Blood Detection In IVUS Longitudinal Cuts Using AdaBoost With a Novel Feature Stability Criterion[1]

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Abstract. Lumen volume variations is of great interest by the physicians given the more it increases with a treatment the less probability of infarction. In this paper we present a fast and efficient method to detect the lumen borders in longitudinal cuts of IVUS sequences using an AdaBoost classifier trained with several local features assuring their stability. We propose a criterion for feature selection based on stability leave-one-out cross validation. Results on the segmentation of 18 IVUS pullbacks show that the proposed procedure is fast and robust leading to 90% of time reduction with the same characterization performance.

Keywords. IVUS, Blood detection, AdaBoost, Texture analysis

1. Introduction

Intravascular Ultrasound Images (IVUS) are an excellent tool for direct visualization of vascular pathologies and evaluation of the lumen and plaque in coronary arteries. However, visual evaluation and characterization of plaque require integration of complex information and suffer from substantial variability depending on the observer. This fact explains the difficulties of manual segmentation prone to high subjectivity in final results. Automatic segmentation will save time to physicians and provide objective vessel measurements [1]. Nowadays, the most common methods to separate the tissue from the lumen are based on gray levels providing non-satisfactory segmentations. This leads to use more complex measures to discriminate lumen and plaque. One of the most wide spread methods in medical imaging for such task is texture analysis. The problem of texture analysis has played a prominent role in computer vision to solve problems of object segmentation and retrieval in numerous applications [2,3]. This approach, encodes the textural features of our image, and provide a feature space in which a classification based on such primitives is easier to perform.

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In general, two approaches are used for texture analysis: supervised and unsupervised analysis. Our scheme will use supervised texture analysis. Texture analysis has an important problem in both approaches, the precise location of textured object boundaries. Previous works in segmentation of IVUS images have shown different ways to segment lumen and to classify tissues [4,5,6]. However, these approaches usually are semi-automatic and very sensitive to image artifacts. The classification process is a critical step in any image segmentation problem. Arcing and boosting techniques have been applied successfully to different computer vision areas. In this paper we analyze the relevance of boosting techniques, and in particular AdaBoost in Intravascular Ultrasound Image analysis for a dual task, creation of a strong classifier and feature selection. Moreover, we propose a fast, efficient and robust process to detect blood in IVUS image sequences. This process is integrated in an automatic framework for discrimination of lumen and tissue in longitudinal cuts of the IVUS sequence of images (figure 1). The method is divided in 4 steps, corresponding to feature extraction, feature selection, classification and higher level organization of data using deformable models. An objective evaluation of the different approaches is made and validated by the physicians in patients with different pathologies and images with different topologies.

(a) (b)

Figure 1. IVUS images: (a) original cartesian image, (b) Longitudinal cut at 45ž of the IVUS sequence

2. Methods

We propose an algorithm for fast and accurate detection of the lumen borders on a longitudinal cut of IVUS sequence that consists on a pixel classification step followed by a morphological postprocessing and a final segmentation.

In order to detect the lumen borders in the IVUS sequences we use a learning approach, in particular the AdaBoost (Adaptive Boosting) classifier formulated by Freund and Schapire in [7]. This technique is a supervised learning and classification tool, created as a method for combining simple classifiers in a multiple classifier in order to obtain a very accurate precision. Roughly, it is an iterative assembling process in which each classifier is devoted to find a good division of the sub-set points formed by the samples that are more difficult classified by the "weak" classifiers estimated up to that point. It is recognized as one of the most accurate processes for high accuracy classification.

2.1. AdaBoost procedure

Adaboost is an iterative method that allows the designer to keep adding "weak" classifiers until some desired low training error has been achieved [7,8]. At each step of the process, a weight is assigned to each of the feature points. These weights measure how accurate the feature point is being classified at that stage. If it is accurately classified, then its probability of being used in subsequent learners is reduced, or emphasized otherwise. Thus, AdaBoost focuses on difficult training points at each stage.

The classification result is a linear combination of the "weak" classifiers. The weight of each classifier is proportional to the amount of data that classifies in a correct way.

2.2. AdaBoost as feature selection process

As an additional feature, AdaBoost is capable of performing a features selection process while training. In order to perform both tasks, feature selection and classification process, a weak learning algorithm is designed to select the single features which best separate the different classes. That is, one classifier is trained for each feature, determining the optimal classification function (so that the minimum number of feature points is misclassified). And then, the most accurate classifier-feature pair is stored at that stage of the process. If feature selection is not desired, the weak classifier focuses on all the features at a time.

The original training set consisted on vectors of 263 features concerning the gray level of the image, the gradient image, a mean of the gray level of the neighbor cuts, the standard deviation, mean and a division between both of local windows of different sizes surrounding the evaluated pixel, a bank of Gabor filters (a special case of wavelets, see [9]) for several frequencies and orientations, Co-occurrence Matrices (defined as the estimation of the joint probability density function of gray level pairs in an image [10]), Local Binary Patterns [11] and Fast Fourier Transform of local windows of different sizes surrounding the evaluated pixel.

2.3. Stability criterion of the selected features

AdaBoost tries to assure the better performance given the training set and the set of features. But several authors have discussed that even the good performance of the classifier, the stability of the features selected is not warranted.

Moreover, in [12] authors assure that 'Learning from examples' is a paradigm in which systems learn a functional relationship from a training set of examples. Within this paradigm, a learning algorithm is a map from the space of training sets to the hypothesis space of possible functional solutions. A central question for the theory is to determine conditions under which a learning algorithm will generalize from its finite training set to novel examples. Therefore, we will need to characterize conditions on the hypothesis space that ensure generalization for the natural class of empirical risk minimization (ERM) learning algorithms that are based on minimizing the error on the training set.

In [13] Feature Space Mapping model is proposed. It describes an adaptive system that measures the contribution of each feature to the final classifier, useful on the reduction of multidimensional searches to a series of one-dimensional searches. It is an exhaustive method to assure that each feature added to the system, combined with the rest, does not decrease the performance of the classifier.

To assure the stability of the features selected by the AdaBoost classifier and to reduce the variance of the error of classification due to a bad election of the samples, we propose a method based on the combination of the features selected by several AdaBoost classifiers taking into account their weight at each classifier.

We left all the samples concerning to the IVUS pullbacks performed to one of the patients out at each time and trained a classifier with a randomized set of samples of the rest of the patients data.

Given that we wanted to speed up the process of blood detection in order to make it feasible in the day by day clinical practice, we did a feature study similar to Feature Space Mapping [13]. We started with a classifier trained with only the feature of maximal accumulated weight ($\theta = \max \omega$) up to a classifier trained with the 15 most relevant features taking into account their accumulated weights.

The feature selection algorithm for N trials following leave-one-patient-out strategy can be defined as follows:

Let C_i be the i^{th} AdaBoost classifier defined as:

$$C_i = \sum_{j=1}^{m_i} \omega_j f_j \tag{1}$$

where ω_j is the weight Adaboost has assigned to the j^{th} feature (f_j).

We define a sub-feature space S_i with the features with higher ω:

$$S_i = \{f_j; j \in 1; m_i / |\omega_j| > \theta\} \tag{2}$$

Note: $|S_i| \leq m_i$ and $\theta \leq \max \omega$

We then define a sub-feature space of the most stable features as:

$$S = \{f_j / f_j \in \bigcap_{i=1}^{N} S_i\} \tag{3}$$

We can then train a final AdaBoost classifier with all the features of S revealed as the more stable.

The results were "surprising" given that, as we can see in figure 2 only 5 features were necessary to obtain an output similar to the one obtained with the 84 features selected by the original classifier.

2.4. *Postprocessing and segmentation of the lumen*

Once we have the output of the classifier obtained, we filtered it to remove scattered misclassified pixels using mathematical morphology to smooth the results and adapt a snake to them.

The morphological filters used are a majority filter (sets a pixel to 1 if five or more pixels in its 3-by-3 neighborhood are 1's; otherwise, it sets the pixel to 0) to connect isolated points and an opening (erosion followed by dilation) of the obtained result with a cross as structuring element (see [14]).

The last step to detect the lumen border is to adapt a B-Snake model to the output of a distance map of the Canny edges (without loss of generality) of the previously obtained image (see [15,16,17]). Figure 3 shows the result of the filtering (a) and the adapted B-Snake model (b).

(a) Original image.

(b) Output with all the selected features.

(c) Output with the 5 most relevant features.

Figure 2. Output of the classifier trained with different features.

(a) Filtered output of the classifier of figure 2(c).

(b) Detected edges (blue) and the adapted snake (red).

Figure 3. B-Snake model adapted to the filtered classifier output.

3. Results

A deep validation process was performed to test the stability criterion, the performance of the final classifier and the speed up of the process.

First of all, we wanted to validate our feature stability criterion. We trained 9 different classifiers. As we said before, to assure the stability of feature set, we left all the samples concerning to the IVUS pullbacks performed to one of the patients out at each time and trained a classifier with a randomized set of samples of the rest of the patients data, performing a real leave-one-out cross validation.

Each classifier reduced the dimensionality of the feature set from 263 initial features to approximately 36 by mean (see figure 4). But if we accumulate the results of all the classifiers, we can see that 84 different features were selected by at least one classifier, that is 179 features have not been selected by any classifier (see figure 5). Moreover, the selected features with higher weights are not the same in all the cases, showing the problem of stability in the feature selection using AdaBoost.

Figure 4. Selected features by one AdaBoost classifier and their weights.

Figure 5. Addition of all the weights assigned by all the trained AdaBoost classifiers for each feature.

In terms of performance, we have trained new classifiers (always following the leave-one-out strategy for the cross validation) with a feature set increasing from 5 up to 15 features. Beginning with a classifier trained with the 5 features of higher weight of figure 5, at each step, we added a new feature, trained a new AdaBoost classifier and tested its performance. Figure 6 shows a plot of the evolution of the mean error, standard deviation and the median of the error of each multiple classifier.

In terms of speed, the most of the features with higher weight in figure 5 take almost the same time in being computed, so we can speed up the process by choosing a number

Figure 6. Evolution of the mean error (in blue, stars), standard deviation (in green, circles) and the median of the error (in red, crosses) of each multiple classifier

of features as low as possible. We can see in figure 6 that choosing a classifier trained with only 5 features we can achieve very good performance and the speed of the process has increased more than the 90% in comparison with the first approach of 84 features. We can can now process a 2400 images cut in a mean time of 1.32 minutes (without code optimizations, written in MatLab) and taking into account that the most of this time is devoted to the sequence decompression and the generation of the cut. Figure 7 shows the result in the segmentation of a 2400 images longitudinal cut with only 5 features selected.

Figure 7. Result of the lumen border detection with a multiple classifier trained with 5 features.

4. Conclusions and future work

We have proposed a novel stability criterion for feature selection with AdaBoost multiple classifiers and applied it for speeding up the blood detection in an IVUS sequence with great performance.

We have seen that with a multiple classifier trained with only 5 "well chosen" features we can detect the lumen borders of any longitudinal IVUS cut with a mean error of 5.24 pixels (0.105 mm) in 1.32 minutes. We have not observed any preference in the results for any classical texton feature. Due to the nature of the data, std and mean of sliding windows of 35 to 45 pixels were selected with a higher weight (!) in the most of the cases as the better descriptors. It is needed to say that this time can be reduced programming the feature calculation and the cut generation with a compiled language like C++ instead of our approach in MatLab.

The results are very promising to be applied in volume calculations to evaluate, for example, the effect of different drugs. In combination with three-dimensional reconstruction of the vessel shape using angiography and exact correspondence with the IVUS data as proposed in [18], we can compute the volume of any vessel in a very fast and accurate way.

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