Using Radio Frequency Reconstructed IVUS Images in Tissue Classification

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Abstract

One of the main uses of the Intravascular Ultrasound (IVUS) images is tissue classification. Some of the most important tissues are calcium, fibrotic, and lipid plaque. Usually, this task is achieved using DICOM images. Here we exposed the use of reconstructed images from RF data to improve the classification process, because it is given the advantage of normalizing the images to a fixed parameter set. In this approach, 6 *different data sets are generated using* 150 *tissue sections obtained from* 54 *images of* 6 *patients. Then, the images are classified employing adaboost classifiers with Error Correcting Output Codes (ECOC) using* 85% *of the data for training and the rest for testing. The pixel classification rate for DICOM images is:* 76.11% *composed of* 72% *for calcified,* 76.13% *for fibrotic, and* 80.21% *for lipid tissue. For reconstructed images the hit rate is 79.03%, from which 77.6% of calcium, 69% of fibrosis and 90.5% of lipid tissue are well detected.*

1. Introduction

Plaque rupture is one of the most frequent cause of coronary diseases. Many studies, nowadays, report a high correlation between an acute coronary syndrome and multiple plaque ruptures. To understand the mechanisms of plaque destabilization, it is relevant to characterize the fragile part of the plaque and to differentiate between low-risk and high-risk plaques.

The Intravascular Ultrasound (IVUS) images offers us a unique view of the arterial plaque, since it displays the morphology and histological properties from a cross-section of the vessel. There are three different types of plaque distinguishable: calcium, fibrous plaque and lipidic or soft plaque. The automatic analysis of these tissue in the IVUS images allows feasible ways to predict and quantify the vulnerable plaques, avoiding the subjectivity due to the physician who performs the study.

The analysis of IVUS images has been approached proposing the inspection of the DICOM images themselves by performing texture analysis [1, 2]. However these images are difficult to normalize since it requires high computational cost and the images are save under different parameter sets depending on the physician. Consequently, it provokes a lack of standardized data sets.

In this paper we propose a framework to reconstruct normalized IVUS images from the raw Radio Frequency (RF) signals coming from the IVUS equipment. Having these images, a texture based characterization process is applied. This data is feeded into an Adaboost with Error Correcting Output Codes (ECOC) framework to perform the tissue classification. The main advantages of our method are twofold, because our method offers the advantage of normalizing all cases to a fixed parameter set with low computational cost, and uses a machine learning technique allowing us to ensure a proper behavior of the classification approach.

In section 2, we present the methodology used. Firstly an explanation of the image reconstruction process is expose where the technical parameters are stated. Secondly it is detailed the feature extraction process based on Cooccurrence Matrix, Local Binary Patterns, and Gabor Filters as texture descriptors. Additionally it is presented the classification scheme performed. In section 3, some quantitative and qualitative results are displayed for different parameter sets. Finally, a discussion and conclusion are presented.

2. Methods

2.1. Image reconstruction process

The IVUS equipment consists of a main computer to reconstruct images, and a catheter which is introduced into the vessel to perform an exploration. This catheter carries an ultrasound emitter which shots a given number of beams, and a transducer that collects the tissue reflections as RF signals.

These signals are acquired using a 12-bit Acquiris acquisition card with a sampling rate of $200MHz$ and the transducer frequency of the catheter is $40Mhz$. Additionally,

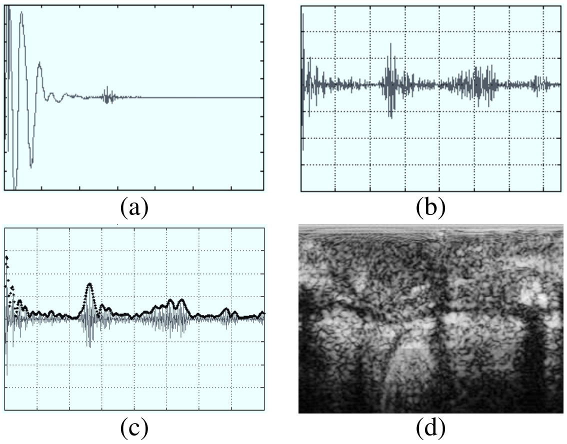


Figure 1. Reconstruction process. (a)acquired RF signal. (b)RF signal filtered and compensated. (c)envelope detection. (d)polar image

it is assumed a sound propagation in tissue of $1565m/s$ [3]. Each IVUS image consists of a total of 256 A-lines (ultrasound beams) with length of $6.5mm$. The acquired RF signals were obtained from *in vivo* patient pullback sequences.

Once the RF sequences have been collected, the image construction process is performed. As a preprocessing steps the signals are filtered at the transducer frequency. Then, it is applied a linear time gain compensation in order to correct the tissue attenuation of $\alpha = 1DbMhz/s$[3]. Once the signals are compensated, the signal envelope is calculated using the Hilbert transform. The result is compressed logarithmically and normalized in order to distribute the gray levels and to enhance the image visualization.

The image is constructed in polar form $R\theta$. To regulate the contrast it is applied a non linear Digital Development Process (DDP) radially [4]. As a final step the IVUS Image is built in cartesian form, and the missing pixels between each angle are filled using interpolation. The process is depicted in figure 1

By fixing the (DDP) parameters, we can normalize images from different patients with the same contrast or gain and low computational cost, which is not an easy task in DICOM images since each study is saved according to the physician who performs the study without any parameter information. The figure 2 shows an example of constructed images with different DDP gain parameter values.

2.2. Feature extraction

To extract image features, we have exploited 3 different texture descriptors: Co-occurrence Matrix, Local Binary Patterns and Gabor Filters.

The Co-occurrence matrix is defined as the estimation

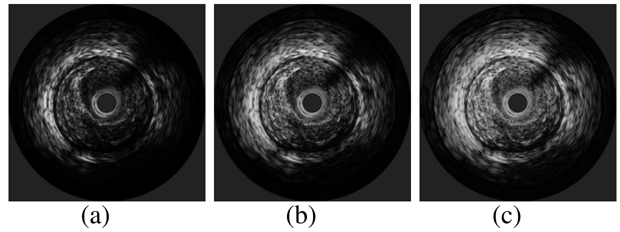


Figure 2. Reconstructed IVUS images from RF signals with different DDP gain parameters. (a)DDP gain parameter fixed to 1.04. (b)DDP gain parameter fixed to 2.20. (c)DDP gain parameter fixed to 3.00.

of the joint probability density function from the gray level pairs on a image [5]. The sum of all element values is:

$$P(i,j,D,\theta) = P(I(l,m) = \\ i \otimes I(l + Dcos(\theta), m + Dsin(\theta)) = j),$$

where $I(l,m)$ is the gray value at the pixel(l,m), D is the distance among pixels and θ is the angle of each of neighbors. The angle orientation θ has been fixed to be $[0^o, 45^o, 90^o, 135^o]$, [6, 5]. After computing this matrix, some characterizing measures, such as energy, entropy, the Inverse Difference Moment(IDM), shade, inertia and promenance, are extracted [5]. With these descriptors, a 48 feature space is built for each pixel, since we are estimating 6 different measures at 4 orientations and 2 distances in pixels $D = [5,8]$.

Local Binary Patterns are operators used to detect uniform texture patterns in circular neighborhoods with any quantization of angular space and spatial resolution[7]. It is based on a circular symmetric neighborhood of P members of a circle with radius R. To achieve gray level invariance, the central pixel g_c is subtracted to each neighbor g_p, assigning to the result 1 if the difference is positive and 0 otherwise. Each neighbor is weighted with a 2^p value. Then, the neighbors are added, and the result is assigned to the central pixel.

$$LBP_{R,P} = \sum_{p=0}^{P} s(g_p - g_c) \cdot 2^p$$

The use of these operators generates a 3 dimensional space in texture analysis, by applying a radius of $R = [1,2,3]$ and a neighborhood of $P = [8,16,24]$.

A Gabor Filter is an special case of wavelets [8], and is essentially a gaussian g modulated by a complex sinusoid s. In 2D,the form of a Gabor filter in the spatial domain is consider as the following:

$$h(x,y) = \frac{1}{2\pi\sigma^2}\exp\{-\frac{1}{2}[(\frac{x^2+y^2}{\sigma^2})]\} \cdot s(x,y), \\ s(x,y) = \exp[-i2\pi(Ux + Vy)], \quad \phi = \arctan V/U$$

where σ is the standard deviation for the gaussian envelope, U and V represent the 2D frequency of the complex

Table 1. ECOC code map used in the classification

Classes	Classifier 1	Classifier 2	Classifier 3
Calcium	1	1	0
Fibrotic Plaque	-1	0	1
Soft Plaque	0	-1	-1

sinusoid, and ϕ is the angle of frequency. We have represented the 2D frequency, (U, V), by a polar representation F, ϕ. Thus, we have created a filter bank using the following parameters:

$\sigma = [12.7205,\ \ 6.3602,\ \ 3.1801,\ \ 1.5901]$,

$\phi = [0^o\ \ ,45^o\ \ ,90^o\ \ ,135^o]$,

$F = [0.0442,\ \ 0.0884,\ \ 0.1768,\ \ 0.3536]$,

Now that we have extracted all the features explained above, we compile them into a unique feature vector of 67 dimensions for each pixel, which will be used to train and test the classifier.

2.3. Classification

Once we have designed the feature characterization, a classification scheme is developed. We have established 3 classes of tissue: fibrotic plaque (characterized by a medium echo-reflectivity and good transmission coefficient), lipid or soft plaque (very low reflectance), and calcium (high echo-reflectivity and absorbtion). We have used the supervised learning technique Discrete Adaboost [9, 10]to train the different classifiers.

Since we have a multiclass problem and adaboost is, by definition, used for two class problems, we have established a combination criterion for the different classifier outputs. To avoid draw among classes we have employed the Error Correction Output Codes (ECOC)[11]. This technique consists in designing a code map table which relates the classifier outputs with the classes. The final classification is obtained by finding the minimum distance among the resulting code and the classes code.

The classification map from the ECOC for our problem is shown in table 1. The number 0's indicate that these classes are not used in the selected classifier. The 1's indicate that the classifier should output a positive value when this class is found, and negative one (-1) when it is not. Here, we have used the Euclidean Distance to find the class likelihood.

3. Results

We have reconstructed IVUS images from *in vivo* sequences, from a set of 6 patients all with the three classes of plaque. For each patient, 5 to 10 different vessel sections are selected, having a total of 54 analyzed images.

The physicians have segmented from the vessel images

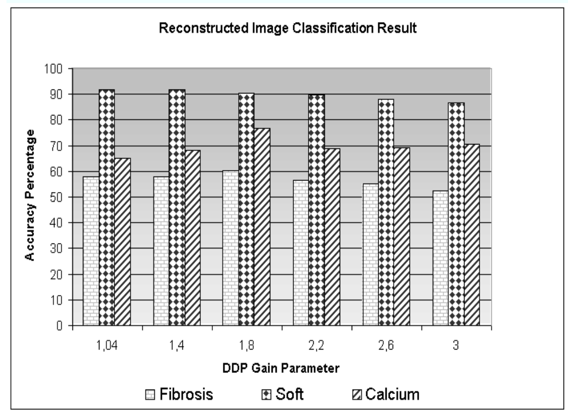


Figure 3. Classification result among different DDP gain parameters for each type of tissue

around of 30 sections of interests per patient. These segmentations were taken as regions of interest (ROI) to create the data set for this experiment. In order to test the performance of our texture based classification approach, we have selected 6 different DDP gain parameters to reconstruct the images (1,1.4,1.8, 2.2, 2.6, 3.0). Then, there has been created six different data sets, and their extracted texture features have been processed separately using the characterization exposed before.

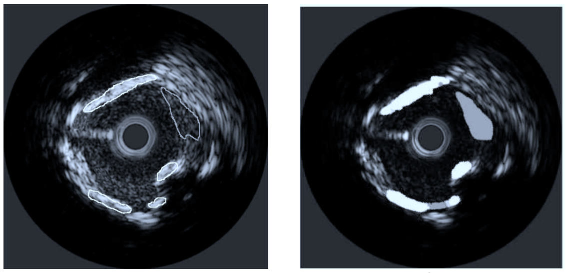
After this, the training and testing set is formed. To avoid any kind of bias, the experiment has been repeated 6 times by picking in each iteration one different patient (10% - 15%) for testing and the rest for training purposes. Notice that this scheme validates inter-patient variability.

For every DDP gain parameter values a classification error has been computed for each kind of tissue. Thus, the accuracy for different DDP gain parameters is shown in figure 3.

It can be seen that the best gain parameter is 1.8 where the classification results with any kind of post processing are: 70% for fibrotic plaque, 90.5% for lipid, and 77.6% for calcium. These results are more accurate than DICOM images analysis where the classification rates are: 76.13% for fibrosis, 80.21% for soft tissue and 72% for calcified tissue well detected. Qualitative results are observed in figure 4

4. Discussion and conclusions

It has been presented a normalization model to analyze IVUS images generated by a RF signals reconstruction process with a fixed set of parameters, which is more accurate than using DICOM images. It suggests the ability to reproduce IVUS images offline where the manual segmentation can be achieve easily since each physician can adjust the image gain to focus on a given tissue. It eases the classification process because the data are still normalized.



a b

Figure 4. Image classification a) image segmented by the physician b)classification result using the best gain. White is calcium, and light gray is lipid plaque

It can be conclude that not only a single gain parameter could enough for the classification process, but also a combination of multiple gain values, each one designed for a different tissue, could be suitable. The inclusion of some postprocessing techniques, such as grouping could improve the classification rates. However, this could decrease the classification resolution or introduce a certain bias.

Additionally some RF signal features could be explored to be attached with the image features in order to increase the accuracy. It is suggested because RF signals represent the raw information obtained from the IVUS catheter, which contain more information than images due to the reconstruction process.

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