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Voxel-based plaque classification in coronary intravascular optical coherence tomography images using decision trees

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Abstract

Intravascular Optical Coherence Tomography (IVOCT) is a high contrast, 3D microscopic imaging technique that can be used to assess atherosclerosis and guide stent interventions. Despite its advantages, IVOCT image interpretation is challenging and time consuming with over 500 image frames generated in a single pullback volume. We have developed a method to classify voxel plaque types in IVOCT images using machine learning. To train and test the classifier, we have used our unique database of labeled cadaver vessel IVOCT images accurately registered to gold standard cryo-images. This database currently contains 300 images and is growing. Each voxel is labeled as fibrotic, lipid-rich, calcified or other. Optical attenuation, intensity and texture features were extracted for each voxel and were used to build a decision tree classifier for multi-class classification. Five-fold cross-validation across images gave accuracies of $96\% \pm 0.01\%$, $90\% \pm 0.02\%$ and $90\% \pm 0.01\%$ for fibrotic, lipid-rich and calcified classes respectively. To rectify performance degradation seen in left out vessel specimens as opposed to left out images, we are adding data and reducing features to limit overfitting. Following spatial noise cleaning, important vascular regions were unambiguous in display. We developed displays that enable physicians to make rapid determination of calcified and lipid regions. This will inform treatment decisions such as the need for devices (e.g., atherectomy or scoring balloon in the case of calcifications) or extended stent lengths to ensure coverage of lipid regions prone to injury at the edge of a stent.

Keywords

optical coherence tomography; atherosclerosis; machine learning; decision tree

1. INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death worldwide. Reports from the World Health Organization indicate that about 17.7M people died from CVDs in 2015 alone, representing nearly 31% of all global deaths^[1]. Percutaneous coronary interventions are the most common coronary revascularization procedure, with more than 600,000 PCIs done each year in the US. Intravascular Optical Coherence Tomography (IVOCT) is a high contrast, high-resolution imaging modality that is currently used to detect atherosclerotic

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and fibro-calcific plaques. Compared to intravascular ultrasound (IVUS), IVOCT has better resolution, contrast and improved penetration depth for calcifications. IVOCT has also been shown to be the only imaging modality that can identify vulnerable thin cap fibroatheroma (TCFA)^[2]. Although IVOCT can be used to treat complex lesions in this manner, current limitations include specialized training and an overload of image data (often more than 500 images in a single pullback) making it tough for interpretation. We aim to address these limitations by creating automatic plaque characterization software of IVOCT images. Previous work has shown that visually discernable features exist between various plaque types in IVOCT images^{[3][4]}. Additionally, the consensus document^[2] by the International Working Group for IVOCT (IWG-IVOCT) has compiled prior work on the methods of IVOCT image acquisition and interpretation.

2. METHODS

We performed supervised voxel-based classification in IVOCT images. A multi-class classification approach is considered, with the following four classes: fibrous, lipid, calcium and other. As the name suggests, the “other” class contains all voxels that are not any of the previously mentioned three plaque types.

2.1 Datasets

For training and testing our classifier, we obtained IVOCT pullbacks of ex-vivo coronary arteries. The arteries are obtained within 72 hours of death and are stored at 4° C. Next, vessels are trimmed to 10 cm in length to prepare for IVOCT imaging. Images are collected using the C7-XR system from St. Jude Medical Inc., Westford, MA. The system comprises of an OCT swept source with a 1310 nm center wavelength, 110 nm wavelength range, 50 kHz sweep rate, 20 mW output power, and ~12 mm coherence length. Pullbacks are performed with an acquisition speed of 10 or 20 mm/s, yielding 5.4 cm pullbacks at 100 or 200 μ m frame intervals.

Cryo-imaging^[5] is a novel imaging technique where block face images of frozen tissue samples are captured with an episcopic microscope and a CCD camera. The method allows for cutting a thin section of the sample, acquiring a bright field image and a fluorescence image. This process is repeated until the entire sample is imaged, creating color and fluorescence volumes of the specimen. For this experiment, we set the section thickness to be 20 μ m with an image resolution of 15 μ m (in plane).

We have previously shown that cryo imaging can be used to readily distinguish between the major plaque types (fibrous, calcium and lipid)^[6]. Voxel-wise labels are created for sub-volumes comprising of calcified or lipid-rich regions using accurately registered cryo images as a reference. We use a method described in Prabhu et al.^[6] to register cryo-volumes to IVOCT pullbacks. Briefly, the method simulates the IVOCT acquisition process within the cryo-volume using a virtual catheter model. The parameters of the virtual catheter model are optimized to ensure maximum overlap between cryo and IVOCT lumen volumes.

The results of the registration between cryo images and IVOCT images and corresponding hand-drawn labels are shown in Figures 1 and 2. In all, five IVOCT pullbacks are considered

for this work. The number of annotated pixels in each annotated sub-volume are shown in Table 1. Vessels 1 to 4 are considered for training the classifier and Vessel 5 is used as the held-out test set.

2.2 Preprocessing

IVOCT images are obtained in the polar domain (r-theta space). We identify A-lines containing guidewire shadow and set pixel values in all such A-lines to zero. Next, lumen border pixels are identified in each image frame using an automatic lumen segmentation algorithm based on a dynamic programming approach^[7]. The back border is fixed at a distance of 1 mm from the lumen, giving us a region of interest for further processing. Pixel shifting is performed to correct for large lumen eccentricity. We hypothesize that this operation will align plaques better when using a square moving window at each voxel which is described in the next section. We also perform a noise reduction operation on the image in order to reduce speckle noise which is characteristic of OCT images. Since speckle noise is multiplicative, we first perform a log transform and then reduce noise with a gaussian filter with kernel size [7, 7] and sigma 1. The images are then corrected for the confocal properties of the IVOCT imaging system and signal roll-off according the following equation as described in van Soest et al.^[8].

$$I_d(r) = I_0 e^{-\mu_t r} T(r) S(r) \quad (1)$$

Where $T(r)$ is the longitudinal point spread function, $S(r)$ is the signal roll-off, μ_t is the attenuation coefficient, and I_0 is the locally available intensity multiplied by the backscattering coefficient and $I_d(r)$ is the expected signal intensity at radius r .

2.3 Feature extraction

A 3D moving window (henceforth referred to as an mBox) is used to select a local volume of interest at every voxel. The mBox dimensions used for this work are (21, 51, 3) in (r, θ , z) view. We employ a “tall” mBox since we are interested in capturing large plaques which are clinically significant. The mBox is moved with a stride of 1 voxel along the region of interest which is bounded by the lumen border and the back border and across all A-lines. Apart from the filter bank responses, all other features are computed using pixel intensities within the mBox. In all, 64 features are calculated and described in Table 2.

2.3.1 Optical features—We use three estimates for the attenuation coefficient which were previously reported in literature. The first approach is to fit each A-line within the mBox to Eq. (1) in order to estimate μ_t . A robust estimate for μ_t is obtained by taking the median across all A-lines. This method was shown to give good estimates of the attenuation coefficient by our group^[9]. Second, we calculate another estimate for μ_t based on a single scattering model^[10]. Third, we employ the sliding window approach across an A-line to estimate the attenuation coefficient as described by Ughi et al.^[11].

2.3.2 Intensity features—Mean signal intensity is computed as $\bar{I} = \frac{1}{N} \sum_{i=1}^N I_i$ where N is the number of pixels within the mBox and I_i is pixel intensity value of the i^{th} pixel. Signal homogeneity is calculated as $H = \frac{\sigma}{\bar{I}}$, where σ is the standard deviation of all pixel values within the mBox. Smoothness of intensity is computed as $S = 1 - (\frac{1}{1+\sigma^2})$. Finally, the entropy is calculated using the normalized histogram of pixel values within the mBox (with a probability distribution p), $E = - \sum_{i=0}^{l-1} p(z_i) \log(p(z_i))$

2.3.3 Morphological features—We account for intensity variations which arise due to large distances between catheter and voxel of interest by measuring the distance to catheter. We observe that a larger distance results in a reduction of the light intensities along an A-line. We also measure the distance between the voxel of interest to the lumen boundary. It is observed that fibrous tissue is usually seen closer to the lumen boundary with high mean intensity, whereas for lipid plaques which have a high attenuation coefficient^[9], the mean intensity drops rapidly with increasing distance from lumen.

2.3.4 Texture features (Gray Level Co-occurrence Matrix)—We select seven texture features out of the 22 possible^[12] features that can be extracted from the co-occurrence matrix. We use those features that were shown to best discriminate between plaque types as mentioned in Ughi et al.^[11]. They are contrast, cluster shade, energy, entropy, homogeneity, information measure of correlation and normalized inverse difference of moment.

2.3.4 Filter bank responses—A total of 48 filter bank responses are collected at every voxel. The Leung Malik filter bank is used since it produces characteristic responses for edges. Calcium plaques are known to have sharp edges, whereas lipid plaques are observed with a blurred starting edge^[4]. The filter bank is visualized in Figure 3.

2.4 Classifier

A decision tree classifier was built using MATLAB software (MathWorks, Natick, M.A.). The feature values of the training examples were normalized by subtracting the mean and dividing by standard deviation. We use a decision tree classifier because they are fast and easy to interpret. Our trained decision tree model was able to predict plaque types for a complete image frame in under 4 seconds when run on a standard 12-core CPU. We limited the maximum number of splits of the decision tree and the minimum leaf size to control overfitting on the training set. Gini's diversity index was used as the split criterion at the nodes of the decision tree during training.

3. RESULTS

As mentioned earlier, we train our classifier using images from four pullbacks. Five-fold cross validation is performed on the training dataset to optimize classifier parameters. The confusion matrix for the five-fold cross-validation on the full training set is shown in Table 3. The classifier is then used to make predictions on the independent dataset. Since voxel-

wise classifier results are noisy, a majority label filter with a kernel size [11 11] is used to clean the classification results. The classification result for an image frame from the independent test dataset is shown in Figure 4.

4. DISCUSSION

In this paper, we presented a method to classify individual voxels in IVOCT images using machine learning. We use physics-inspired optical features, intensity features and texture features to distinguish different plaque type. We categorize voxels into four classes, namely fibrotic, calcified, lipid-rich and other. Features are computed over a moving window of size (51, 21, 3) while the filters used to generate the texture features have a kernel size of 48 by 48 pixels. A five-fold cross-validation scheme is applied to tune the classifier parameters (maximum number of splits and minimum leaf size). We achieve a good accuracy of 92 percent across all the folds and all plaque types in the training set. The classifier is then applied to an independent dataset, giving us promising results. We believe that the lower accuracy on the independent dataset is due to the training set not fully representing all data possibilities and that the error rates should improve with a larger training data set size.

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Figure 1.

Example labeling using information from registered cryo images. (a) OCT image containing lipid (10 o'clock to 3 o'clock), (b) Lipid deposit has a yellow appearance whereas fibrous tissue is characterized by a pink appearance in the color image, (c) Lipid deposits are also seen as a dark region and fibrous tissue has a medium to bright appearance in fluorescent image and (d) corresponding hand drawn labels, where blue is fibrous, green is lipid, and red is calcification. The presence of the guide wire in IVOCT results in the drop out at 12 o'clock.

Figure 2.

Similar example as in Figure 1, for a calcified plaque. (a) OCT image containing calcified and fibrous tissue, (b) Calcified tissue has a chalky white appearance in the bright field image, (c) Calcified tissue is also seen as a bright green region in fluorescence image and (d) corresponding hand drawn labels, where blue is fibrous, green is lipid and red is calcification.

Figure 3.
Leung Malik filter bank used in this work

Figure 4.

(a) OCT image, (b) Ground truth labels, (c) Predicted Labels and (d) Predicted Labels after noise cleaning

Table 1

Plaque compositions of annotated sub-volumes in each pullback (in number of pixels).

	Fibrous	Lipid	Calcium	Other
Vessel 1 (18 frames)	341,901	0	205,460	1,010,430
Vessel 2 (40 frames)	363,872	0	86,939	2,628,537
Vessel 3 (48 frames)	1,130,059	1,230,249	0	1,975,964
Vessel 4 (65 frames)	2,224,671	1,174,794	0	2,221,968
Vessel 5 (40 frames)	1,303,061	371,268	3,168	1,924,389

Table 2

Computed features for each voxel in the region of interest

Feature type	Feature Name	Number of features
Optical	Attenuation coefficient estimates	3
Intensity	Mean signal intensity within mBox, signal homogeneity, smoothness of intensity and entropy	4
Morphological	Distance to lumen, distance to catheter	2
Texture	Gray Level Co-occurrence Matrix features	7
Texture	Leung Malik filter bank responses	48

Table 3

Confusion matrix for five-fold cross-validation on the training set

	Predicted Fibrous	Predicted Lipid	Predicted Calcium	Predicted Other
True Fibrous	96.33 %	1.47 %	0.19 %	2.01 %
True Lipid	2.68 %	90.44 %	0.24 %	6.64 %
True Calcium	3.02 %	2.02 %	90.37 %	4.59 %
True Other	1.09 %	1.95 %	0.15 %	96.81 %