

Assessment of Automatic Classification of Artery Plaque Composition in IVUS Images Using Histology Correlation

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Nowadays, atherosclerosis, with its complications, is the leading cause of mortality and morbidity in the developed world. The composition of atherosclerotic plaques is variable, and complex, and it is the interaction between the various cell types within a plaque that determines the progression, complications, and outcome of the disease. Among all of the materials which are forming the vessels' plaque, calcium, fibrous, necrotic core, and lipid core are the most important ones; there are several diseases (e.g. FA, TCFA, and AIT) that are classified based on the different combinations and the amount of each of these four materials [1]. Therefore, eligible characterizing of these plaques would help the physician to make the proper decision in order to save the patient's life.

Intravascular ultrasound (IVUS) is becoming accepted as an imaging technique that allows precise tomographic assessment of the coronary anatomy in vivo in the latest 90's. Clinical studies have documented the sensitivity of IVUS in detecting atherosclerosis and in quantifying the morphology of coronary lesions [2]. More importantly, IVUS can potentially quantify the structure and composition of normal and atherosclerotic coronary rather than relying on histological data which can only be obtained at autopsy. Mainly, there are two practical information that can be obtained by processing the IVUS data; one of them lead to detecting the Intima and Media-Adventitia borders, and the other help us to interpret the composition of arteries plaques.

In this paper, we are focusing on characterizing the composition of atherosclerotic plaques via processing the IVUS images. A manual processing of images, apart from being a tedious time consuming task, might suffer from intra- and interobserver variability. Besides, it is not possible for an expert to

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completely characterize the different composition of atherosclerotic plaques [4]. Therefore, automatic characterization of IVUS images becomes a necessity. The effect of several texture analysis features have been investigated for this purpose in the literature [3, 4]. The limitation of these papers is that the result of their method was compared with the characterized image by expert. On the other hand, in some papers methods based on processing of IVUS signal have been proposed in order to recognizing different substances in atherosclerotic plaques [5, 6].

Here, three feature extraction methods were used for recognizing four substances (i.e. calcium, fibrous, necrotic core, and lipid core). One is Local Binary Pattern (LBP) [7] and the others are Gabor filter and Co-occurrence matrix [8].

So, in the first step, the IVUS images are decomposed in $7*7$ overlapping windows and the features extracted from the distribution of gray-scales in each window is assigned to the central pixel of that window. For considering the influence of all pixels in the windows, LBP was applied in three levels (i.e. with radius ranging from 1 to 3). In the second step, the Fisher linear Discriminant (FLD), which is one the most powerful feature conditioning techniques, was employed to improve the outcome of our research. Since the FLD reduces the dimension of feature vectors to number of classes – 1, three features was achieved after applying FLD. And in the sequel, the result of the whole process was validated with corresponding histological images via a three layer perceptron. 70% of dataset was used for training and the others were tested through the trained neural network.

The database used in this research was taken from a bigger database including 7 patients. We just used 10 IVUS images (Volcano therapeutics Inc. InvisionTM, IVG-EE) which there exist the corresponding Histological images for validation.

Table 1

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Table I

Feature Extraction Method	Calcium		Fibrous		Necrotic core		Lipid core	
	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
LBP (FLD)	69% (73%)	78% (80%)	82% (85%)	64% (65%)	48% (52%)	49% (52%)	54% (58%)	59% (61%)
Co-occurrence (FLD)	71% (75%)	81% (82%)	88% (90%)	61% (64%)	50% (53%)	47% (50%)	51% (55%)	49% (50%)
Gabor filter(FLD)	62% (66%)	63% (76%)	87% (91%)	54% (55%)	43% (45%)	44% (48%)	41% (43%)	44% (45%)
All features+ FLD	75% (79%)	87% (76%)	88% (93%)	69% (72%)	56% (58%)	60% (61%)	59% (62%)	63% (65%)