Automated Segmentation of Atherosclerotic Plaque Using Bayes Classifier for Multi-Contrast In Vivo and Ex Vivo MR Images

Xueying Huang¹, Chun Yang², Jie Zheng³, Pamela K. Woodard³ and Dalin Tang¹

Summary

Atherosclerotic plaques may rupture without warning and cause acute cardiovascular syndromes such as heart attack and stroke. Accurate identification of plaque components will improve the accuracy and reliability of computational models. In this article, we present a segmentation method using a cluster analysis technique to quantify and classify plaque components from magnetic resonance images (MRI). 3D in vivo and ex vivo multi-contrast (T1-, proton density-, and T2-weighted) MR Images were acquired from a patient of cardiovascular disease. Normal distribution Bayes classifier was performed on ex vivo and in vivo MR Images respectively. The resulting segmentation obtained from cluster analysis showed very good agreement with histological data. 3D visualization of the plaque was presented. Combination of in vivo and ex vivo MRI data enabled us to quantify the shrinkage between the ex vivo plaque sample and its in vivo state. For this patient, the average shrinkage is 9.14% at cross section and 33.33% in axial direction. This information is essential to determining proper initial stress/strain conditions for computational plaque models.

Introduction

Cardiovascular disease (CVD) is the No. 1 killer in the western world [1]. Many critical cardiovascular events such as stroke and heart attack are related to rupture of a vulnerable atherosclerotic plaque in diseased arteries. It is of great importance that non-invasive methods be developed to assess and identify vulnerable atherosclerotic plaques and predict possible plaque rupture before it actually happens. MRI-based computational models can be used to perform mechanical analysis non-invasively to identify critical flow and stress/strain conditions which may be related to possible plaque rupture [4-5]. Plaque morphology is the most basic element needed to construct computational models.

High resolution MRI is capable of quantify plaque morphology and plaque components. Most of these are generally based on a manual extraction of numerous contours. Automated segmentation procedure would permit combination of multi-contrast weighting MR Image. It was hypothesized that multi-contrast MR images could enhance the differentiation of various tissue components based on their signal intensities in different MR Weightings. In this paper, an automated multi-contrast weighting

¹Mathematics Department, Worcester Polytechnic Institute, Worcester, MA 01609, USA
²Mathematics Department, Beijing Normal University, Beijing, China
³Mallinkrodt Institute of Radiology, Washington University, St. Louis, MO 63110, USA
plaque segmentation method using Bayesian Classifier with Normal distribution probability is introduced. Results from in vivo and ex vivo MRI of a patient were obtained and validated by histological data. Artery shrinkage in cross-section and axial direction were quantified by comparing in vivo and ex vivo MRI data.

**Materials and Method**

3D in vivo, ex vivo MRI, and histological images of a patient were provided by Dr. Zheng’s group using protocol approved by Washington University Institutional Review Board with informed consent obtained. The in vivo imaging data set included multi-contrast weighting images with T1-, T2- and proton density (PD) weightings. Each contrast weighting session consists of 14 2D slices with high resolution (200×200 μm², slice thickness=3mm). The ex vivo imaging data set included T1-, T2-, gradient-echo (GRE) and proton density (PD) weighted MR Images. Each contrast weighting session has 30 2D slices with high resolution (109×109 μm², slice thickness=1mm).

The intensity of each image was not uniform due to the effects of coil inhomogeneity and was adjusted (see Fig. 1). A 14mm×14mm region was selected as the region of interest (ROI). The contrast of the images was increased by linear transformation. The effect of this pre-processing is shown by Fig. 1.

![Pre-Processing results of selected slices from all 32 slices of ex vivo MR Images: (a) original T2-weighted MR images; (b) resultant images after contrast increase.](image)

Figure 1: Pre-Processing results of selected slices from all 32 slices of ex vivo MR Images: (a) original T2-weighted MR images; (b) resultant images after contrast increase.

From ex vivo MRI slices with matching histological slices, slices 14 and 26 were selected to generate the training set for segmentation. Images of those two slices were manually segmented based on registered histological results and relative intensity. A total of 573 pixels (each pixel contains 4 densities representing all 4 different contrast weightings) were selected randomly for study. From these segmentation results, each location was determined to belong to one of the 4 issue types including lipid (denoted as Z₁), normal issue (denoted as Z₂), calcification (denoted as Z₃) and others (including lumen or outer issue, denoted as Z₄). The training set was used to generate the probability function which was used to determine the probability of tissue type for each pixel.

The most important part of the segmentation algorithm is to determine the prob-
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abilities of each pixel. These probabilities represent the likelihood that the tissue at the location of the pixel is lipid, calcification, normal issue or others. We determine those probabilities base on all the intensity of each weighting MR Images. The intensity vector \( \vec{I} = (I_1, I_2, I_3, I_4) \) is used to represent the intensity of the pixel in one of the contrast weighting MR Images and \( Z_i \), \( i=1, 2, 3, 4 \), corresponds to the label of the issue. We used \( P(Z_i | \vec{I}) \) to represent the probability of \( \vec{I} \) belongs to \( Z_i \). Assume that \( I_i \) is conditional independent of \( I_j, (i \neq j) \), that is, the intensity of one of the contrast weighting MRI do not depend on other contrast weighting MRI. This assumption allows us to calculate the posterior probability using naive-Bayes decision theory [2],

\[
P(Z_i | \vec{I}) = \frac{P(Z_i)P(\vec{I}|Z_i)}{\sum_{i=1}^{4} P(Z_i)P(I_1|Z_i)P(I_2|Z_i)P(I_3|Z_i)P(I_4|Z_i)}
\]

(1)
The prior probability \( P(Z_i) \) was estimated by the frequency of each of the 4 tissue from the training set. Assume that the conditional probability density function (pdf) is a normal distribution, denoted by \( P(I_j|Z_i) \sim N(\mu_{ji}, \sigma_{ji}) \), where \( \mu_{ji} \) and \( \sigma_{ji} \) is the unbiased estimation of mean value and standard deviation respectively of ith issue type for jth contrast weighting images.

Maximum classifier was used to determine which issue type the pixel belongs to. Fig. 2 gives the flowchart of our maximum decision probability functional classifier. Where \( \vec{I} \) is multi-contrast weighting MR Images transformed by preprocessing, \( g_i(\vec{I}) \) is the decision function pdf \( P(Z_i | \vec{I}) \). If \( g_i(\vec{I}) \) is the maximum value, then pixel \( \vec{I} \) belongs to \( Z_i \) and be labeled i.

Figure 2: Flowchart of maximum decision probability functional classifier.

Result

Fig 3 shows the results of segmentation of slice 24 of ex vivo MR images based on probabilities. Fig 3(a) gives the results of classifier with lipid in red, calcification in yellow, normal issue in blue, and others (including lumen) in green. Fig 3(b) gives the contour result based on 3(a). Fig 3 (c)-(f) gives the segmentation result on all different contrast weighting MR Images. Fig 3 (g) shows the corresponding histological images, C, L represent calcification, lipid respectively. The results match pathology well. Fig 4 shows contour results of all ex vivo MR Images.

Applying the method to in vivo MR Images, the contours obtained from S1-S9 is given by Fig 5 (b). In vivo, ex vivo, and histologic images were registered to
Figure 3: A segmentation example of selected slice using multi-contrast MR Images. (a) Automatic segmentation result of classifier process; (b) Segmented contour result; (c)-(f) give segmentation results on T1, PD, T2, GRE weighting images respectively; (g) shows corresponding histological images. Our contour results show excellent agreement with histopathological data.

Figure 4: Segmented contour plots of all ex vivo MRI slices showing plaque components match each other. Fig.5 shows the corresponding slices of ex vivo, in vivo MRI and histology. 3D reconstruction geometry was shown on Fig 6.

Since 1983, when the significance of the zero-stress state of living tissues was recognized, many experiments have been done using 2D artery rings ex vivo to quantify the zero-stress state [3]. However, to our knowledge, there has been no report demonstrating the shrinkage (which is by nature 3D) of the artery using ex vivo and in vivo MR images. Inner circumferences of plaque samples (diameter is not used since plaques are normally very asymmetric) and axial length will be used as the two measures to compute shrinkage rate based on accurate automatic identification of lumen in both in vivo and ex vivo MRI. Table 1 shows the inner circumferences in same cross section and shrinkage between ex vivo and in vivo state. The average shrinkage is 9.14%. The inner circumferences did not change too much. Since the slice thickness is 1mm and 3 mm of 3D in ex vivo and in vivo MRI data set respectively, the length of the specific part of carotid artery is 16mm (S3-S19) at ex vivo state and 24 mm (S1-S9) at in vivo state. The stretch ratio of length is 33.33%. The shrinkage rate in length of artery is significant. Axial stretch has to be taken into consideration for 3D fluid-structural interaction (FSI) models.

Conclusion

A method to automatically segment ex vivo and in vivo MRI data set is in-
Figure 5: Compare in vivo, ex vivo, and histological images and the result of segmentations for in vivo and ex vivo MR Images. (a) Segmentation results on 9 in vivo MRI (T1W) slices (S1-S9); (b) Segmented contour plots for (a) showing plaque components; (c) Segmentation results on 17 ex vivo MRI (T1) slices (S3-S19); (d) Segmented contour plots for (c) showing plaque components.

Figure 6: 3D reconstructed geometry of in vivo MRI with contour lines.

Table 1: Circumferences and shrinkages of lumen measured from segmented contours of in vivo and ex vivo MRI. Cin and Cex is the circumference of lumen of in vivo and ex vivo MRI respectively.

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introduced. The maximum decision probability functional classifier was applied to multi-contrast weighted MR image processing. Histological images were used to validate the reliability of the segmentation method for multi-contrast weighting in vivo and ex vivo MR Images. By comparing in vivo and ex vivo MR images, the shrinkage of artery was calculated. A 9.14% shrinkage in circumferential dimension and 33.33% shrinkage in axial dimension were observed. The combination of in vivo, ex vivo MRI and Histology may be an important research tool in future studies. Large-scale patient studies are needed to further validate our method and
findings.

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References