Machine learning based image segmentation of intravascular optical coherence tomography images

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Abstract

This work tests several methods for implementation of automatic segmentation of Intravascular Optical Coherence Tomography (IVOCT) images, then provides a considerable approach. This method aims to provide convenience to clinical diagnosis. This work is based on machine learning and exams performance of different classification means. Meanwhile, different sets of features extracted from particular tissues are added in with the purpose to improve the accuracy of the automatic segmentation method of IVOCT images.

Keywords: attenuation coefficient, image segmentation, IVOCT, pattern recognition

Introduction

Intravascular Optical Coherence Tomography (IVOCT) has been widely utilized in the clinical diagnosis of coronary atherosclerosis. A standard nomenclature file [1] for IVOCT image reading provides consensus in patterns in IVOCT images. However, plaque characterization is mainly performed manually and requires well-trained experts for interpretation of a large amount of data.

Different methods has been developed to implement automatic or semi-automatic segmentation of IVOCT images. These methods rather act poor in identification of lipid pool or fail in dealing with some artificial like stents.

This job aims to implement automatic segmentation of IVOCT image and provide convenience to clinical diagnosis. Our job is based on raw images obtained from IVOCT systems which is stored in Polar coordination. Intensity information and most of the features are extracted from raw images. Several machine learning methods [2][3][4][5][6] are implemented to check their performance. Cross-validation are performed to select a high effective feature subset.

Method

4 well-trained OCT readers conduct manual segmentation on Cartesian images according to the nomenclature file. 5 out from 25 images data sets are chosen to be the training-set.

The method is briefly presented below:

Step 1: Preprocessing: To eliminate the disturbance of sparkle, filtering is applied to the raw images; for manual segmentation purpose the raw images are converted into Cartesian form. Then, vessel lumen of each image are located in order to set the region of interest (ROI). The regions out of ROIs of each image will be eliminated in further analyze.

Step 2: A-Line Analysis: each A-scan line of a single frame IVOCT image is analyzed. Several features, including lumen-end distance, A-line Energy (integration of A-line intensity), maximum attenuation coefficient and some features derived from attenuation coefficient are extracted through the whole line. Figure 1 shows the dynamic range of two features (lumen-end distance and attenuation coefficient) obtained from lipid-containing line and fibrous-containing line respectively.

Next, based on the obtained features, a pattern-recognition work (using SVM or BP neural-networks) is implemented to recognize lipid-containing A-line from others. Figure 2 gives out the A-Line recognition results, red-lines on the lumen implies a lipid-containing A-line.

Step 3: Based on the obtained segmentation results from A-line analysis, another sets of features (including multiple texture features) [7] are then obtained from the low signal intensity regions, this step aim to identify the lipid region from tissues that beyond the media of the Endothelium which is low-intensity as well. A feature subset was chosen by the CSE (Classifier Subset Evaluator) feature selection algorithms.

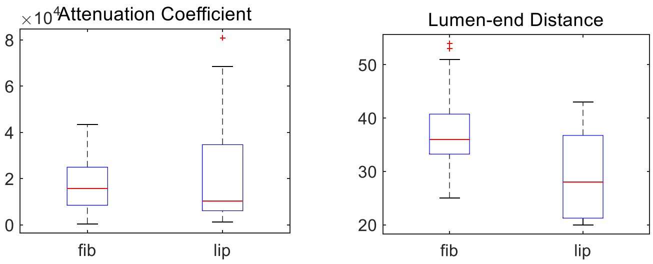

Figure 1. dynamic range of Attenuation coefficient and Lumen-end Distance

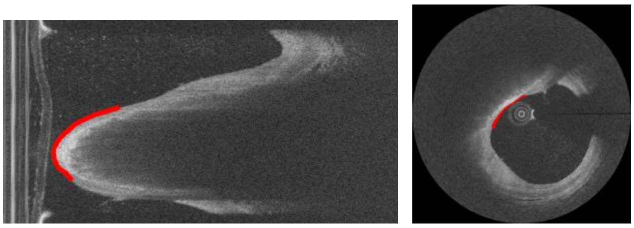

Figure 2. A-line analysis, in which the red line implies a lipid-containing line, with results presented in Polar and Cartesian coordination

Results

The average consistency between manual segmentation of each two OCT readers over the total 25 data sets is 85%. In this study, results from manual segmentation are chosen to be a standard reference for machine learning.

For plaque tissue segmentation, the aim is to recognize fibrous plaque and lipid plaque, trying to identify calcification. Several features present good performance. Attenuation coefficient[2] and Lumen-end Distance and several derived features act well on A-line analysis, the total accuracy over 9800 picked out A-lines is 82%.

Texture features such as homogeneity and correlation act well in further analysis. Linear configuration patterns and local binary patterns, possibly due to its ability to provide details, make up well-performed subset together with attenuation coefficient.

The Support Vector Machine (SVM) based on the sequential minimal optimization (SMO) algorithm receives the best performance among all classification method as expected.

Conclusions

This job tests several machine learning methods and multiple features, then presents a considerable methods for automatic IVOCT image segmentation.

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