# Questions and Answers

# Chapter 8

## Questions

(Q1) *What are the motivations and research directions in carotid artery atherosclerosis study?*

(Q2) *Why is the study of constituents within carotid vessel wall very important?*

(Q3) *Technically, what are the unique challenges in MRI obtained from advanced lesions in human carotid arteries?*

(Q4) *What is the region segmentation method applied to single contrast MR image?*

(Q5) *What is the advantage of using the MRF-based active contour model?*

(Q6) *What are the criteria used in selecting the control points for active contour model?*

(Q7) *How is dynamic weighting defined in multiple dimension MRF model?*

(Q8) *What is dynamic mean shift density estimation in clustering multiple dimension data?*

(Q9) *Why is automatic detection of fibrous cap status important?*

(Q10) *What are the primary image features used in automatic fibrous cap detection?*

## Answers

(A1) Histological investigations have tied clinical complications to the existence of vulnerable plaques and shown that certain plaques posed increased danger of causing clinical events. These vulnerable lesions are characterized by a large lipid core that is separated from the vessel lumen by a thin or weakened fibrous cap. Cap rupture is believed to lead to rapid plaque progression and/or patient symptoms. In diagnostic imaging, efforts have been made in at least two directions in the study of plaque features that are believed to be related to clinical outcome, the size of plaque, and its tissue constituents. The focus of the first direction is more on the morphological features such as degree of vessel lumen narrowing and plaque's area/volume. The focus of the second direction is trying to identify the tissue type distribution in plaque, which is the only way to distinguish vulnerable plaques from stable plaques of similar size.

(A2) The study of constituents within carotid vessel wall is based on the evidence that different plaque tissue types yield different vulnerabilities to plaque rupture. Also, the location of plaque tissues, such as the distance to lumen, may play a role in plaque rupture.

(A3) Technically, MRI obtained from advanced lesions in human carotid arteries present unique challenges. (1) *Small size of artery wall*: carotid artery is usually less than 1 cm in diameter. Its dimension is normally about 40 by 40 to 100 by 100 pixels ranges. (2) *Complexity of tissue constituents*: over 10 types of plaque tissues are identifiable within carotid artery wall, including lipid, hemorrhage, calcification, and fibrous tissue among the most clinically important. The plaque constituents may or may not be present, are generally unpredictable in terms of location, and can be intermixed. (3) *Difficulties in tissue separation*: many studies have shown that any individual MR image can only distinguish between a limited numbers of plaque tissues, regardless of contrast weighting. Therefore, a need exists to integrate the information obtained from several different contrast weightings, like T1W, T2W, PDW, and TOF, so as to provide a single representation of all plaque constituents. (4) Special processing requirement on fibrous cap are required.

(A4) The segmentation algorithm applied to single contrast MR images is called Quad-Tree Highest Confidence First (QHCF). Comparing to the original HCF algorithm proposed by Chou and Brown [21], a Quad-Tree procedure is employed to presegment the image instead of using $K$-means. The advantages are as follows: (1) There is no need to predefine the number of classes because the Quad-Tree algorithm can dynamically decide the partitions based on its splitting criterion; (2) $K$-means is a clustering method, in which the grouping is done in the measurement domain and has no spatial connectivity constraint to those pixels with the same label during the iteration process, while in the Quad-Tree splitting process, the grouping of pixels is done in the image spatial domain so that each region will not share labels with others. In addition, QHCF also proposed an optimized energy function with edge constraints included.

(A5) The design of MRF-based active contour model is based on the following assumption: *a successful segmentation is an optimal local contour detection based on an accurate global understanding of the whole image*. This assumption stems from the fact that the global information of an image is generally crucial in local object identification, automatic searching initialization, and energy optimization. In this model, MRF-based segmentation is employed as the solution for global region partition, and then an enhanced version of the active contour model (ACM) and minimum path approach (MPA) is adopted for the basic region boundary tracking. A new scheme is designed to find ACM initial points based on the MRF region segmentation results so that it can automatically provide initialization. This model provides reliable and flexible solution for object tracking.

(A6) The labeling process of each pixel in an MRF model is decided by the maximum *a posteriori* probability (MAP), $\max\{p(x_i \mid y), i = 1, 2, \ldots, N,$ where $N$ is the number of labels$\}$. To reach the optimal contour tracking, it is necessary to select those most reliable ones as control points and search the other object boundary points by adhering to MPA constraints. Assume the boundary of the object of interest is divided into $M$ sections and section $m$, $0 < m \leq M$, contains $i_m$ total points. To simplify the problem formulation, we considered only the boundary points that have one adjacent region (they belong to another region). Suppose a particular boundary point is labeled $p$, its adjacent region's

label is $q$, the *a posterior* probability of this point with label $p$ and $q$ can be expressed respectively as

$$p(x_s = p|y) \propto \exp\left\{-\left(y_{i_m} - \mu_p\right)^2 - \sum_{s\in S_{i_m}} \left[U_N\left(x_s = p\right) + U_E\left(x_s = p\right)\right]\right\},$$

$$p(x_s = q|y) \propto \exp\left\{-\left(y_{i_m} - \mu_q\right)^2 - \sum_{s\in S_{i_m}} \left[U_N\left(x_s = q\right) + U_E\left(x_s = q\right)\right]\right\}.$$

Assume this point belongs to region with label $p$, it is obvious that its *a posteriori* probability with label $p$ should always have higher value than that with its adjacent region's label $q$. In a real MR images, noise affects the capturing process in boundary regions making the above assumption invalid. Distortion due to noise can blur edges and create a lack of separation in the *a posterior* probabilities of the true "edge points." To assure good measurement of the probability difference, reliability of boundary points is defined as

$$r(s) = 1 - \left[p\left(x_s = p|y\right) - p\left(x_s = q|y\right)\right].$$

The value of the reliability is within the range $[0, 1]$. If $s$ from the segmented contour is more likely to be a boundary point, its *a posteriori* probability with label $p$ and $q$ will be quite similar. It then leads to the value of $r(s)$ being closer to 1 and makes point $s$ more reliable. Therefore, in the control point searching process, we use *maximum reliability* as a criterion, which can be expressed as

$$s = \max_{0<i\le i_m} \left\{r(s_i)\right\}.$$

(A7) In multichannel data/image processing, different channels usually convey different amount of information. However, since there is no prior knowledge about the tissue type sensitivity layout in each channel, it is very impractical for human interaction involved in the segmentation process. In this study, a dynamic weighting system is proposed as a simulation of human's decision process, which automatically decides the weighting coefficient for the energy calculation among channels. Two factors are significant in managing the dynamic weighting:

1. *Complexity factor* (CF): It measures the amount of details that each channel provides at a certain location. In the surrounding region of

each location, it is assumed that the complexity is proportional to the number of edges. Based on the requirements of segmentation performance, two ways are proposed to evaluate the complexity factor.

(i) *Local CF*: The number of edge points within a local neighboring region in each channel.

(ii) *Global CF*: The number of edge points in the whole image in each channel (it is equivalent to local CF with neighboring range as the whole image).

2. *Weighting factor* (WF): It is used to calculate the exact weighting of each channel based on the measurement of complexity factor. Assume the complexity factor from each channel is represented as follows: $CF_i$, $i = 1, 2, \ldots, d$, the weighting factor is denoted as

$$WF_i = \frac{CF_i}{\sum_{i=1}^{d} CF_i},$$

and the clique energy at each locataion $V_s(x)$ can be computed as

$$V_s(x) = \sum_{i=1}^{d} WF_i \left[ V_{sN,i}(x) + V_{sE,i}(x) \right].$$

(A8) In previous mean shift methods, the size of the local estimation sphere is always fixed. This may not work well in locations where the density distribution is relatively uniform or very close to the mode. To solve these problems, a *dynamic search range* is proposed with multiple levels; at each level, a different searching radius is selected. In the search process, the initial radius starts from the largest radius. If the mean-shift vector is over the stopping threshold $T_{\text{stop}}$, it moves to the next location with the same sphere radius as the previous position. If the mean-shift vector is lower than $T_{\text{stop}}$, it uses the next smaller radius to calculate the mean-shift vector again. Once the mode is found, a small perturbation is applied and the procedure is repeated to avoid a local maximum.

(A9) The important cause of stroke and heart attacks is thrombogenic material from arterial walls initiating thrombosis or embolism in the carotid and coronary arteries respectively. The fibrous cap separates thrombogenic material of the atherosclerotic plaque such as lipid in the plaque core

from the blood stream. Thinning and rupture of the fibrous cap leads to vascular events by allowing the contents of the plaque core to come in contact with the blood. Thus fibrous cap rupture is the most significant event in the pathogenesis of atherosclerosis. By automatically detecting whether the cap is rupture prone, treatment modalities can be targeted to patients at high risk. Automatic detection will allow a quantitative index to be developed for risk stratification.

(A10) A thick cap is identified by the presence of a dark band on 3-D TOF MR. A thin cap is identified by the absence of the dark band, while a ruptured cap shows a focal contour abnormality of the lumen surface in addition to the absence of the dark band. Other markers of rupture such as intraplaque hemorrhage and luminal thrombus, inferred from multiple contrast weightings, are also used by radiologists to classify fibrous cap status.