Effectiveness of Averaged Learning Subspace Method for Application to Coronary Plaque Tissue Classification

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Abstract

A coronary plaque tissue classification is essential for diagnosis of acute coronary syndromes. We have applied the Averaged Learning Subspace Method (ALSM) with consideration for the neighborhood information, to classify coronary plaque tissues. We have succeeded in classifying the tissues whilst keeping the merit of the subspace method. Simple parameter settings and low computing cost have been realized, and compared to our previous method more accurate classification results have been obtained.

1. Introduction

The main cause of Acute Coronary Syndromes (ACS) is the rupture of unstable plaque. Plaque is an intimal thickening, mainly composed of fibrous, fatty, and fibrofatty tissues. Plaque is classified into stable plaque and unstable plaque by its tissue composition, which influences the ease of rupture.

Stable plaques have thick capsules of fibrous tissue which cover the relatively small cores of fatty tissue, whilst unstable plaques have thin capsules of fibrous tissue which cover the relatively large cores of fatty tissue. High accuracy tissue classification of coronary plaque is essential for the diagnosis of acute coronary syndromes.

The IntraVascular UltraSound (IVUS) [1],[2] method is a medical imaging methodology using a specially designed catheter with an ultrasound probe at the tip. IVUS has been the best technology to observe the anatomy of the artery wall, and thus it is often used to evaluate coronary plaque.

The Radio Frequency (RF) signals, which are the ultrasound signals reflected from the tissues within coronary arteries, are obtained by the IVUS method. The coronary plaque can be visualized by converting RF signals into luminosity values, and then a cross-sectional image of the coronary artery is constructed. The information of coronary plaque, such as size and location, is given to medical doctors, however the tissue composition of coronary plaque can not be evaluated by the cross-sectional images, as they are unclear due to noise and the information deficit which occurs during conversion.

Studies to evaluate the tissue composition of coronary plaque from the RF signals have been conducted. Integrated Backscatter (IB) analysis [1],[2] is a typical method to classify coronary plaque tissues. In IB analysis, IB values are used as the feature values for tissue classification. IB values are the locally averaged power of RF signals. IB analysis is simple and fast, and also effective in restricted cases, but not always accurate since some tissues have similar IB values.

It is reported that classification using frequency features as the feature values, is effective [3]-[5]. We have applied the subspace method using frequency features of tissue with special consideration of the neighborhood information as a discriminator [6]. In our previous studies, we realized improved tissue characterization than that of IB analysis. However, the discriminator was not optimized.

In this paper, the Averaged Learning Subspace Method (ALSM) [7] is employed to obtain more accurate classification. The effectiveness of ALSM for coronary plaque tissue classification has been verified by comparing its classification results with those of the IB analysis and our previous studies.

2. IB Analysis

IB values [1],[2] are obtained by averaging the squared RF signals in each local area, and transforming the values into a log scale for classification.

In this paper, coronary plaque tissues are classified into three classes. Therefore, IB values are divided into three groups, and two thresholds are selected. Here we select the threshold values through experimentation, and the values which give the highest accuracy of classification are chosen.

3. Present Method

3.1 Subspace method
In the subspace method [7], the subspaces of each class are constructed, and are used for calculating the similarities between an unknown vector and the vectors of each class. Based on similarity, the unknown vector is classified into the most similar class.

Suppose there are \(c\) subspaces \(L_1, L_2, \ldots, L_c\) of each class \(\omega_1, \omega_2, \ldots, \omega_c\), and the dimensions of each subspace are \(d_1, d_2, \ldots, d_c\). The subspace \(L_i\) of class \(\omega_i\) is constructed by the basis vectors \(u_{i1}, \ldots, u_{id_i}\), obtained by applying the Principal Component Analysis (PCA) to \(\omega_i\). Principal components of \(\omega_i\) are obtained by performing the eigenvalue decomposition to the correlation matrix, which is derived from the pattern of \(\omega_i\). The dimension \(d_i\) is the number of significant basis vectors in subspace \(L_i\).

Simple similarity \(S_{Simple}^i\) and multiple similarity \(S_{Multiple}^i\) are defined as follows:

\[
S_{Simple}^i(x) = \sum_{j=1}^{d_i} (x^T u_{ij})^2 \\
S_{Multiple}^i(x) = \sum_{j=1}^{d_i} \frac{\lambda_{ij} (x^T u_{ij})^2}{\lambda_{11} x^T x}
\]

where \(x\) is an unknown vector, and \(\lambda_{ij}(\lambda_{11} > \lambda_{12} > \cdots > \lambda_{id_i})\) is an eigenvalue corresponding to the eigenvector \(u_{ij}\).

### 3.2 ALSM

The Averaged Learning Subspace Method (ALSM) [7] is a method to optimize the subspaces heuristically for discrimination between classes. This method aims to modify the subspace during the training period.

In the case where training vector \(y_i\), which belongs to class \(\omega_{y_i}\) is misclassified to \(\omega_j\), the correct subspace \(L_i\) is rotated towards the misclassified vector \(y_i\), and the wrong subspace \(L_j\) is rotated away from it. This is realized by modifying the correlation matrices and then updating the basis vectors.

The initial correlation matrix \(R_i(0)\) is defined as follows:

\[
R_i(0) = \sum_{y_i \in \omega_i} y_i y_i^T
\]

The eigenvectors corresponding to \(d_i\) principal eigenvalues of \(R_i\) are assumed to be the basis vectors of \(L_i\). The update of the correlation matrix \(R_i\) for each epoch \(k\) is performed as follows:

\[
R_i(k + 1) = R_i(k) + \alpha \sum_{y_i \in A_i} y_i y_i^T - \beta \sum_{y_i \in B_i} y_i y_i^T
\]

where \(\alpha\) and \(\beta\) are parameters, \(A_i\) is a set of the training vectors belonging to class \(\omega_i\) but misclassified to other classes. \(B_i\) is a set of the training vectors not belonging to class \(\omega_i\) but misclassified to class \(\omega_i\). The basis vectors are re-solved after each epoch. Here, the dimensions \(d_1, d_2, \ldots, d_c\) are kept constant.

### 3.3 Consideration of neighborhood information

In the classification of coronary plaque tissue, a problem exists where the distribution of frequency feature vectors of each class of tissue widely overlaps each other. Therefore, we proposed in [6] to use the centroid vector \(w\), instead of using the unknown vector itself, for calculating the similarity between the unknown vector \(x\) and each class. Accordingly, the similarity measures of Eqs.(1) and (2) are modified as follows:

\[
S_{Simple}^i(x) = \sum_{j=1}^{d_i} (w^T u_{ij})^2
\]

\[
S_{Multiple}^i(x) = \sum_{j=1}^{d_i} \frac{\lambda_{ij} (w^T u_{ij})^2}{\lambda_{11} w^T w}
\]

where \(w\) is defined by:

\[
w = \frac{1}{l} \sum_{x_n \in N_x} x_n
\]

\(N_x\) is a set of the feature vectors for the target tissue and for the neighborhood tissues. \(l\) is the number of the elements included in \(N_x\).

### 4. Experiments

#### 4.1 Frequency analysis

The RF signals in the local area are analyzed and the power spectra are evaluated [3]-[5]. Those spectra are used as the feature vectors to construct the subspace [6].

#### 4.2 Experimental settings

In the experiments, RF signals for two different cross-sections of a coronary artery are prepared. One is used for constructing the subspaces of each tissue class and for modifying the subspaces, while the other is used as the test data for classification.

Each subspace’s dimension \(d_i\) were all set to 5, a value obtained through experimentation. The neighborhood tissue number \(l\) was kept to 9 as a fixed number.

In the modification, the update is performed only when the number of misclassification has decreased. The parameter \(\beta\) of Eq.(4) was set as 0 to make the update simple. The parameter \(\alpha\) also of Eq.(4) was increased gradually from a small value in each epoch, until the number of misclassification decreased. The modification of the subspace for the training data set is finished when the number of misclassification is minimized.

In case all the training vectors are used in the modification of each subspace, almost all of the coronary tissues are classified into fibrous tissue. This problem occurs because most
of the training vectors belong to fibrous tissue, and that the subspaces are modified until the number of misclassification is minimized.

Therefore, we created a set of training data with the ratio of the number of fibrous, fatty, and fibrofatty training vectors to be 1.25 : 1.00 : 1.00, respectively. Here, the training vectors of each tissue are selected randomly. We have made 50 different training data sets and applied the Averaged Learning Subspace Method (ALSM) to each training data set.

### 4.3 Experimental results

Figures 1 and 2 show the results for the training data, and the results for the test data, respectively. In those figures, (a) shows the tissue composition of coronary plaque given by a medical doctor through examination of the dyed tissue using a microscope. Likewise, (b) to (f) show the classification results, where (b) is the result of the conventional IB method, (c) and (d) are those of our previous method, and (e) and (f) are those of the present method. From those results, it can be quickly observed that the present method gives better results than the conventional and the previous methods.

The quantitative evaluations of tissue classification are given in Tables 1 and 2. Those tables show the results of True Positive Rate (TPR) and True Negative Rate (TNR) for the training data and for the test data, respectively.

If we focus on the lowest accuracy of each method, the conventional method gives the lowest TPR for fibrous tissue. The previous method 1 gives its maximum value among the lowest accuracies for the training data, however the present method 1 gives it for the test data. This means that the generalization ability of the previous method was reduced because of over-fitting. Therefore, it is considered that the present method gives better results compared to the conventional and previous methods.

By comparing the present methods with simple similarity and with multiple similarity, each method demonstrates its own advantage for different cases, which requires further studies for more discussions.
5. Conclusions

We have presented in this paper a procedure to apply the Averaged Learning Subspace Method (ALSM) for tissue classification of coronary plaque. The neighborhood information around the target tissue is also considered. In the experiments, the present method has provided better results than the conventional method and our previous method. In future studies of the present method, we aim to determine the training dataset analytically for the modification of subspaces.

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