Tissue Classification of Coronary Plaque Using Intravascular Ultrasound Method by Extended Multiple k-Nearest Neighbor

Kazuhiro Tokunaga, Eiji Uchino, Hiroki Tanaka, Noriaki Suetake

***Abstract*—In this paper, we propose an extended algorithm of the multiple k-nearest neighbor (MkNN) for an intravascular ultrasound (IVUS)-based tissue classified of coronary plaque. In the proposed algorithm, a weighted decision based on the distance between the input vector and the training vectors is employed instead of the majority decision in the labeling process of k-nearest neighbor (kNN). The fibrous and lipid tissues were thus classification more accurately. Furthermore, the accuracy of tissue classification was improved even if the number of the prototype vectors in MkNN is small. They are examined by the actual experiments using the true IVUS data.**

***Index Terms*—intravascular ultrasound (IVUS), tissue classification, multiple k-nearest neighbor.**

I. Introduction

A Myocardial infraction is caused by the failure of plaque built inside the coronary arteries. Accordingly, it is very important to investigate the tissue classification of plaque in order to prevent early myocardial [1]. In general, the tissue classification is carried out by analysing the radio frequency (RF) signal obtained from the intravascular ultrasound (IVUS) method [2] using catheter.

In our past works, we proposed a multiple k-nearest neighbor (MkNN) that is an extension of the k-nearest neighbor (kNN) [3] in order to get the better results applied to the tissue classification problem of coronary plaque [4]. Although a good tissue classification by MkNN had been established in that work, it still remained a problem that MkNN takes a lot of computing time for classification.

The computing time for classification depends mainly on the number of the prototype vectors in kNN [5], since the kNN has to calculate the distances between the input vector and all the prototype vectors.

On the other hand, it is necessary to adjust the number of prototype vectors to keep the accuracy of tissue classification, since the classification results of MkNN are influenced by the distribution of the prototype vectors.

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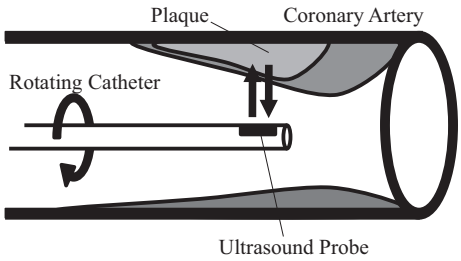

Fig. 1. An ultrasound probe attached to the distal end of a catheter.

Hence, we propose an extended algorithm of a multiple k-nearest neighbor (MkNN) for an intravascular ultrasound (IVUS)-based tissue classification. In the algorithm, a weighted decision based on the distances between the input vector and the training vectors is employed instead of the majority decision in the labeling process.

The experiments show that the accuracy of tissue classification by the extended MkNN is good, even if a small number of the prototype vectors are selected at random. This paper presents the outline of the proposed method, and shows its effectiveness by the experiments using the real IVUS data.

II. Tissue Classification by IVUS Method Using Multiple k-Nearest Neighbor

This chapter shows briefly the intravascular ultrasound (IVUS) method, the multiple k-nearest neighbor (MkNN), and the tissue classification by the IVUS method using MkNN.

A. IVUS method

The ultrasound probe attached at the tip of the catheter is inserted into a blood vessel (see Fig. 1). After that, the signals are transmitted forward and then the reflected ultrasound signals are received while rotating the probe.

The ultrasound signal transmitted from the probe is called a radio frequency (RF) signal. The intensity of the RF signal depends on the location of the probe and also on the characteristics of the plaque tissue.

The B-mode image of Fig. 2 is created from the RF signals observed in all directions in the blood vessel. Fig. 2 shows the cross section of the blood vessel. It is difficult however to see the condition inside the blood vessel only from this B-mode image.

B. Multiple k-nearest neighbor

The multiple k-nearest neighbor (MkNN) is an extension of the traditional k-nearest neighbor (kNN). In MkNN, the

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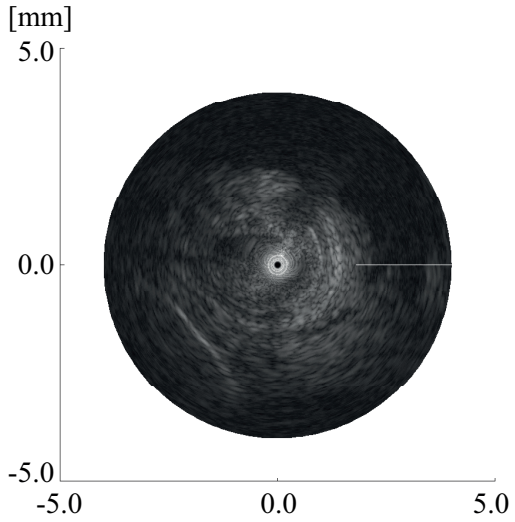

Fig. 2. An example of the B-mode image obtained by the IVUS method.

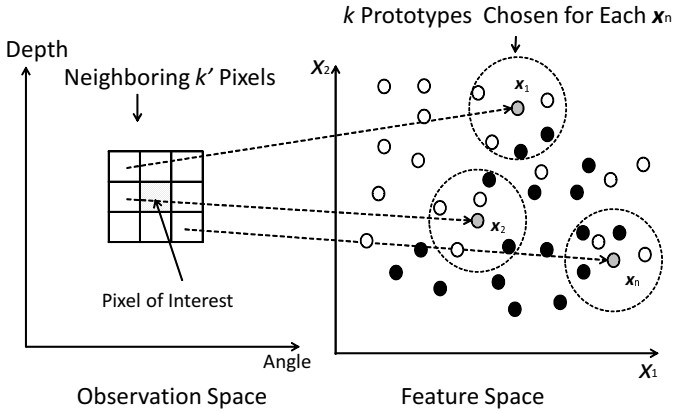

Fig. 3. Basic scheme for classification by MkNN using the information both in the observation space and the feature space [3].

class label is determined based on the information both in the feature space and in the observation space (see Fig. 3).

In the algorithm of MkNN, the classification by kNN in the feature space is first performed, and the classification by kNN in the observation space is then followed.

■ *kNN in the feature space*

Suppose that the feature vectors $\boldsymbol{w}_i (i = 1, 2, .., N)$ are given, and let the class label ω_i of each feature vector be known. We use the feature vector as the prototype vector in MkNN.

When the input vector $\boldsymbol{x}$, whose class label is unknown, is given to MkNN, the class label of the input vector is determined as follows [6]:

$$l = \arg\max_{\omega} \sum_{i=1}^{N} \delta\left(\boldsymbol{x}; \boldsymbol{w}_i \mid \omega_i = \omega\right), \tag{1}$$

$$\delta\left(\boldsymbol{x}; \boldsymbol{w}_i \mid \omega_i = \omega\right) = \begin{cases} 1 & \text{if } \|\boldsymbol{w}_i - \boldsymbol{x}\| \leq r\left(k\right), \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where $r(k)$ represents the Euclidean distance between the input vector $\boldsymbol{x}$ and the k-th nearest prototype vector.

In the first step, the prototype vectors within the k-th nearest neighbor are determined by calculating the distances of Eq.(1). After that, the class label of the input vector is determined by a majority vote for the class labels of the k-th nearest neighbor prototype vectors by Eq.(2).

■ *kNN in the observation space*

The kNN is applied also to the observation space after determining the class labels of the input vectors $\{\boldsymbol{x}_n\}$ in the feature space. Except for calculating the distances between the input vector and the prototype vectors on the observation space, other calculations are the same as Eqs.(1) and (2).

C. Tissue classification by the multiple k-nearest neighbor

In the tissue classification using the IVUS method using MkNN, the power spectrums calculated from the RF signals by the short-time Fourier transform are employed as the prototype vectors in MkNN. The class label of each prototype vector is known from the findings of a medical doctor examining the dyed tissue using microscope.

In this work, the fibrous tissue, the lipid tissue, and other tissues are classified. Concretely, the power spectrums are calculated from each of the corresponding RF signals, i.e., from fibrous tissue, lipid tissue, and other tissues.

The computing time for classification depends mainly on the number of the prototype vectors in MkNN (see Fig. 4). On the other hand, the accuracy of classification also depends on the number of the prototype vectors, since the classification results by MkNN are influenced by the distribution of the data.

The purpose of this study is thus to innovate the mechanism that the classification accuracy is not affected by the number of the prototype vectors.

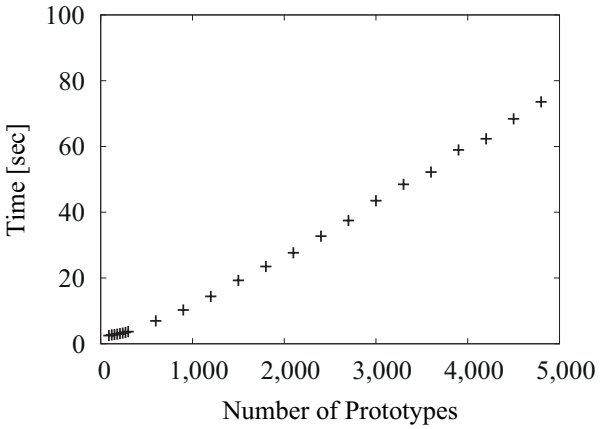

Fig. 4. Relation between the number of prototype vectors and the classification time by MkNN.

III. Tissue classification using extended MkNN

In our past tissue classification by MkNN, all the feature vectors observed from the tissues were used as the candidates of the prototype vectors. The representative vectors that were

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used as the prototype vectors were selected manually or selected according to the simple rules. The classification results thus depended on the selected prototype vectors.

Moreover, the accuracy of the tissue classification is decreased if the number of the prototype vectors is reduced, since in that case the distribution of the prototype vectors in the feature space becomes sparse. Hence, it is needed to adjust the number of the prototype vectors in order to keep the accuracy of the tissue classification.

In the extended MkNN, a weighted decision, based on the distances between the input vector and the training vectors, is employed instead of the majority decision [7]. As a result, it is expected that the tissue classification dose not depend on the number and the distribution of the prototype vectors.

In the classification of the input vector, the distances between the input vector and the prototype vectors are calculated and employed as weight for the weighted decision. In the extended MkNN, Eqs.(1) and (2) are replaced by the following equations:

$$l = \arg\max_{\omega} \sum_{i=1}^{N} \delta\left(\boldsymbol{x}; \boldsymbol{w}_i \mid \omega_i = \omega\right) \tag{3}$$

$$\delta\left(\boldsymbol{x}; \boldsymbol{w}_i \mid \omega_i = \omega\right) = \begin{cases} \exp\left(-\|\boldsymbol{x}_i - \boldsymbol{w}_k\|/\epsilon\right), \\ \qquad \text{if } \|\boldsymbol{w}_k - \boldsymbol{x}_i\| \leq r\left(k\right) \\ 0 \qquad \text{otherwise,} \end{cases} \tag{4}$$

where ϵ is a decay parameter that is adjusted according to the distribution of the data.

IV. Experiments

A. Experimental settings

The perfomances pf the normal MkNN and the extended MkNN for the tissue classification of coronary plaque are compared. In this experiment, RF signals are observed from two different sections of the blood vessel. One is used as the training data, and the other is used as the test data.

The prototype vectors are selected from the training data. The feature vectors used as the prototype vectors are the power spectrums that are calculated from each of the corresponding RF signals reflected from each tissue, i.e., fibrous tissue, lipid tissue, and other tissues.

Thirty prototype vectors are selected at random from each of the three kinds of tissues, for both the normal MkNN and the extended MkNN. In addition, the width of window for the short-time Fourier transformation is 64 points for both methods.

B. Experimental results

Fig. 5 shows the classification results for the training data. Fig. 5 (a) shows the tissue composition given by the medical doctor by examining the dyed tissue using microscope. Fig. 5 (b) shows the results of tissue classification by the normal MkNN. The number of the prototype vectors is manually adjusted to get the best accuracy of classification. The number of the prototype vectors for fibrous, lipid and other tissues are 300, 100, and 850, respectively.

Fig. 5 (c) shows the results by the normal MkNN. Thirty prototype vectors are selected at random for each tissue. Fig. 5 (d) shows the results by the extended MkNN. The similar results to Fig. 5 (b) are obtained even if the prototype vectors are selected at random.

It is observed form those results that the accuracy of the tissue classification is kept even if the number of the prototype vectors is reduced and the prototype vectors are selected at random.

Fig.6 shows the classification results for the test data. Though the classification accuracy is a little bit behind, the superiority of the extended MkNN still can be seen.

V. Conclusions

In this study, we have proposed an extended algorithm of a multiple k-nearest neighbor (MkNN) for an intravascular ultrasound (IVUS)-based tissue classification. of coronary plaque. In the proposed algorithm, a weighted decision based on the distance between the input vector and the training vectors is employed instead of the majority decision in the labeling process of the classes.

The experimental results show that the accuracy of the tissue classification is kept even if the number of the prototype vectors is reduced. Future studies are to apply to other IVUS data, and to find out the best feature vectors for the best classification accuracy.

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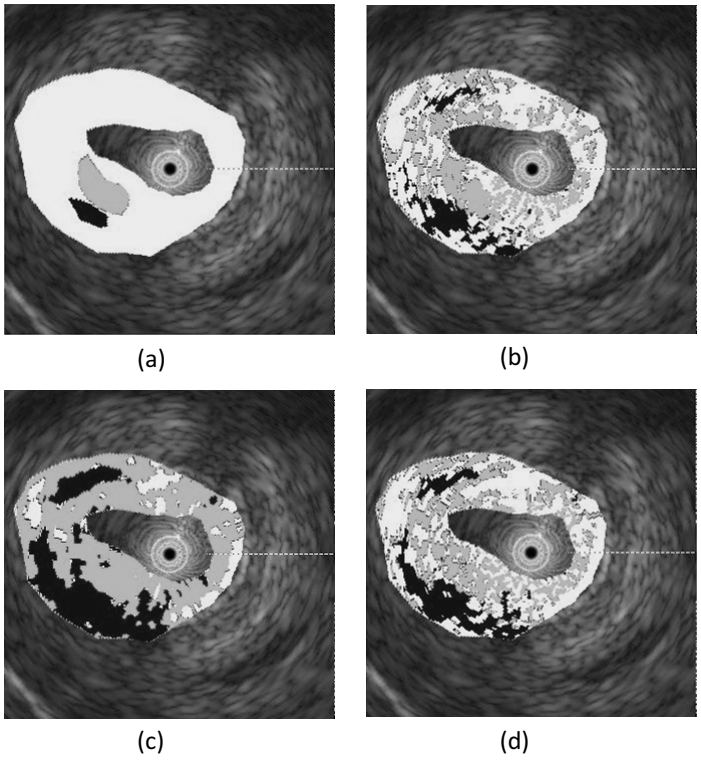

Fig. 5. Tissue classification results by the normal MkNN and by the extended MkNN for the training data. (a) The tissue composition given by the medical doctor by examining the dyed tissue using microscope. (b) The classification results by the normal MkNN. The number of the prototype vectors for fibrous, lipid and other tissues are 300, 100, and 850, respectively. (c) The classification results by the normal MkNN The number of the prototype vectors are 30 for each tissue. The prototype vectors are selected at random. (d) The classification results by the extended MkNN where the number of the prototype vectors are 30 for each tissue. The prototype vectors are selected at random.

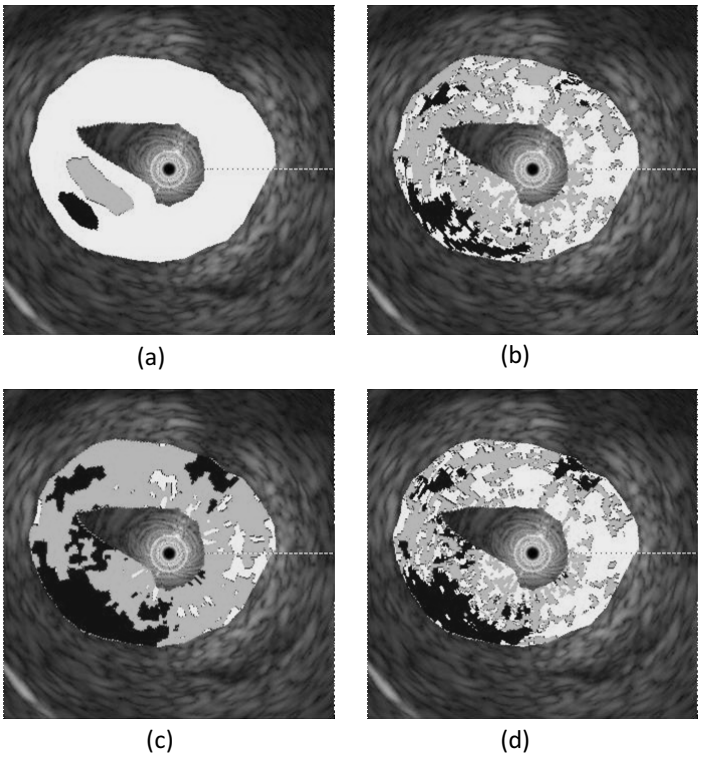

Fig. 6. Tissue classification results by the normal MkNN and by the extended MkNN for the test data. (a) The tissue composition given by the medical doctor by examining the dyed tissue using microscope. (b) The classification results by the normal MkNN. The number of the prototype vectors for fibrous, lipid and other tissues are 450, 130, and 800, respectively. (c) The classification results by the normal MkNN. The number of the prototype vectors are 30 for each tissue. The prototype vectors are selected at random. (d) The classification results by the extended MkNN. The number of the prototype vectors are 30 for each tissue. The prototype vectors are selected at random.

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