtained by minimizing Eq. (4) with respect to \( a_i \) and \( \phi_i \).

That is, the updating rule of \( a_i \) is given as follows [5][6]:

\[
\hat{a}_i = b_i - \sum_{k=1}^{M} R_{ik} a_k - \frac{\beta}{\sigma} S' \left( \frac{a_i}{\sigma} \right),
\]

where \( b_i \) is \( \sum_{j=1}^{L} \phi_{ij} x_j \), \( R_{ik} \) is \( \sum_{j=1}^{L} \phi_{ij} \phi_{kj} \), and \( S'(y) \) is a differential of \( S(y) \).

The updating rule of \( \phi_i \) is as follows:

\[
\Delta \phi_{ij} = \eta \left( a_i \left( x_j - \sum_{i=1}^{M} a_i \phi_{ij} \right) \right),
\]

where \( \eta \) is a learning rate.

\( a_i \) are updated by Eq. (5) according as each input signal is applied, and \( \phi_{ij} \) are updated after about 100 input signals are applied.
2.2.4 Code Patterns of $a_i$

The basis functions are extracted from the learning signals which are reflected from the fibrous and lipid tissues. Many local parts of the RF learning signal reflected from the fibrous tissue are reconstructed by the basis functions extracted, and let $A^{fib}$ be the set of the code patterns obtained from the learning signals for the fibrous tissue. Let $A^{lip}$ be the set of the code patterns obtained from the learning signals for the lipid tissue.

An input signal, reflected from the tissue of concern, is classified by using $A^{fib}$ and $A^{lip}$.

2.2.5 Feature Extraction

The characteristics of the basis functions obtained from the learning signals by using the sparse coding are as follows:

1. The frequency characteristics of the obtained basis functions and those of the learning signals are similar to each other.

2. The code pattern (pattern of $a_i$) when the learning signal is represented by the basis functions is sparse.

In order to verify the above feature 1, the averaged power spectrum of the learning signals and that of the basis functions are shown in Fig.1. From those results, it is observed that the basis functions well capture the frequency characteristics of the learning signals.

Also, in order to verify the above feature 2, the code pattern of $a_i$ when a local part of the RF learning signal is represented by the basis functions is shown in Fig.2. It is seen from this figure that the code pattern (pattern of $a_i$) is sparse. In this paper, we use those code patterns as the features of the RF signal for the tissue characterization.

2.2.6 Classification

In the proposed method, the Fisher linear discriminant analysis is used [12]. This is used to classify the feature vector into the two classes by mapping it onto one dimensional space. The transformation matrix [12] is decided from $A^{fib}$ and $A^{lip}$ obtained from the learning signals.

3 Comparative Methods

3.1 IB Analysis

The IB analysis is a typical method for the tissue characterization using IVUS. In this analysis, the tissue is classified by the IB value (IBS) defined by [2]:

$$IBS = 20\log\left(\frac{\frac{1}{T} \int_0^T V^2 dt}{\frac{1}{T} \int_0^T V_0^2 dt}\right),$$

(7)

where $V$ is a signal voltage from a region of interest, $V_0$ is the smallest signal voltage that the system can detect, and $T$ is an integration interval.

The IB analysis is simple, and is very good in a restricted case. However, it can not always accurately classify the tissues of the plaque, because some types of tissues have similar IB values with each other, and the IB value depends in essence on a distance from the probe to the tissue. This is a fatal defect of the IB analysis.

3.2 Frequency Analysis

The frequency analysis is another approach for the tissue characterization. In this method, the Fourier spectrum of the RF signal is used. However, since the frequency characteristics of some tissues are similar to others, a precise tissue classification is not yet achieved. The normalized power spectrum of the local part of the RF signal is used as the feature vector.
3.3 Classification

In the IB analysis, the threshold of the IB value for the classification of the fibrous and lipid tissues is decided so that the learning signals are most precisely classified. In the frequency analysis, the Fisher linear discriminant analysis is used. The transformation matrix [12] is decided from the learning signals.

4 Experimental Results

The proposed method is applied to the tissue characterization problem for the RF signal obtained from a rabbit coronary artery.

In the classification, the tissues of plaque are classified into the fibrous and lipid tissues. The classification performance of the proposed method by using the sparse coding is compared to that of the IB analysis and that of the frequency analysis.

In the IB analysis, the IB value is calculated at each point of a section of a coronary artery by shifting the window of a size of 32 points in depth direction along a radial line. In the proposed method and also the frequency analysis, the length of the local part of the RF signal is set to 32 as well.

Figure 3: Classification results of the fibrous tissues by the proposed method. (a) Fibrous tissue 1. (b) Fibrous tissue 2.

Figure 4: Classification results of the lipid tissues by the proposed method. (a) Lipid tissue 1. (b) Lipid tissue 2.

Table 1: Correct classification rates by each method.

<table>
<thead>
<tr>
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<th>IB analysis</th>
<th>Frequency analysis</th>
<th>Proposed method</th>
</tr>
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<tbody>
<tr>
<td>Fibrous tissue 1</td>
<td>0.70</td>
<td>0.99</td>
<td>0.91</td>
</tr>
<tr>
<td>Fibrous tissue 2</td>
<td>0.46</td>
<td>0.86</td>
<td>0.90</td>
</tr>
<tr>
<td>Lipid tissue 1</td>
<td>0.64</td>
<td>0.86</td>
<td>0.96</td>
</tr>
<tr>
<td>Lipid tissue 2</td>
<td>0.29</td>
<td>0.48</td>
<td>0.89</td>
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</tbody>
</table>

Figures 3 and 4 show the classification results of the fibrous and lipid tissues by the proposed method. The white and gray areas correspond to the fibrous and lipid tissues, respectively.

Table 1 shows the correct classification rates. It is seen that the proposed method has good performance compared to the other methods.

5 Conclusion

This paper proposed a novel method for the tissue characterization of coronary plaque based on a sparse coding. In the proposed method, the RF signal was represented by the basis functions, and the code patterns (coefficient patterns) of the basis functions were used for the tissue characterization.

The effectiveness of the proposed method was verified by comparing it with the IB analysis and the frequency analysis. The experimental results show that the proposed method has good performance compared to the other methods.

Future work is to apply the proposed method to the RF signal obtained from the human patients.

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References:


