Rotational Effect on ROI's for Accurate Lumen Quantification in Bifurcated MR Plaque Volumes

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Abstract

This paper presents a use of geometric-based method integrated with classifier for lumen wall estimation using MR plaque volumes. The following are the new things the readers will observe when it comes to plaque imaging. (a) Application of three different sets of classifiers (Fuzzy, Markovian and Graph-based) for lumen region classification in plaque MR volumes. These classifiers are used in multi-resolution framework. (b) Usage of rule-based region merging applied to the sub-classes of lumen region. (c) Rotational effect on region of interest in arterial bifurcation zones for accurate lumen region identification and boundary estimation.

We have used our diagnostic system with three different classifying methods on actual patient data. We measure performance of the system by computing the mean distance error with respect to boundaries traced manually by human experts. Overall, the system consists of 22,500 boundary points. The in-plane pixel resolution is 0.25 millimeters. Using Markovian classifier method, the average error was 0.61 pixels; using Fuzzy classifier method, the average error was 0.62 pixels; using Graph-based classifier method, the average error was 0.74 pixels. All these methods lead to error less than 0.185 mm. We also validated our system by simulating the lumen images with additive Gaussian perturbations. This system works on a Linux platform and is written in C++.

1: Introduction

It is challenging to estimate the lumen wall in atherosclerotic vessels imaged with black blood MRI protocols (Suri [1]). There are several reasons for this: (a) blood flow in the arteries has a complicated spatial velocity profile. This can cause a variety of effects, but most often results in higher signal amplitude along the edges, compared to the central

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region of the lumen. Thus, the pixel-based classifiers give multiple classes in the edge region, leading to inaccuracies in the lumen quantification process; (b) over time, plaque deposits in the vessel wall which causes the lumen area to decrease. The signal amplitude of plaque within the wall is variable. Since it is not a fixed class type, this further hinders the region-based classification. Characteristics of vulnerable and stable plaque are also different which presents challenges for statistical pixel-classifiers; and (c) plaque present at the arterial bifurcation causes the shape of the lumen to change from simple circular cross-section to elliptical cross-sections, and in some cases the elliptical cross-sections have multiple orientations. Analysis of our database on plaque characteristics in MRI has demonstrated these variations in shape and signal amplitude. Together, these reasons pose significant challenges in detection, identification and quantification of the vessel wall lumen (Suri [5]).

2: Our Design Methodology

We have developed three major systems for very accurate lumen wall detection, identification and quantification, given the black blood MRI slices of carotid volumes. Each slice has two lumen cross-sections corresponding to the left and right carotid arteries. We used three pixel-based classifiers: the Markov Random Fields (MRF) (see Zhang [3]), the Fuzzy C Means (see Bezdek [2]), and the Graph Segmentation method (GSM) (see Felzenszwalb [4]) for pixel classification, given an *a priori* number of classes. After an image is classified using one of the three methods of classification, the image is binarized to isolate the left and the right lumens. Since the lumen region can contain multiple classes; the binarization process merges these classes when necessary, based on a rule-based system. Since the carotid arteries bifurcate in the middle of the MR volume, and the region of interest of the lumen changes shape from a circular to an elliptical or even to a rotated elliptical form, the binarization process is performed with masked lumen regions having rotational-effects, leading to accurate lumen detection. The multiple class region merging process uses a rule-based system in these rotated elliptical ROI's. The merged binary regions corresponding to the left and right lumens are then automatically identified using connected component analysis. Finally, the region-to-boundary extractor estimates the boundaries of left and right lumens automatically. These boundaries undergo performance evaluation using the polyline-distance method.

3: Synthetic and Real Lumen Detection and Quantification System (LDQS): Implementations

The object process diagram for accurate lumen detection, identification and quantification system is shown in Figure 1 (left). The details of the synthetic modeling process, the noise model, and its detection and identification process is discussed in chapter in the forthcoming book by Suri et al. [5]. As shown in the Figure 1 (left). the main engine is the LDQS block which accepts several sub-engines: Circular or Elliptical ROI's, three classifiers: MRF, FCM and GSM; connected components analysis block, binarization block; region-to-boundary estimator block, ruler block and visualization block. The elliptical ROI's are computed after scaling and rotating the circular ROI's. The binarization block embeds the rule-based region merging based on the statistical distributions of different classes inside the lumen region. In our implementations, the left and right lumens are simultaneously processed automatically, as a result, the output of the system are two sets of boundaries, corresponding to the left and right boundaries. These boundaries are then overlayed over the gray scale image for visualization. These boundaries are also quantified with respect to ground truth. using polyline and shortest distance methods.

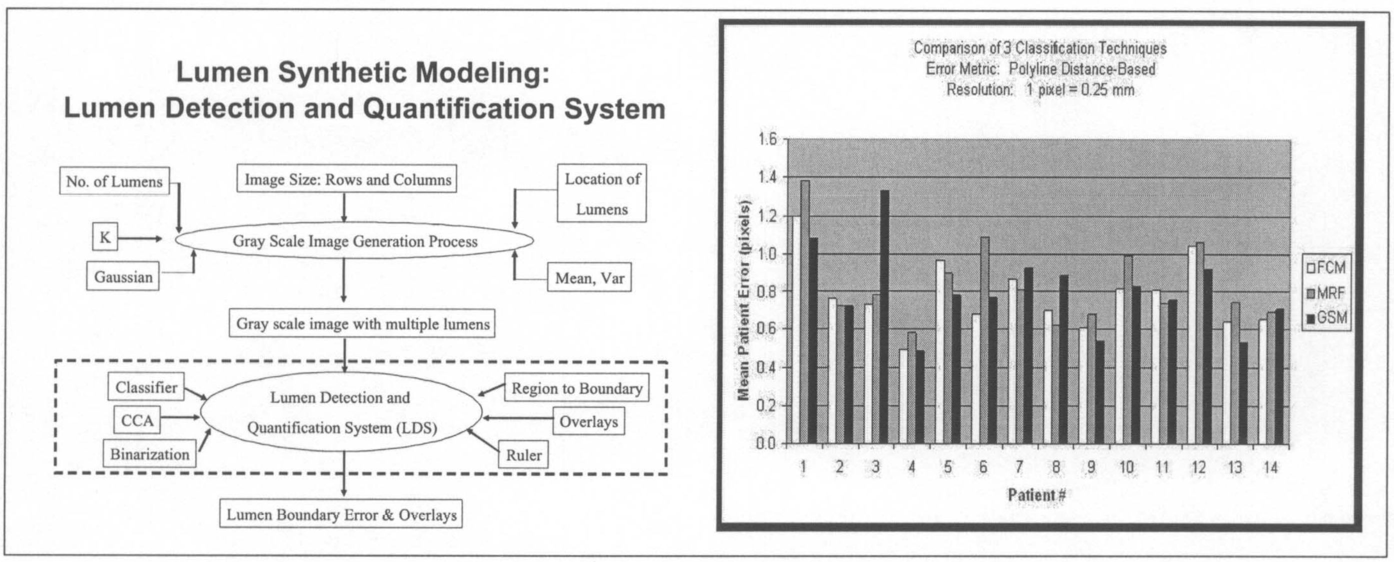

Figure 1. Left: Block Diagram of the Lumen Detection and Quantification System. Right: Performance using FCM, MRF and GSM classification methods, with mean error of 0.62, 0.61, and 0.74 pixels respectively.

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4: Performance Evaluation of Three Techniques

Figure 1 (right) shows the mean error bar charts for the three pipelines (i.e., using three classification systems: MRF, FCM and GSM methods). We ran the system using each of the three different classifying methods on real patient data. Ground truth boundaries of the walls of the carotid artery were traced for 14 patients having different arterial problems (see details in [5]). The system had a total of 22,500 boundary points. Pixel to mm resolution was 0.25 millimeters. Using MRF, the average error was 0.61 pixels; using FCM, the average error was 0.62 pixels; using GSM, the average error was 0.74 pixels. Figure 2 shows the comparison between the outputs of the systems when the system uses circular ROIs vs. elliptical ROIs. The visualization results from the two systems (one with circular ROI vs. elliptical ROI) are shown in pairs: the top row corresponds to circular ROI methodology while bottom row corresponds to the elliptical ROI methodology based on the rotational effect.

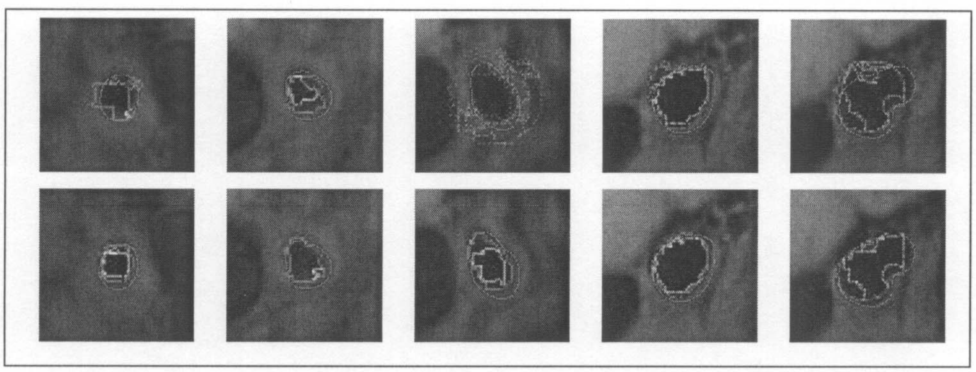

Figure 2. Representative results of estimated boundary using Circular vs. Elliptical-based methods. The system used was FCM-based. Top rows are circular-based ROI while the corresponding bottom rows are elliptical-based ROI's. FCM, MRF and GSM classification methods had mean error of 0.62, 0.61, and 0.74 pixels respectively.

5: Conclusions

System Strengths: The article presented the following new implementations when it comes to MR plaque imaging. (a) Application of three different sets of classifiers for lumen region classification in plaque MR protocols. These classifiers are done in multi-resolution framework. Thus sub-regions are chosen and sub-classifiers are applied to compute the accuracy of the pixel values belonging to a class. (b) Rule-based region merging for sub-classes in the lumen region to compute accurate lumen region and lumen boundary in cross-sectional images. (c) Rotational effect on the region of interest in bifurcation zones for accurate lumen region identification and boundary estimation. (d) System is fast and takes few sections to process. (e) Shell scripts are all automatic running on Linux.

System Weakness: (a) The rotational angles are sometimes visually adjusted. We need an automatic methodology. (b) The number of classes are pre-determined.

6: Acknowledgements

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