

# 1 General Notes

## 1.1 Image

### 1.1.1 Image Types

1. Pathology images
2. Fluorescence microscopy
3. Confocal images
4. H&E stained cancer images

### 1.1.2 Microscopy Models

1. Bright field
2. Fluorescence
3. Phase contrast

## 1.2 Random Summary

Seems a lot of the problems w/ different models are parameter selection. And usually, we can use some adaptive methods to optimally choose the parameter.

**Mechanism**

**Advantage**

**Disadvantage**

**Improvement**

**Further**

## 2 [1]

## 3 [2]

### 3.1 Detection

#### 3.1.1 Distance Transform

**Mechanism** Local maxima = centroids of nuclei or cells. Often paired with "Watershed Segmentation".

**Advantage**

**Disadvantage** Only effective on regular shapes in a binary image. Susceptible to small changes. Complex image  $\rightarrow$  variations  $\rightarrow$  over-detection.

**Improvement** Gaussian filter, then trace gradient vector field. Accumulated pixels threshold to distinguish b/w local and non-local maxima.

**Further** Lin et al. gradient weighted-distance transform for 3D fluorescence image.

### 3.1.2 Morphology Operation

**Mechanism** Binary morphological filtering for images w/ certain structure element, circle, square, cross... Examining the geometrical and topological structures of objects w/ predefined shape. Four basic shift-invariant operators:

1. Erosion
2. Dilation
3. Opening
4. Closing

The four can be used to generate more basic morphological operations, boundary, hole, skeletonizing... Binary morphology can be extended to gray-scale morphology. Widely used operators: top-hat, bottom-hat transforms. For example, UE (Ultimate Erosion). Erosion until can't.

**Advantage** Can be used to basic image enhancement, preparing for further analysis. UE: can separate touching or overlapping cells.

**Disadvantage** UE: can produce multiple marker for each cell.

### Improvement

1. Improved UE, Park et al. noise robust stopping criterion. Perform until convex. However, binarization.
2. Conditional Erosion: Yang et al. Coarse erosion preserves shapes, and fine erosion avoids under-segmentation

### Further

Hodneland 3D fluorescence images. Adaptive threshold for ridge extraction, then link gaps.

Plissiti gray-scale, not converting.

### 3.1.3 H-minima/maxima Transform

**Mechanism** Based on morphology operation, used in local minima detection. Image  $A$ , depth value  $h$ ,  $H(A, h) = R^\epsilon(A + h)$ , where  $R^\epsilon$  is reconstruction by erosion. Some regional minima are suppressed. Initially connected parts can be split in terms of the detected minima,  $h$  leads to under/over-segmentation. Usually used to generate markers for watershed transform based segmentation.

**Advantage** Compared with DT (EDT), all minima  $\rightarrow$  H-minima. Very popular in biomedical images.

**Disadvantage** Suppress minima, so needs enhancement beforehand. Properly defined  $h$  value is needed.

#### **Improvement**

1. Adaptive HIT., iteratively increase  $h$  until a region merging. Ignores nucleus size.
2. Jung and Kim, adaptively choose  $h$  to minimize segmentation distortion.
3. Variance in cell areas.

#### **Further**

##### **3.1.4 LoG, Laplacian of Gaussian**

**Mechanism** In medical image analysis, LoG is one of the most popular for small blobs.

#### **Advantage**

#### **Disadvantage**

1. Might fail in touching / overlapping objects.
2. Scale issue.

#### **Improvement**

1. Lindeberg introduces normalizing factor for multiscale LoG blob detector.
2. Kong generalized LoG, for elliptical structures (oblique elliptical Gaussian)
3. Hessian analysis to identify optimal scale
4. Unsupervised GMM can be used to refine blobs

#### **Further**

##### **3.1.5 Maximally Stable Extremal Regions**

**Mechanism** Maximally Stable Extremal Regions. Set of nested extremal regions based on level sets in the intensity landscape. Local intensity minimum-based criterion.

1. Generate sufficient number of extremal regions.
2. Recognize those regions corresponding to real nuclei or cells.

- (a) Eccentricity
- (b) Blob appearance + shape properties
- (c) Arteta formulates an optimization problem, candidates - $i$  scores - $i$   
DP for maximal total score
- (d) Multilevel thresholding

**Advantage**

**Disadvantage**

**Improvement**

**Further**

### 3.1.6 Hough Transformation

**Mechanism** Circular/elliptical nuclei in pathological images. From  $xy$ -plane transform to circular  $a, b, r$  parameter space. Discrete voting strategy? Most votes corresponding to parameter? Locate the targets by seeking peaks in parameter space (e.g. gradient descent).

**Advantage**

**Disadvantage** False peaks due to noise, incorrect edge extraction, touching objects. Further analysis is needed.

**Improvement** Gaussian smoothing to denoise, morphology operations to reconstruct. SVM classifier. Optimization problem can be solved by some ILP.

**Further**

1. Can deal with arbitrary shapes.
2. 3D transformation can be done.
3. Randomized version

### 3.1.7 Radial Symmetry Based Voting

**Mechanism** Locate the centroids of nuclei or cells. High radial symmetry points highlighted.

**Advantage**

**Disadvantage** High computational complexity. False peaks due to clustered nuclei. Radius range. What if not circular?

**Improvement** FRST. Candidates, thresholding. Affine transform to deal with non-circular.

## **Further**

**3.1.8 SVM**

**3.1.9 Random Forest**

**3.1.10 DNN, esp. CNN**

## References

- [1] L. Chen, L. L. H. Chan, Z. Zhao, and H. Yan, “A novel cell nuclei segmentation method for 3d c. elegans embryonic time-lapse images,” *BMC Bioinformatics*, vol. 14, p. 328, Nov 2013.
- [2] F. Xing and L. Yang, “Robust nucleus/cell detection and segmentation in digital pathology and microscopy images: A comprehensive review,” *IEEE Reviews in Biomedical Engineering*, vol. 9, pp. 234–263, 2016.