Adaboost to Classify Plaque Appearance in IVUS Images

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Abstract. Intravascular Ultrasound images represent a unique tool to analyze the morphological vessel structures and make decisions about plaque presence. Texture analysis is a robust way to detect and characterize different kind of vessel plaques. In this article, we make exhaustive comparison between different feature spaces to optimally describe plaque appearance and show that applying advanced classification techniques based on multiple classifiers (adaboost) significantly improves the final results. The validation tests on different kind of plaques are very encouraging.

1 Introduction

The composition and structure of the vessel change with age, hypertension, diabetes mellitus and many other factors. Until this moment, it is feasible to discriminate different morphological structures of the vessel as calcium deposits, fatty, fatty fibrous and fibrous materials. Today, it is not completely clear what the vulnerable plaque is. The common researcher opinion is that a vulnerable plaque consists of: lipid core, fibrous cap, presence of inflammatory cells and is affected by the vessel remodelling and its 3D morphology. Still a complete morphological, mechanical and chemical information is necessary in order to characterize the vulnerable plaque in a robust way.

IVUS displays the morphology and histological properties of a cross-section of a vessel. Figure 1 shows a good example of IVUS images. It is generally accepted that the different kind of plaque tissues distinguishable in IVUS images is threefold: *Calcium formation* is characterized by a very high echoreflectivity and absorbtion of the emitted pulse from the transducer. This behavior produces a deep shadowing effect behind calcium plaques. In the figure, calcium formation can be seen at three o'clock and from five to seven o'clock. *Fibrous plaque* has medium echoreflectivity resembling that of the adventitia. This tissue has a good transmission coefficient allowing the pulse to travel through the tissue, and therefore, providing a wider range of visualization. This kind of tissue can be observed from three o'clock to five o'clock. *Soft plaque* or *Fibro-Fatty plaque* is the less echoreflective of the three kind of tissues. It also has good transmission

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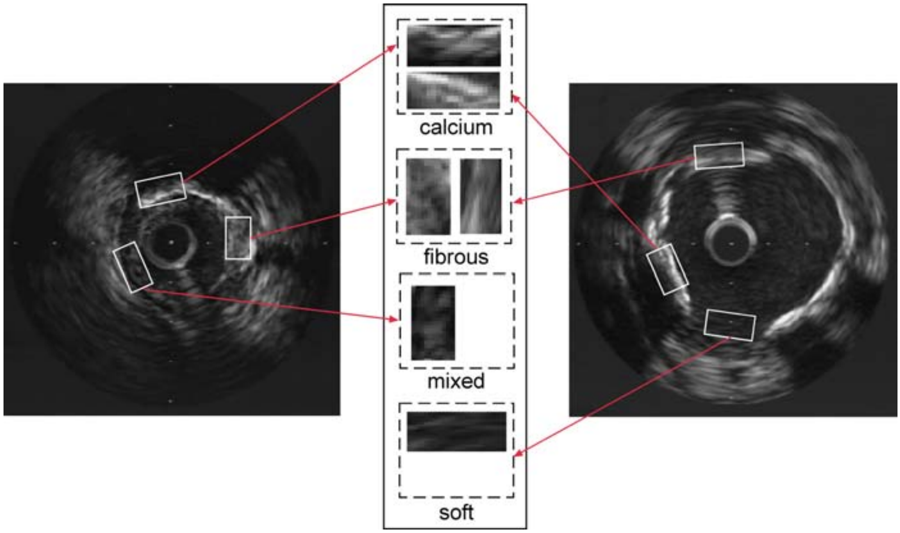

Fig. 1. Typical IVUS images presenting different kind of tissues

coefficient allowing to see what is behind this kind of plaque. Observing the figure, a soft plaque configuration is displayed from seven o'clock to three o'clock.

Textural analysis is one of the closest related processes in computer vision to the physicians expertise when dealing with IVUS images; due to the fact that plaque discrimination is performed using, mostly, morphological issues. Visual textural analysis is a difficult, subjective and time-consuming process highly depending on the specialist. Therefore, there is an increasing interest of the medical community in developing automatic tissue characterization procedures of IVUS images. The problem of automatic tissue characterization has been widely studied in different medical fields. The unreliability of gray level only methods to achieve good discrimination among the different kind of tissues forced us to use more complex measures, usually based on texture analysis.

Several researching groups have reported different approximations to characterize the tissue of intravascular ultrasound images [1] [2] [3]. Most of the literature found in the tissue characterization matters use texture features, being co-occurrence matrices the most popular of all feature extractors. Further work has been done trying to use other kind of texture feature extractors and IVUS images. And, although not specifically centered on tissue characterization, the usage of different texture features in plaque border assessment is reported. This work can be easily extrapolated to tissue characterization. In [6], derivative of gaussian, wavelets, co-occurrence matrices, Gabor filters and cumulative moments are evaluated and used to classify blood from plaque. The work highlights the discriminative power of co-occurrence matrices, derivatives of gaussian and cumulative moments. Other works such as [7] provide some hints on how to achieve a fast framework based on local binary patterns and fast high-performance classifiers. This last line of investigation overcomes one of the most significant drawbacks of the texture based tissue characterization systems, the speed, as texture descriptors are inherently slow to be computed.

In this paper we make an exhaustive comparison study of different feature spaces: *co-occurrence matrix measures*, *statistical descriptors*, *local binary patterns*, etc. The originality of the paper consists in applying a novel classification method to analyze the optimal feature space. Applying adaptative boosting techniques allow us to deal with high dimensional spaces by using an intelligent feature selection process while training the classifier. This technique is proven to optimize the final classification results when compared to standard supervised pattern recognition techniques.

2 Feature Spaces

Plaque recognition is usually approached as a texture discrimination problem. We focus our study on two different kind of texture descriptors. The first class of texture descriptors is formally acknowledged to be fully representative and highly discriminant. In this class we place co-occurrence matrices descriptors [9] and a bank of filters approach, based on derivatives of gaussian [11]. The second class is less recognized since the techniques involved are relatively new. This class comprehends descriptors characterized by its low complexity and, therefore, fast to be computed. This gain in speed, however has a cost, the lost in accuracy of the description. In this category we are placing, cumulative moments [10] and local binary patterns [12].

These sets of techniques include examples of the two most important lines of work when dealing with texture, the statistical approach (co-occurrence matrices measures and cumulative moments) and the kernel-based approach (bank of filters and local binary patterns). The first line of work are concerned with density estimation techniques or parameters. The second line of work is centered on sampled forms of analytic functions. In this sense, the local binary patterns approach is the less conventional of the methods, but we have chosen to include it in the kernel-based approach for sake of simplicity.

3 Adaboost Classification Process

Adaptative Boosting (AdaBoost) is an iterative arcing method that allows the designer to keep adding “weak” classifiers until some desired low training error has been achieved [13] [14] [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. This way, 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. As an additional feature, AdaBoost is capable of selecting the features with best performance.

The general algorithm is described as follows:

- Determine a supervised set of feature points $\{x_i, c_i\}$ where $c_i = \{-1, 1\}$ is the class associated to each of the features classes.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $c_i = \{-1, 1\}$ respectively, where m and l are the number of feature points for each class.
- For $t = 1..T$:
  - Normalize weights
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,i}}$$
  so that w_t is a probability distribution.
  - For each feature, j train a classifier, h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i |h_j(x_i) - c_i|$.
  - Choose the classifier, h_t with the lowest error ϵ_t.
  - Update the weights:
  $$w_{t+1,i} = w_{t,i} \beta_t^{e_i}$$
  where $e_i = 1$ for each well-classified feature and $e_i = 0$ otherwise. $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$. Calculate parameter $\alpha_t = -log(\beta_t)$.
- The final "strong" classifier is:
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Therefore, the strong classifier is the ensemble of a series of simple classifiers ("weak"). Parameter α_t is the weighting factor of each of the classifiers. The loop ends when the classification error of a "weak" classifier is over 0.5, the estimated error for the whole "strong" classifier is lower than a given error rate or if we achieve the desired number of "weaks". The final classification is the result of the weighted classifications of the "weaks". The process is designed so that if $h(x) > 0$, then pixel x belongs to one of the classes.

Figure 2 shows the evolution of the error rates for the training and the test feature points. Figure 2(a) shows the test error rate. One can observe, that the overall error has a decreasing tendency as more "weak" classifiers are added to the process. Figure 2(b) shows the error evolution of each of the "weak" classifiers. The figure illustrates how the error increases as more "weak" classifiers are added. Figure 2(c) shows the error rate of the system response on the training data. As it is expected, the error rate decreases to very low values. This, however does not ensure a test classification error of such accuracy.

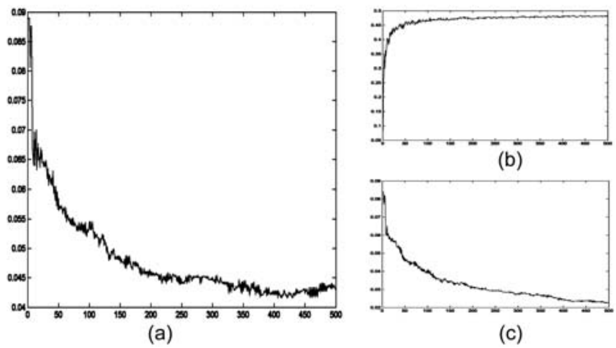

Fig. 2. Error rates associated to the AdaBoost process. (a) Test error rate. (b) "Weak" single classification error (c) Strong classification error on the training data

4 Experimental Results and Conclusions

One of the main problems in the IVUS scientific community is the lack of a standard reference set for validation of the IVUS tissue classification. Regarding this matter, we have devoted a great amount of time in collaboration with expert physicians to create a database with ten thousand samples of each of the four tissues acknowledged by experts, soft tissue, fibrous tissue, mixed tissue and calcium. Those samples have been extracted from 20 different patients, using a *Clearview* device from Boston Scientifics Corp. and a 40 MHz *Atlantis* catheter. Using this database, several texture descriptors have been selected.

Particularly, we have chosen: First, derivatives of gaussian filter bank, up to the third derivative. A five level multi-resolution framework is used, with scales $\{0.2, 0.5, 1, 2, 4\}$. For each scale, a set of directional derivatives is extracted. Second, a set of descriptors of the co-occurrence matrices at angles $\{0, 45, 90, 135\}$ with neighborhoods of 11×11 pixels and distance for the co-occurrence pair of $D = 2$ and a 17×17 pixels neighborhood with a distance of $D = 3$. In third place, a tissue description set based on local binary patterns and local variance, using radius 1 with 8 samples, radius 2 with 16 samples and radius 3 with 24 samples. And finally, a feature space based on cumulative moments, with moments up to $(9, 9)$.

Regarding the Adaboost procedure, we use a composition of 500 classifiers in the original feature space for each description set. The classification process is performed in the following way: Given the data samples in the desired feature space, a training subset is selected (images of the 40% of the total patient cases). This subsets are used to feed the Adaboost training step. As a result, a set of parameterized classifiers is obtained. The linear combination of those classifiers describes the "strong" decision rule. Each sub-classifier, "weak", is combined with a mixing value proportional to the classification error measured at the stage of its incorporation to the ensemble. The "weak" classifier used for our study is a ROC based classification process.

To compare the performance of the boosting method we have selected a well-known classifier, Fisher Linear Discriminant Analysis. The results of this classifier are our ground-truth, to which we refer in order to compare the results of the Adaboost technique.

Plaque discrimination	**Feature Set**	**Initial Error**	**Final Error**
fibrous vs. calcium	BOF	33.13%	13.09%
fibrous vs. calcium	COOC25	20.90%	13.74%
fibrous vs. calcium	COOC38	20.67%	11.04%
fibrous vs. calcium	LBP	24.76%	21.81%
fibrous vs. calcium	MOM	43.62%	38.04%
soft vs.calcium	BOF	17.75%	5.80%
soft vs.calcium	COOC25	9.81%	7.27%
soft vs.calcium	COOC38	8.88%	4.29%
soft vs.calcium	LBP	15.31%	14.68%
soft vs.calcium	MOM	45.49%	33.00%
mixed vs. calcium	BOF	26.29%	9.79%
mixed vs. calcium	COOC25	16.36%	12.44%
mixed vs. calcium	COOC38	15.91%	7.46%
mixed vs. calcium	LBP	20.54%	19.15%
mixed vs. calcium	MOM	44.16%	35.75%
soft vs. fibrous	BOF	28.63%	26.41%
soft vs. fibrous	COOC25	27.58%	27.53%
soft vs. fibrous	COOC38	26.57%	25.98%
soft vs. fibrous	LBP	31.62%	30.93%
soft vs. fibrous	MOM	44.41%	38.43%
fibrous vs. mixed	BOF	37.74%	36.28%
fibrous vs. mixed	COOC25	39.99%	37.33%
fibrous vs. mixed	COOC38	39.40%	35.65%
fibrous vs. mixed	LBP	41.31%	40.90%
fibrous vs. mixed	MOM	43.42%	40.92%
soft vs. mixed	BOF	40.44%	37.36%
soft vs. mixed	COOC25	37.72%	33.09%
soft vs. mixed	COOC38	35.42%	29.29%
soft vs. mixed	LBP	39.35%	39.01%
soft vs. mixed	MOM	46.45%	41.26%

Fig. 3. Classification of plaques

The table in figure 3 shows the figures for the error rate in our problem. The characterization of the calcium tissue seems to be the less difficult one since the calcium tissue has a very high echo-reflectivity and homogeneity (see 3). When compared with the fibrous plaque, the Adaboost procedure refines the classification increasing the recognition rates to an average of 88%. On the other hand, it is surprising that LBP has a relative good performance, close to 80%, making it an ideal candidate if we aim for fast processing. The recognition rate of the high complexity spaces in the soft versus calcium problem is pretty high,

(a) (b) (c)

Fig. 4. Example of classification in a real image. (a) Original image. (b) Classification result masks. (c) Classification masks over the original image

and it is further increased by the AdaBoost process, up to an average over 95%. Three important remarks can be made looking at the figures. First, there is a huge improvement in performance using derivatives of gaussian, of about 12%. Second, LBP still has pretty good results: over 85%. Third, MOM still performs bad in this stage. LBP lowers its error rate by 30% and BOF lowers its error rate by 20%. The discrimination between calcium and mixed plaque are not as good as the soft versus calcium problem, but are better than the fibrous versus calcium one. This is logical if we recall that the mixed tissue is a combination of both fibrous tissue and lipid tissue in an interleaved way. COOC25 seems to perform the worst of the trio formed by the high complexity classifiers. If we compare this results to the ones obtained using FLD, BOF lowers its error rate by 20%, and COOC38 by 10%. Discriminating soft vs. fibrous plaque, the AdaBoost process does not help very much. This fact, seems to show that the way data is distributed in the feature spaces is clearly entwined. This fact hinders the process of the combination of classifiers. In this case, the comparison of the results with the reference of Fisher, improves the recognition rate by 10%. Discriminating fibrous vs. mixed plaque as well as the soft vs mixed plaques are by far the most complex ones. The difference between mixed and pure plaque is simply the spatial overall distribution of the tissues. Most of the methods we have tried are purely local, and therefore are destined to fail in this problem. In fact, we have seen that the mixed label is also the most disagreed of the plaques among the experts labelling. It is remarkable the fact that COOC38 is able to distinguish both plaques with an average recognition rate of over 70%. This is due to the fact that COOC38 use a 17×17 neighborhood and therefore is susceptible to pick up the spatial distribution of the entwined fibrous and soft plaques. The fibrous vs. mixed and soft vs. mixed using linear discriminant analysis can not be made, since the results show that the decision is nearly random (recognition rates of about 55%). However, using AdaBoost the problem seems to have a weak solution, that is, a solution of nearly 70% of recognition. Figure 4 shows an example of the classification result using the fibrous (light gray), calcium (white) and soft tissue (dark gray) classifiers.

5 Discussion and Conclusions

In summary, AdaBoost is a very high performance classifier, the results show that plaque characterization based only on texture can not be made accurately if we want recognition rates over 85%. Furthermore, the most different kind of tissue, calcium is easily identified even without context information, with an overall accuracy of over 95%. However, mixed plaques are really difficult to distinguish. This points out that if we want to classify mixed plaques, texture descriptors alone are not suitable for the task. The "fake-plaque" effect (plaque resembling other tissues) opens the possibility to create a new kind of classification process that takes into account the particular test set to infer context information and therefore adapt the classification process to the particularities of the test set.

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