A Penalized Fuzzy K-means Algorithm for Multi-contrast MRI of Atherosclerotic Plaque Constituent Classification

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Introduction

Evaluation of atherosclerosis by multi-contrast MRI is based on the differentiation and classification of atherosclerotic plaque constituents [1]. A major limitation of this method lies in the fact that manual classification based on several different contrast images is time-consuming, operator dependent, and can only be done by trained personnel. In this study, we report an unsupervised clustering algorithm that can label different constituents in atherosclerotic plaques based on multi-contrast MR images. More specifically, this penalized fuzzy k-means clustering algorithm groups pixels based on their intensity similarity, and includes spatial information as penalty terms in the clustering algorithm.

Methods

The algorithm was applied to eight coronary artery specimens harvested from heart transplant patients. Five of the vessels were imaged 'fresh'; they were imaged in an MR-compatible tissue culture chamber within 24 hours of transplant. The other three vessels were 'preserved'; they were preserved in formalin and kept at room temperature (~20°C) during the imaging session. All vessels were imaged on a 4.7T small animal MR scanner (INOVA, Varian, Inc.). Proton Density Weighted (TE/TR=10ms/2.1s), T2 Weighted (TE/TR=60ms/2.1s) and T1 Weighted (TE/TR=10ms/0.7s) images were obtained with a FOV of 3cm by 3cm, a matrix of 512x256, slice thickness of 1mm and four signal averages. Twenty slices were acquired per vessel.

The penalized fuzzy k-means algorithm for clustering has the following objective function:

$$J_{PFKM} = \frac{1}{2}\sum_{j=1}^{c}\sum_{i=1}^{n} M_{i,j}^{m}\left\|\vec{x}_i - \vec{w}_j\right\|^2 + \frac{1}{2}\alpha\sum_{j=1}^{c}\sum_{i=1}^{n} M_{i,j}^{m}\sum_{\substack{t=1\\ t\neq j}}^{c}\sum_{l\in \text{Neighborhood(i)}} M_{l,t}^{m} - \frac{1}{2}\beta\sum_{j=1}^{c}\sum_{i=1}^{n} M_{i,j}^{m}\sum_{\substack{t=1\\ t\neq j}}^{c}\sum_{l=1}^{n} M_{l,t}^{m}$$

Here, $M_{i,j}$ is the membership function of pixel i to be class j, X_i is the intensity vector of pixel i (I_{T1}, I_{T2}, I_{PD}), W_j is the centroid vector for class j (W_{T2}, W_{T1}, W_{PD}), α and β are positive constants assigning weights to spatial information. The first term of the function is the traditional fuzzy k-means term that grouping the pixels according to their intensity similarity. The second term reduces the membership function $M_{i,j}$ when the neighboring pixels of pixel i have a large sum of memberships in classes other than class j [1]. This term makes the k-means method more noise resistant. The third term increases the membership function $M_{i,j}$ when the neighboring pixels has a small sum of membership in class j. This term preserves the small features in the image. The combination of the last two penalty terms suppresses noise more than the second term alone. By taking the derivative of the J_{PFKM} with respect to W_j with the constraint that the membership of each pixel is summed to one, we can find a numerical scheme for updating the centroids and recalculating the membership function. The updating of the centroids will terminate when the maximal change of the memberships for all pixels is less than a preset error. A detailed algorithm flow chart is shown in figure 1. The initial centroids are chosen as the typical pixel intensity for each tissue constituent, and the initial membership function is estimated purely based on Euclidian distance.

Results

The algorithm was successfully applied to all 160 slices (4 images/slice). All classified results compared well with histological stains for the distribution and morphology of plaque constituents. Figure 2 shows an example of the comparison of histology and classified result. It can be seen that the lipid core is labeled correctly by the PFKM algorithm. Another example of the classified result for a preserved coronary artery is shown in figure 3 along with source images. In this classified result, 5 classes (background, calcium, lipid core, healthy media/connective tissue and adipose fat) are labeled, and are shown in different gray scales. Nulling the background label can provide vessel geometry information (lumen and outer boundary).

Discussion

The traditional fuzzy k-means clustering algorithm is susceptible to noise so it is often hard to detect the correct morphological features. Post processing can reduce the noise but at the same time smoothes out many informative small features, such as a thin fibrous cap and lipid core. The method used in this study includes the spatial information in the penalty terms not only to make classification noise resistant, but also to preserve small features in the image.

References

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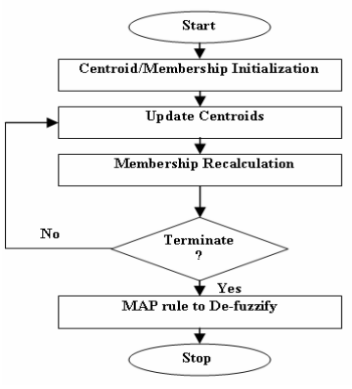

Figure 1. Algorithm Flow Chart

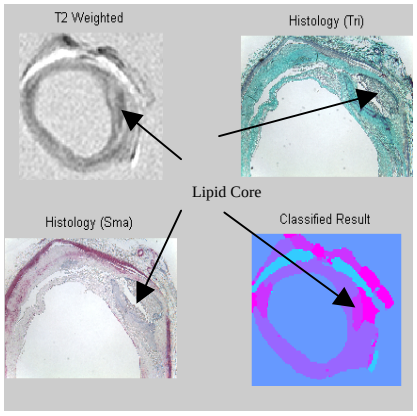

Figure 2. Classification by T2W image alone with histology

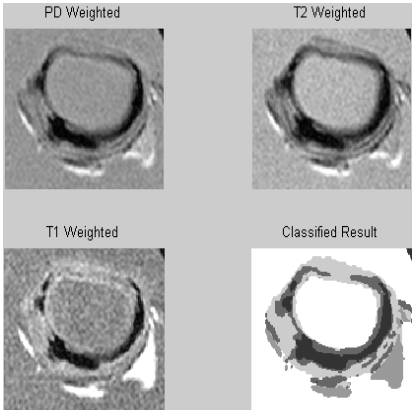

Figure 3. Multi-Contrast MRI of diseased vessel with PFKM result comparison