Questions and Answers

Chapter 4

Questions

(Q1) *What are the physical characteristics of helical CT scans that may impact CAD algorithm design and performance?*

(Q2) *What are the clinical characteristics of pancreatic cancer that may impact CAD algorithm design?*

(Q3) *What is the general approach for image segmentation of medical images?*

(Q4) *Advantages and disadvantages of unsupervised, supervised, and semi-supervised clustering methodologies for image segmentation.*

(Q5) *What is FCM and when is it used for image segmentation? List any advantages over classical segmentation techniques.*

(Q6) *What are the differences between FCM and ssFCM? List advantages and disadvantages of the two techniques.*

(Q7) *List methods that can be used for the optimization of FCM for image segmentation.*

(Q8) *What are the metrics used for the validation of a segmentation output?*

(Q9) *What are the major limitations and problems associated with the validation of segmentation algorithms in medical imaging applications?*

(Q10) *What are the statistical tools used for the analysis of the segmentation results including tools to determine the agreement between different algorithms and observers or within groups.*

Answers

(A1) Physical characteristics of the helical CT scans that may influence CAD algorithm design and performance include: slice thickness, slice separation or incrementation (step or index), image spatial and dynamic resolution, exposure parameters (kVp and mAs) including the Hounsfield unit(s), pitch, contrast material, reconstruction algorithms and reconstruction interval. Scanners from different manufacturers have similar characteristics but not identical. Their properties should be known and well understood for the development of image processing techniques.

(A2) There is variability in the imaging characteristics of pancreatic tumors on CT images that increases detection and diagnostic difficulty relative to other organ abnormalities. Most characteristics are reported for the pancreatic adenocarcinoma because it is the most common type of pancreatic cancer and, hence, the one most seen and better understood. Pancreatic adenocarcinoma characteristics include: (a) generally isodense appearance relative to normal pancreatic tissue in enhanced studies but also abrupt changes in density within the gland due to the presence of a mass, (b) distortion of the smooth gland shape and disruption of the fat plane that is usually present around the gland, (c) change in the size of the pancreas, (d) duct dilation that is the most significant consequence of adenocarcinoma and is one of the most important associated clinical findings.

(A3) Methods commonly reported for the segmentation of CT images include pixel based (usually thresholding), edge-based, region-based, and clustering techniques. Segmentation results are usually improved by preprocessing the images to (a) remove artifacts or unwanted signal(s) and (b) enhance contrast or reduce image noise with various techniques from the spatial or frequency domains. Spatial domain preprocessing methods include histogram equalization, logarithmic transformation, image smoothing, and image subtraction to name a few. In the frequency domain, low pass, high pass, and band pass filters are commonly employed for image smoothing and sharpening.

(A4) Unsupervised clustering techniques: The advantages of these methods are that there is no need for training or labeled data and no need of *a priori* knowledge about the image; the number of clusters is obtained without specifying them as inputs. The disadvantages are that there are usually several misclassified pixels in the results, the computational cost of these algorithms is very high, the segmented image may not have the desired number of classes or clusters for further analysis or computation, and that user intervention is required in assigning classes to rows.

Semi-supervised clustering techniques: The advantages of these methods are that fewer pixels are misclassified with these algorithms relative to the unsupervised approaches, the segmented image has exactly the desired number of clusters or classes and the computational cost is significantly reduced compared to the unsupervised techniques. The disadvantages are that user intervention is required for partially labeling the data, the number of clusters or classes should be given as input during initialization, and the cost of obtaining good training data is usually very high.

Supervised clustering techniques: The advantage of these algorithms is that they can perfectly classify all the pixels of an image into the right clusters. The disadvantages are that expert user intervention is required to label the entire dataset, data labeling is a very time consuming and very expensive procedure to follow when the dataset is large, and it is nearly impossible when medical information is involved.

(A5) Fuzzy C-Means (FCM) clustering is a method where image pixels with similar characteristics are clustered (grouped) together based on conditions that measure the similarity of a pixel to the characteristics of the cluster. FCM allows a pixel to be a member of different clusters by assigning a weight from 0 to 1; the higher the weight, the higher the likelihood that the pixel belongs to that particular cluster. The pixel similarity concept of FCM is particularly attractive in medical imaging where irregularity and fuzziness of organ margins and unclear separation of organ boundaries are commonly encountered.

(A6) FCM does not require data labeling prior to clustering. In contrast, semi-supervised (ssFCM) requires that a small subset of the data is properly labeled in clusters prior to clustering. General advantages and disadvantages are the same as those mentioned above for the unsupervised and semi-supervised clustering methods. The additional requirement of ssFCM is that a C-means weight needs to be added for the labeled data to avoid merging small with large clusters.

(A7) FCM clustering may be optimized by using validity-guided clustering processes that check the quality of the clustering results and determine the correct number of clusters in a dataset based on cluster compactness and separation. Knowledge-based systems and genetic algorithms are also used for optimizing FCM performance.

(A8) Commonly used metrics for validating clustering or segmentation results include: (a) Hausdorff distance between two contours of the same object, (b) the degree of overlap between the areas encompassed by two contours, (c) the mean absolute contour distance, which is a one-to-one correspondence between the points of the two contours. All these metrics require the existence of a “gold standard” or “ground truth information” for the object or area of interest to which the segmentation algorithm’s output is compared.

(A9) Segmentation validation requires a “gold standard” or “ground truth information” about the size and shape of the object of interest. This is usually the weakest link in the validation of the segmentation of medical data. In the majority of medical imaging applications, human experts establish ground truth information and, as a result, there is always the risk of introducing bias and significant inter- and intra-observer variability. An alternative to observer-generated ground truth information is to use simulation and phantom models to evaluate results and measure performance that could then be extrapolated to real clinical data. Given the nature of the ground truth information, identifying the right metric(s) for the validation of the results is another challenge in medical image segmentation.

(A10) Statistical tools commonly used for the analysis of segmentation results include: (a) linear regression analysis to study the relationship of the means in various segmentation sets, (b) paired t-test to determine the agreement between the computer methods and the experts, (c) Williams index to determine inter-observer or inter-algorithm variability, and (d) ROC or FROC or LROC analysis to measure clinical performance.