Questions and Answers

Chapter 7

Questions

(Q1) *Why do usual shade correction algorithms darken pixels close to bright objects?*

(Q2) *How can this darkening effect be prevented?*

(Q3) *What is the difference between an algebraic and a morphological closing?*

(Q4) *How can dark details in a gray scale image be extracted using Mathematical Morphology?*

(Q5) *How can dark details with a maximal extension of λ be extracted?*

(Q6) *How does the use of markers in the watershed transformation work and what is their influence on the result?*

(Q7) *How can the watershed transformation be used for the detection of thin dark lines in a gray scale image?*

(Q8) *How can the watershed transformation be used for the detection of object contours?*

(Q9) *Which morphological operator can be used for removing bright objects preserving the borders of all remaining objects?*

(Q10) *In the analysis of fundus images, specificity cannot be used for an assessment of the quality of a pathology detection algorithm. Why?*

Answers

(A1) Shade correction algorithms calculate the difference between an image f and a background approximation $A(f)$:

$$[SC(f)](x) = f(x) - [A(f)](x) + c$$

The background approximation $A(f)$ is often calculated by means of large low pass filters, for they remove smaller details, giving a good approximation of the slow gray level changes. However, also bright objects are blurred and for background pixels close to these objects the difference between the blurred image and the original one is therefore negative. Hence, these pixels are darkened.

(A2) The darkening of background pixels close to bright objects is indeed a systematic source of false positives in feature and lesion detection. In fact, large bright or dark objects should not be considered as "background". Hence, one possibility to resolve this problem is to remove all bright patterns that do not correspond to illumination changes from the image before calculating the background approximation. This can be achieved by means of an area opening, a diameter opening, or—even simpler—an opening by reconstruction.

(A3) An algebraic closing is an increasing, extensive and idempotent transformation. A morphological closing is the successive application of dilation and erosion; it is therefore associated to a structuring element B. It "fills" all the depressions (dark details) that cannot contain the structuring element. A morphological closing is an algebraic closing, but an algebraic closing is not necessarily a morphological closing. However, it can be shown that any algebraic closing can be written as the infimum of morphological closings with a class of structuring elements.

(A4) Dark details can be extracted from a gray scale image f by the top-hat transformation $\vartheta f = \phi f - f$. The closing ϕ "fills" the depressions, i.e. it removes the dark details. Hence, these details are extracted by building the difference between closed and original image. ϕ can be an arbitrary closing, e.g. a morphological closing. A top-hat transformation associated to a morphological closing with a circular structuring element extracts all dark details in an image into which the structuring element does not fit. Indeed, the tricky part is to use (or conceive) a closing that removes only the details to be extracted and that lets the other dark details unchanged.

(A5) The top-hat strategy can be applied to this problem. The closing to use has to fill all "holes", i.e. to remove all dark details, in a gray scale image whose maximal extension is lower than λ. This cannot be achieved by a morphological closing. For the binary case, it is simple to determine the maximal extension of each connected component in the image, and to remove all among them with a diameter lower than λ. For gray scale images, a flooding simulation is used: The image is flooded from its local minima and each basin is filled up to the level where its diameter is larger than or equal to λ. This operation can be efficiently implemented by means of hierarchical queues.

(A6) The watershed transformation produces a partition of the image, where there is one region (catchment basin) per local minimum. Unfortunately, there are often many parasite minima due to noise or irrelevant features. The sense of using markers is to reduce the number of minima and to keep only the important ones. There is no general method to find a marker; it can be found interactively, using other sources, or by filtering and raw segmentation procedures. Once the marker is determined, the reconstruction by erosion is calculated; in the result image, all non marked minima are removed.

(A7) First, the dark details have to be extracted using the morphological top-hat transformation associated to a morphological closing. In the top-hat image, the thin structures correspond to crest lines; these crest lines can then be found by means of a marker controlled watershed transformation. The watershed lines delimit the catchment basins, but the thin structures do not necessarily enclose regions. As a consequence, we have a lot of false positives due to this special character of the watershed transformation. Considering the branches of the watershed lines separately, we can calculate the difference between the mean gray level on the branch and the mean gray level on the adjacent regions. For thin structures, this difference must be relatively high. In this way, it is not difficult to remove false positives from the result.

(A8) When we want to find the contours of an object, it is necessary to work on a gradient image. A gradient image represents gray level changes in the original image and therefore, the object contours correspond to crest lines. Then, two markers have to be found: An internal marker (one per object) and an external marker which is completely outside the object. Only in this way, the lakes built by the flooding process meet at the contours of the object (the crest lines of the gradient).

(A9) An excellent morphological filter that does not alter the contours of remaining objects is the opening by reconstruction:

$$\psi(f) = R_f\big(\varepsilon^{(sB)}(f)\big)$$

This operator has been used in this chapter for the filtering of the optic disc: The image f is first eroded by the SE B of size s. The erosion removes all bright object that cannot contain the SE, but it also alters the contours, it reduces bright regions and it enlarges dark ones. By successive dilation and intersection with the image f (now mask), the reconstruction enlarges εf (marker) horizontally until it is "blocked" by f, but it does not enlarge it vertically. This means that only elevations completely razed by the opening will not be reconstructed, the contours of all other features remain unchanged.

(A10) In contrast to classification problems, the number of true negatives, i.e. the number of correctly classified non-pathological patterns cannot be determined in detection problems. In the case of the detection of exu-dates for instance, we could consider any correctly labeled non-exudative pixel as true negative. This would give a specificity of about 100%, and it would be completely meaningless. Another possibility is the definition of sensibility and specificity for the set of candidates, as it is done in some publications. Indeed, this allows one to define true negatives, but unfortunately, the specificity obtained in this way is not the specificity of the algorithm, but the specificity of the post-candidate-detection part of the algorithm (normally the classification step). With other words: If an algorithm finds in a first step more candidates and removes them afterwards, it will have a better specificity in accordance with this definition. This is not reasonable. Hence, specificity cannot be used for the evaluation of the algorithm's quality.