

# Automatic Plaque Characterization Employing Quantitative and Multicontrast MRI

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**Introduction:** Multicontrast MRI has shown promise in identifying and characterizing atherosclerotic plaques [1]. One of the limitations of this technique is the lack of a practical automated plaque characterization scheme. The purpose of this study is to develop an automated plaque characterization routine to address this issue.

Currently, the majority of automated plaque characterization techniques rely solely on signal intensity values in multicontrast MRI data to differentiate plaque constituents. Pixel intensities on multicontrast MR images are used either directly (supervised techniques) or indirectly (clustering based techniques) to characterize plaque constituents. Despite the use of this approach, there are several issues that hinder its ability to perform automated plaque characterization. One issue is that a specific tissue's intensities on MR images are imaging parameter and field strength dependent, which causes either the classifier be trained repetitively (supervised techniques) or the comparative contrast table (clustering technique) be generated exclusively for the chosen set of imaging parameters. To resolve this, a *Prior Information Enhanced Clustering* (PIEC) technique using both multicontrast MR and quantitative T2 values is proposed. In PIEC, the high signal to noise ratio (SNR) multicontrast MR images are used to classify different tissue groups while low SNR quantitative T2 maps are used to label the segmentation results. Potentially, T2 maps' independence from imaging parameters makes PIEC more robust than characterization schemes using multicontrast MRI alone. Moreover, no additional data acquisition is needed for PIEC since a rough T2 map can be generated using the proton density-weighted and T2-weighted images already acquired in the multicontrast MR dataset.

**Background:** PIEC is composed of two separate steps: classification and labeling. Classification of the multicontrast MR images was performed based on a spatial penalized FCM clustering algorithm. Details about the implementation and parameter selection of this technique are published previously [2]. The labeling of the classification results were achieved based on a Bayesian formulation (Eq. 1).

$$p(c = C_j | t = T) = \frac{p(t = T | c = C_j)p(c = C_j)}{\sum_i p(T = T | c = C_i)p(C_i)} \quad (1)$$

In Equation 1, the left hand side is the posterior probability defined as the possibility of a specific tissue belongs to type  $C_j$  under the condition that its T2 value equals  $T$ . The numerator of the right hand side is the multiplication of the conditional probability (probability of T2 value being  $T$  given tissue type is  $C_j$ ) and the prior probability (probability of tissue' type being  $C_j$ ). In our application, the conditional probabilities (T2 distributions of each plaque constituents) are measured using a subset of vessel samples. The prior probabilities can be assumed to be equal for all the constituents initially, meaning all tissues have equal probability of presence in plaques. After calculating the first slice, the prior probability of the adjacent slice can be updated to be the posterior probability of the previous slice to increase the calculation accuracy. Based on this Bayesian model, the detailed scheme of our proposed plaque labeling is as follows: First, calculate a quantitative T2 map using proton density and T2-weighted images. Second, compute the posterior tissue probabilities of being among all the tissue types, employing Eq. 1 for each pixel. Third, determine the overall posterior probability for each segmented class (of the classified results) by summing up the posterior probabilities of all the pixels belonging to this region. Each segmented region can then be labeled using the tissue type with maximum posterior probability.

**Methods:** To evaluate the performance of the algorithm, PIEC were applied to both simulated and *ex-vivo* multicontrast MR images of coronary vessel samples. The simulated multicontrast MR data was calculated based on a known computational phantom. *Ex-vivo* Coronary multicontrast MR images were acquired on fifteen explanted coronary arteries containing atherosclerotic plaques. The MR scans were conducted on a 4.7T small animal MR scanner (INOVA, Varian, Inc., USA) using a 37-mm-diameter 16-element birdcage quadrature coil at 37±2°C. Proton density-weighted (TR/TE = 3.5second/15ms), T2-weighted (TR/TE = 3.5second/50-60ms) and T1-weighted spin echo (TR/TE = 0.9-1.4second/15ms) images were obtained for the multicontrast MR dataset. In addition, two partial T2-weighted spin echo images with TR = 3.5s and TE = 30~50ms were acquired for quantitative T2 distribution measurement. Seven of the fifteen vessels were randomly selected to measure plaque tissues' T2 distributions needed in Eq. 1. The performance of PIEC was assessed by comparing: 1.Characterization results of the simulated data with the computational phantom on pixel by pixel basis and 2.Characterization results of coronary scans with corresponding histological stains. Note that only labeling accuracy was evaluated since the classification accuracy was accessed by previous research [2].

**Results:** Two sets of multicontrast MRI data (T1, T2 and proton density-weighted) were simulated based different imaging parameters. Characterization sensitivity, specificity and true positive rate for the two situations are summarized in Table 1. Overall, the The performances of PIEC on the two simulated dataset are comparable and both demonstrate excellent characterization accuracy. These results suggest that PIEC is independent of imaging parameters. For the simulated datasets, excellent specificity(81.2%-99.8%), sensitivity(97.4%-99.9%) and true positive rate(93.5%-99.8%) were achieved. The comparatively lower accuracy for fibrocellular and media tissues is caused by the low contrast between them since their compositions are similar.

After evaluation of the proposed PIEC characterization on simulated multicontrast MR data, we applied the technique to the multicontrast MR images of excised coronary atherosclerotic plaques. A typical plaque characterization result is shown in Figure 1. Visually, the PIEC result identifies various plaque tissues consistent with histological stains. For all the multicontrast MRI data we acquired, the PIEC characterization results correlate well with the histological stains. The true positive rate of labeling for each of the six tissue categories (fibrocellular, media, necrotic tissue, adipose fat and M199 solution) is summarized in Table 2. The true positive rate ranged from 69.3% (media/loose matrix) to 100% (M199 culture media).

**Discussion and Conclusions:** In the current study, we employ plaque tissues' quantitative T2 distributions to label classification results based on a Bayesian approach. It should be noted that the Bayesian labeling can be easily generalized to use more MR properties by replacing the 1-dimensional T2 distribution to multivariate distribution (containing T2, PD, T1...) in the Bayesian formulation (Equation 1).

In conclusion, we developed a *Prior Information Enhanced Clustering* (PIEC) plaque characterization scheme that relies on the information from both multicontrast MRI and quantitative MR properties. The evaluations on simulated and *ex vivo* multicontrast MRI data demonstrate that PIEC is robust and accurate thus is a very promising candidate for automated plaque characterization.

## Reference

- [1]. Yuan C, et al. JMRI 2004; 19(6): 710-719.
- [2]. Sun B, et al. JMRI 2006;24(4):833-841.

	Calcification		Adipose Fat		Media(Loose Matrix)		Necrotic Tissue		Fibrocellular	
	Set 1	Set 2	Set 1	Set 2	Set 1	Set 2	Set 1	Set 2	Set 1	Set 2
Sensitivity	99.8%	99.5%	99.8%	99.7%	96.9%	94.8%	98.7%	97.9%	90.2%	81.2%
Specificity	99.9%	99.9%	99.6%	99.9%	98.4%	97.4%	99.7%	99.3%	99.4%	99.2%
True Positive Rate	99.7%	99.8%	98.4%	99.8%	94.9%	92.2%	95.8%	90.5%	95.9%	93.5%

	Calcification	Adipose Fat	Media(Loose Matrix)	Necrotic Tissue	Fibrocellular	M199
True Positive Rate	88.9%	70.6%	69.2%	94.7%	75.0%	100.0%

Number of PIEC labeled segments is 9 for calcium, 17 for adipose fat, 26 for media, 19 for necrotic tissue and 16 for fibrocellular

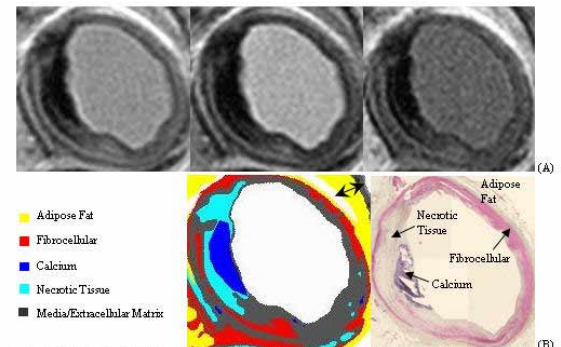


Fig. 1. (A) Multicontrast MRI of coronary plaque tissue (from left to right: proton density-weighted, T2-weighted and T1 weighted), and (B) Color coded PIEC characterized result (left) and corresponding smooth muscle actin stain (right).