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AUTOMATED GLAND SEGMENTATION AND CLASSIFICATION FOR GLEASON GRADING OF PROSTATE TISSUE IMAGES

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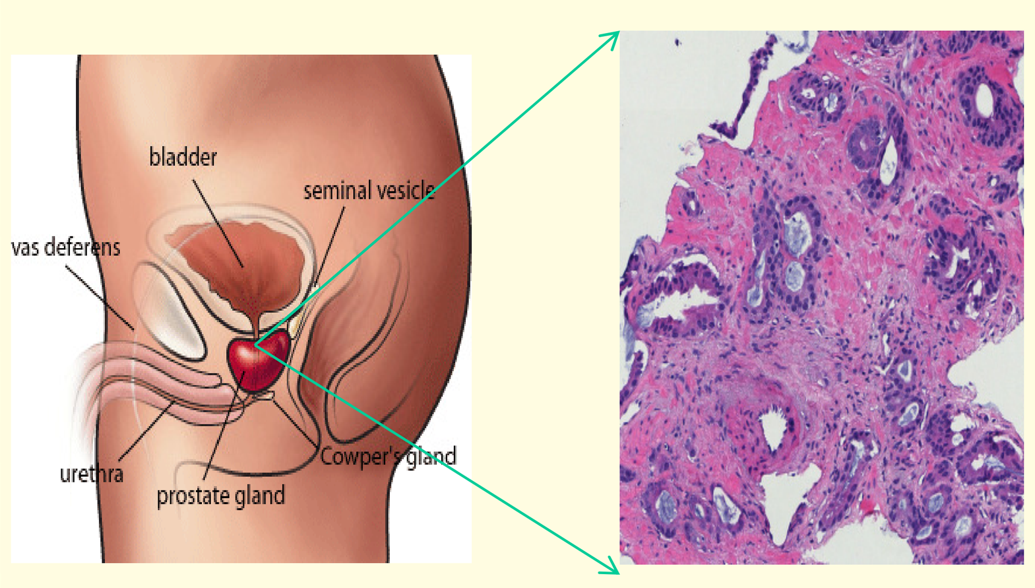
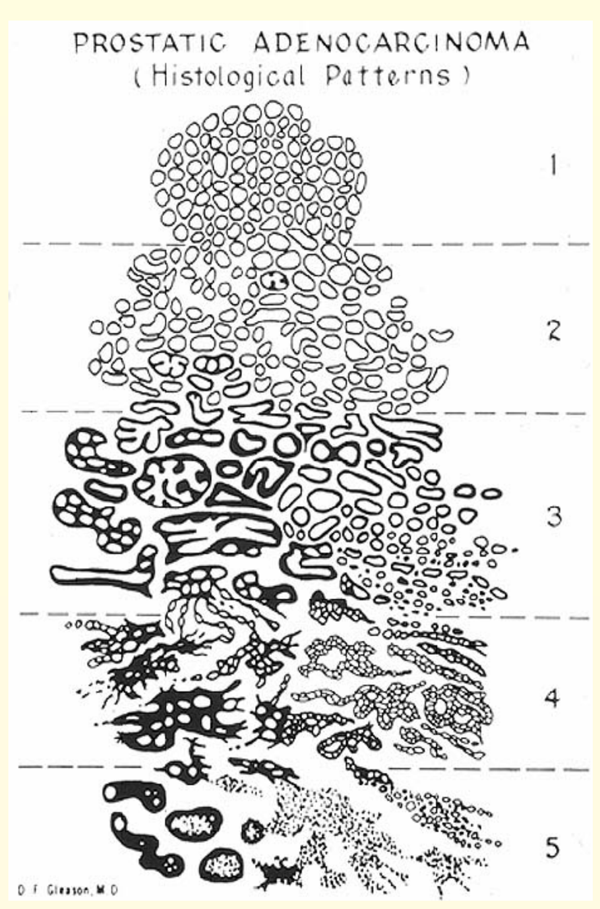
Abstract

The well-known Gleason grading method for an H&E prostatic carcinoma tissue image uses morphological features of histology patterns within a tissue slide to classify it into 5 grades. We have developed an automated gland segmentation and classification method that will be used for automated Gleason grading of a prostatic carcinoma tissue image. We demonstrate the performance of the proposed classification system for a three-class classification problem (benign, grade 3 carcinoma and grade 4 carcinoma) in this research.

Prostate Cancer

According to the 2005 United States Cancer Statistics (USCS), prostate cancer is the most prevalent among the top ten cancer types.

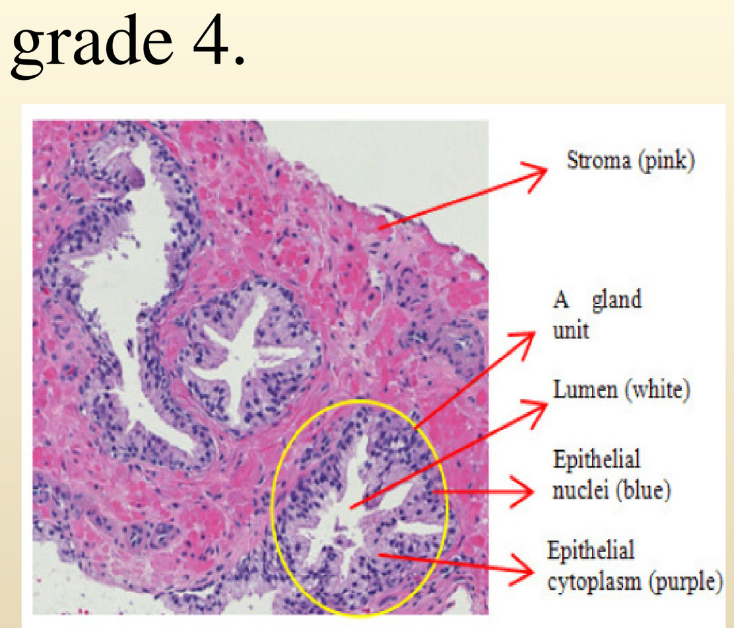




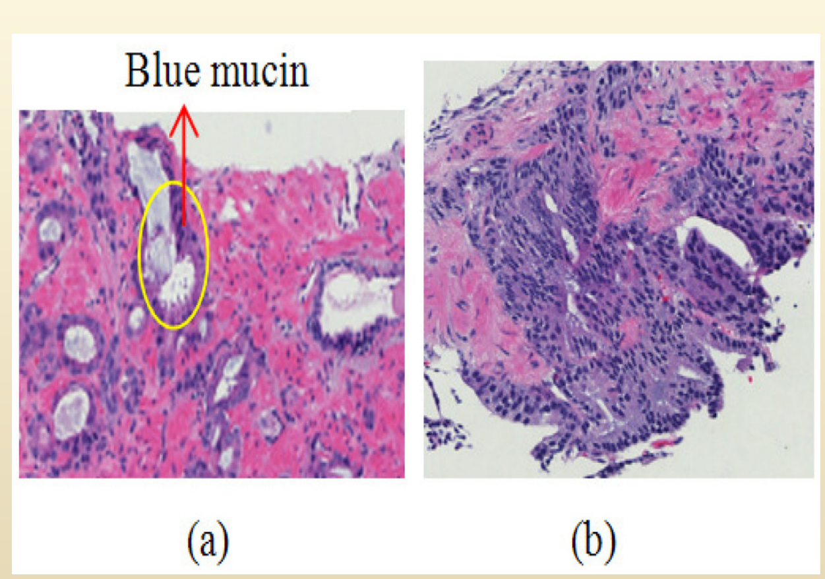
Gleason grading for prostate cancer

Gleason grading method uses morphological features of histology patterns to classify a prostate tissue into 5 grades of cancer.

Our automated grading system currently classifies a tissue pattern into three classes: benign, grade 3 and grade 4.



Benign pattern & gland structure



Grade 3 (a) and grade 4 (b) carcinoma

Related work

Two types of approaches in the literature:

1). Texture-based approach: Use image texture for classification**.**

Diamond et al. divided the tissue image into sub-regions of size 100x100 to classify each into: normal tissue, stroma or prostatic carcinoma (Pca). Haralick texture features were used to classify between stroma and PCa. An accuracy of 79.3% was reported.

Doyle et al. extracted textural and wavelet features at multiple image scales and combined these features by AdaBoost algorithm. They performed two-class classification (cancer vs non-cancer) and reported 88% accuracy.

2) Gland segmentation-based approach:

Naik et al. first detected basic elements of a gland including lumen, nuclei, cytoplasm based on their color using a Bayesian classifier. Then, lumen objects were identified and the inner boundary of the glands is found by Level set method. The shape features were used to build a SVM classifier with the following classification results: grade 3 vs. benign (86.3%), grade 4 vs. benign (92.9%), grade 3 vs. grade 4 (95.2%).

Proposed gland segmentation technique

Three main stages:

1)Pixel classification

Each pixel is represented by a 3-component feature vector in La*b* color system. We use a nearest neighbor classifier to classify a pixel (x,y) as $L(x, y) \in \{S,L,N,C,M\}$, where S,L,N,C,M correspond to stroma (pink), lumen and non- tissue area (white), epithelial nuclei (dark blue), epithelial cytoplasm (purple) and blue mucin (light blue).

2) Gland boundary extraction

Gland boundary consists of nuclei intermixed with cytoplasm, so we need to unify cytoplasm pixels and nuclei components of the same gland together to construct the gland boundary.

Let W_i be a window of size $S_1 \times S_1$ centered at the nuclei component N_i. A cytoplasm pixel c_j and a nuclei component N_i are unified, denoted as Unified(c_j ,N_i) provided:

(i) $c_j \in W_i$ and

(ii) $card\{L(x, y) = N, (x, y) \in W_i\} > T_1$, where T_1 is a nuclei density threshold.

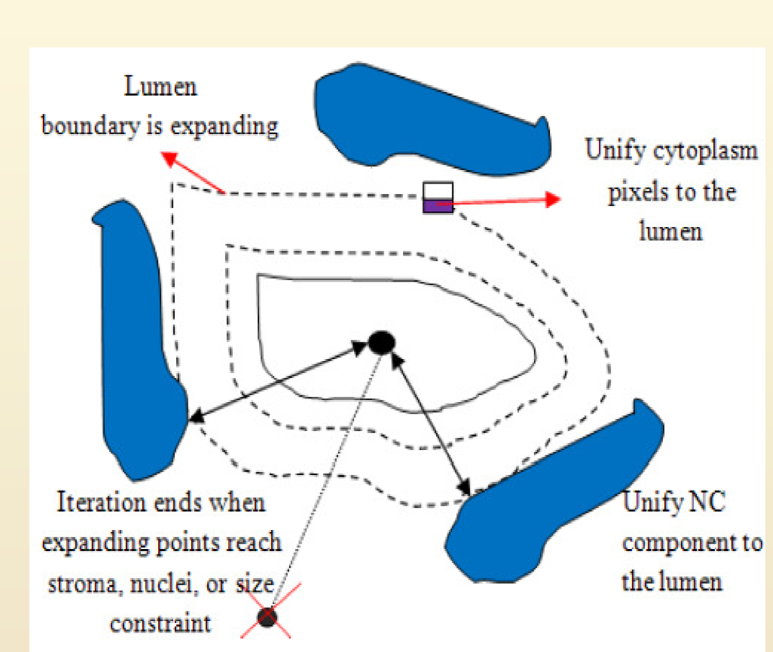
Two nuclei components N_i and N_j are unified if one of the following two conditions hold:

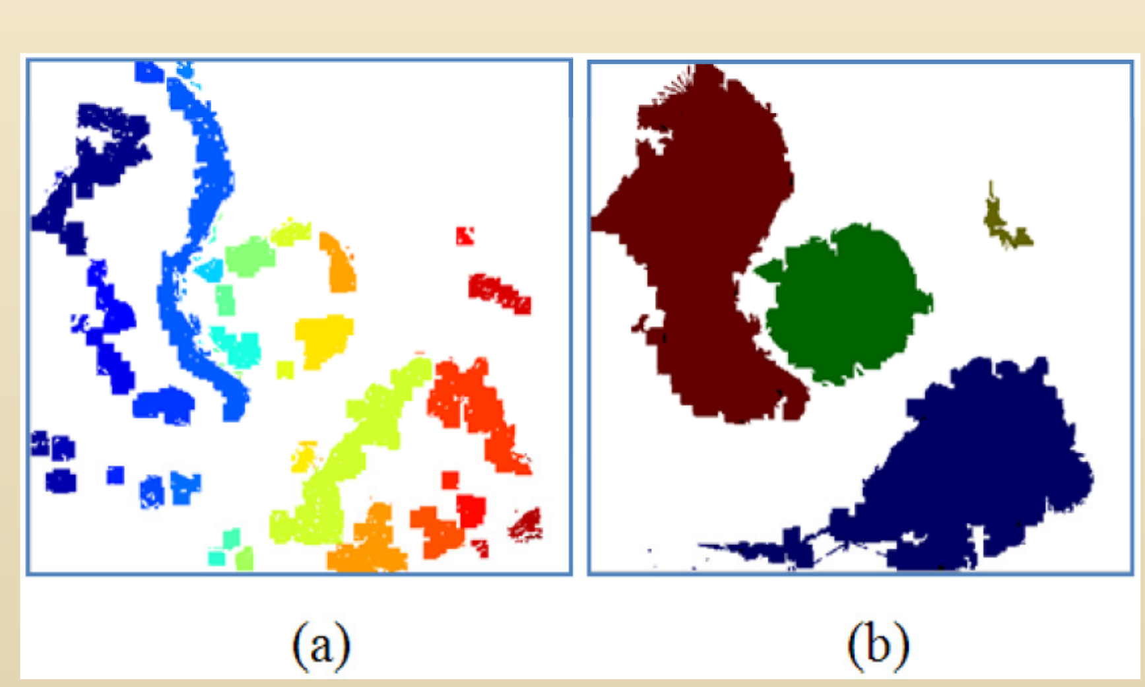
(i) There exists a cytoplasm pixel c_k such that Unified(c_k,N_i) and Unified(c_k,N_j) hold true

(ii) There exists a chain of nuclei components $\{N_{i+1}, N_{i+2}, . . . , N_{j-1}\}$ such that Unified(N_i,N_{i+1}), Unified(N_{i+1},N_{i+2}), . . . , and Unified(N_{j-1},N_j) hold true.

3) Complete gland construction

We develop a lumen expanding algorithm to unify the lumen and gland boundary components to form the final gland





Gland segmentation result : (a) Gland boundary extraction; (b) Complete gland construction.

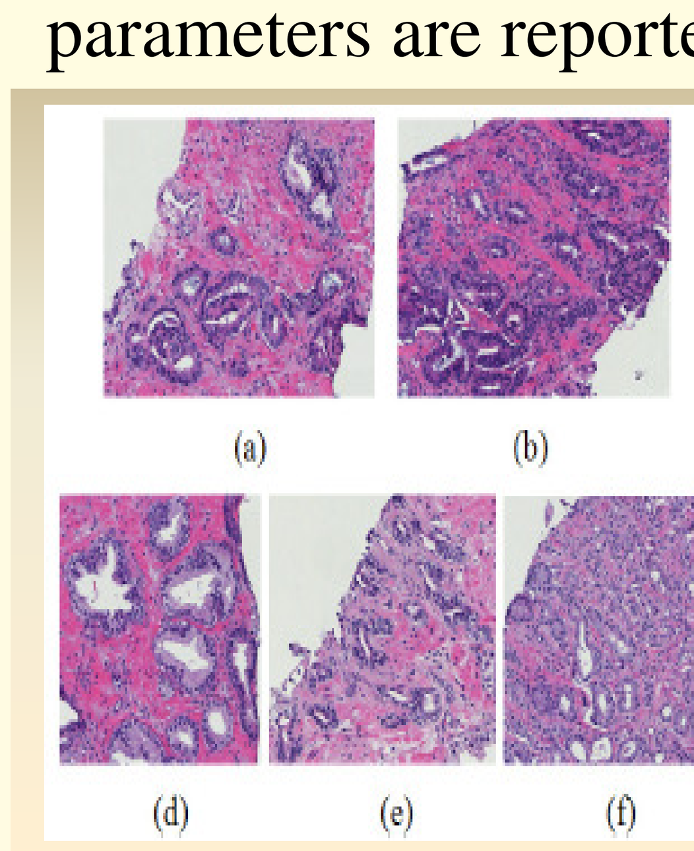
Feature extraction

Feature type	Feature description
Ten lumen features	Average, variance, max of lumen area; average, variance, max of lumen perimeter; average and variance of lumen roundedness; number of lumen and ratio of lumen area to total segment area.
Two nuclei features	Nuclei density and ratio of nuclei area to total segment area.
Two gland size features	Average and variance of the distances from the lumen center to the nuclei boundary
Blue mucin feature	Ratio of blue mucin area to total segment area.

Experimental results

Dataset: The dataset was created by selecting sub-images of benign (30), grade 3 (28) and grade 4 (20) carcinoma patterns from 52 10x whole-slide images with an average size of 90,000 x 45,000 pixels. The average size of each sub-image is approximately 501 x 526 pixels.

Experimental Setup: A number of classifiers (SVM, Neural Networks and K-NN) were used. The mean and variance of the classification accuracy over 10 different runs of 10-fold cross validation for the best parameters are reported.



Classification examples

Misclassifications: (a) Grade 3 is classified as grade 4; (b) grade 4 is classified as grade 3.

Correct classifications: (d) Benign; (e) grade 3 carcinoma; (f) grade 4 carcinoma.

A best-first-search feature selection is done to get the best subset of 9 features.

Three-class classification: Best result is 88.4% accuracy with 6.2% variance using Neural Network (16 hidden nodes).

Baseline: To compare our results with Doyle et al. and Naik et al., we also solved the four two-class classification problems.

Classification Problem	Accuracy (Variance)
Benign vs. Grade 3	97.8% (1.35%)
Benign vs. Grade 4	94.0% (3.55%)
Grade 3 vs. Grade 4	87.3% (0.43%)
Benign vs. Carcinoma (grades 3 and 4)	98.6% (0.16%)

Work being accepted by ICPR 2010