Finding Dots: Segmentation as Popping Out Regions from Boundaries

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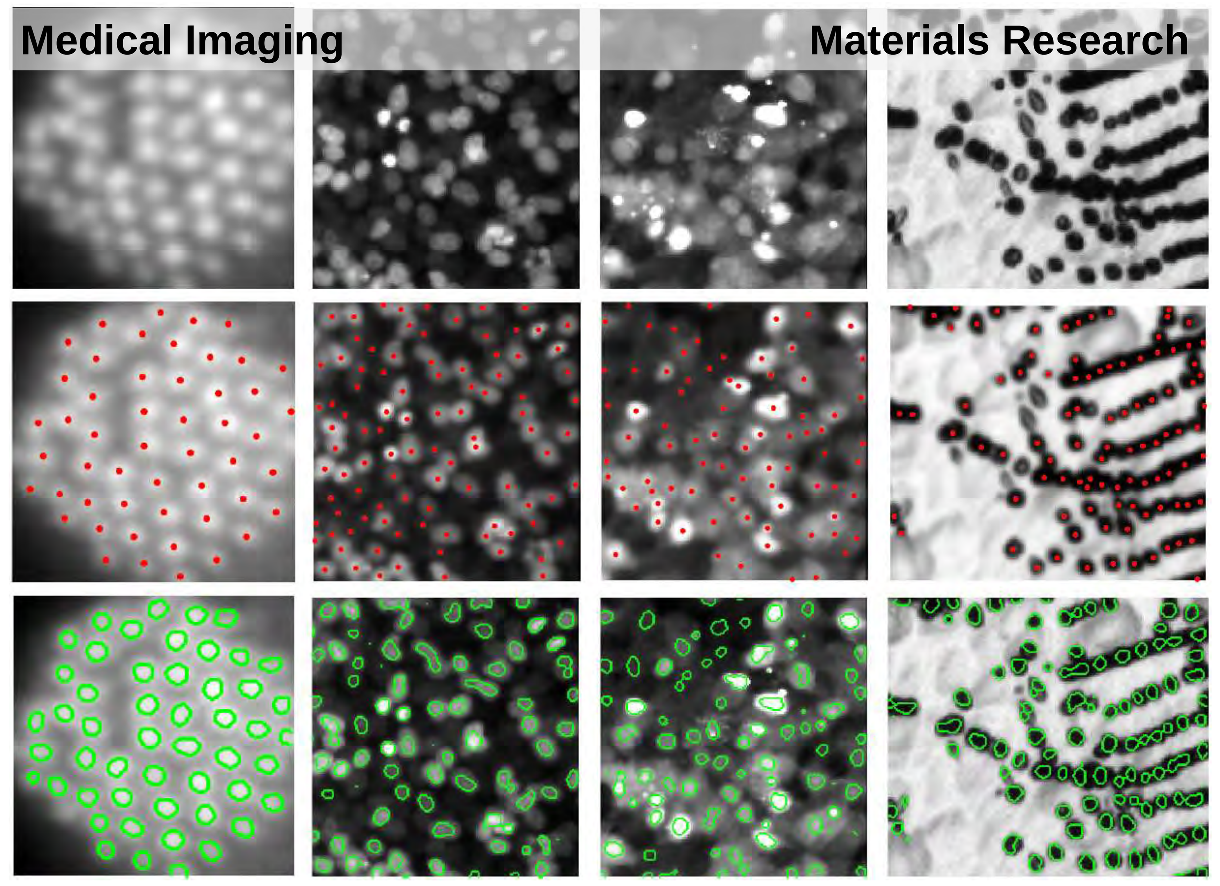
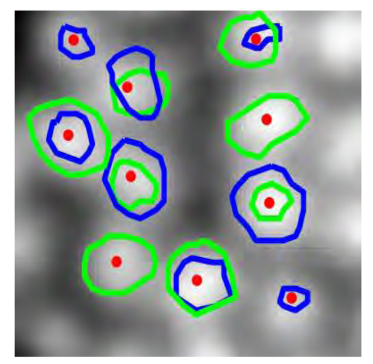
Why 'Dots'? 'Dots' are Everywhere!

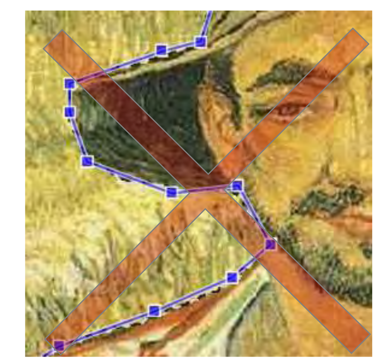


Challenges
- → Poor imaging quality
- → Large intensity variation
- → Occlusion
- → Conjunction between dots



Flexible boundary

Vs.



Precise Cutout
[Li et al., Lazy Snapping, SIGGRAPH 2004]

Region Popout Approach

Intuition

Popout regions in a two-way segmentation
- Boundaries are flexible
- Use local geometry: convexity cues
- Use foreground/background perception to drive segmentation: short-range attraction & long-range repulsion

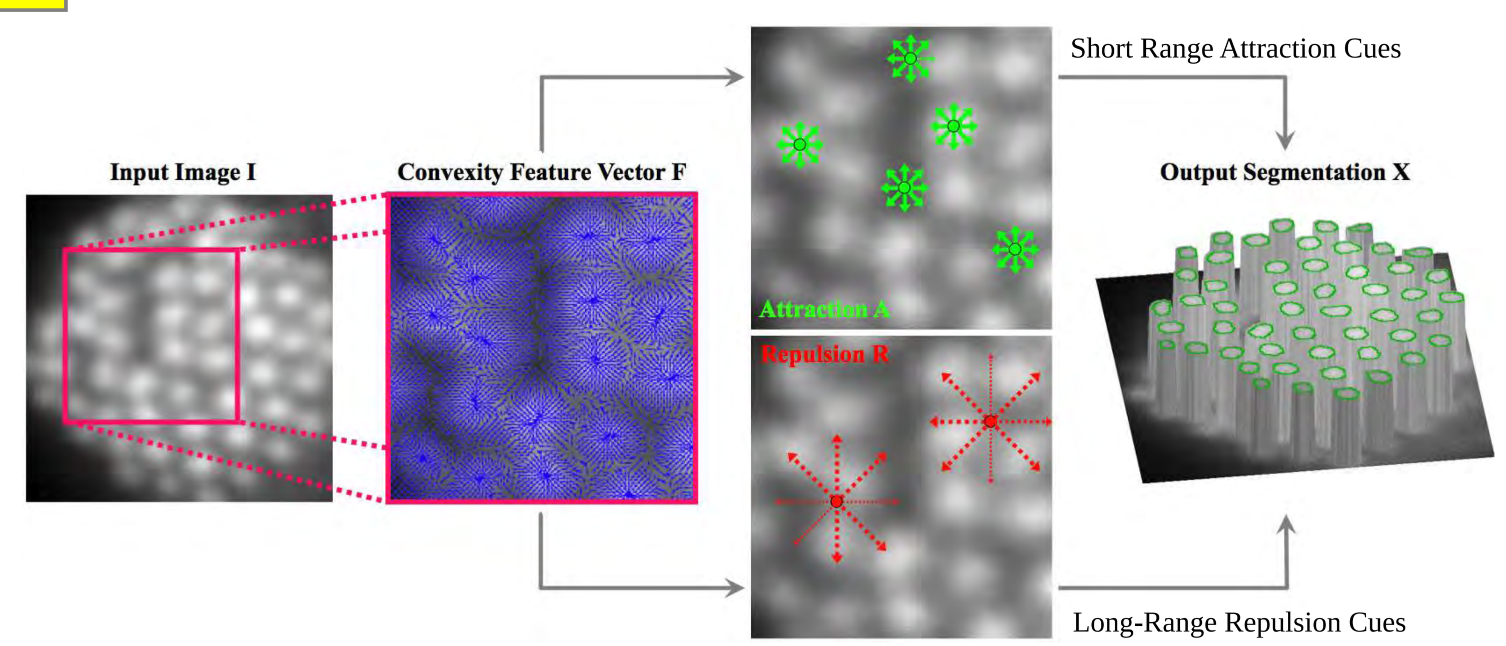
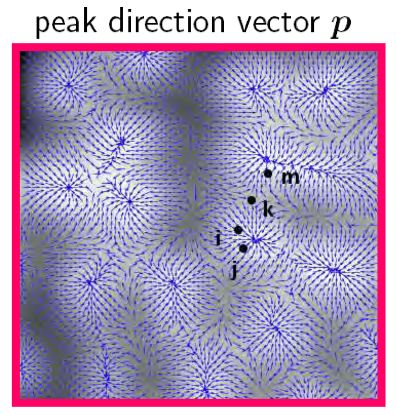
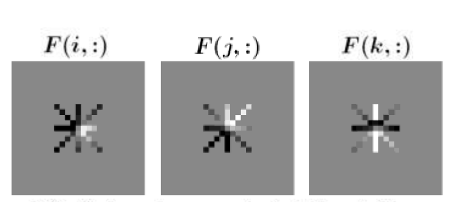


Image Intensity→ Convexity Feature Vector F

peak direction vector p



$$F(i,a) = < p(i), p(a) >$$



$F(i,:)$ shows how much pixel i's neighbours agree with i on the direction the dot lies in.

$$p(i) \propto \sum_{a \in N(i)} T(i,a)(L(a) - L(i)), \ |p(i)| = 1$$

$$T(i,a) = \sum_{\substack{I(m_1) \le I(m_t) \le \ldots \le I(m_k) \\ m_1 m_2 \ldots m_k = \text{line}(i,a)}} I(m_t)$$

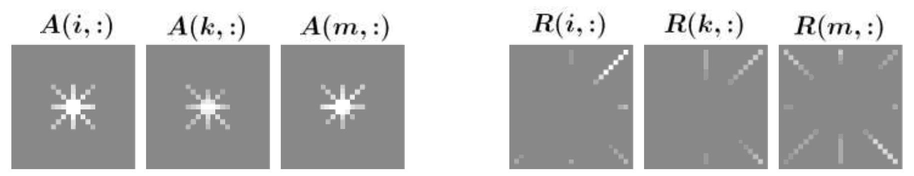
$p(i)$ indicates where pixels of higher intensity are located in the local convex vicinity of pixel i; $T(i,a)$ is the total nondecreasing intensity along the straight line from i to a and $L(i)$ is the 2D location of pixel i.

Convexity Feature Vector → Attraction & Repulsion

$$S(i,j) = \frac{< F(i,:), F(j,:) >}{|F(i,:)| \cdot |F(j,:)|}, \quad j \in N(i)$$

$$A(i,j) = e^{-\frac{1 - S(i,j)}{\sigma}}, \quad |L(j) - L(i)| \le r_A$$

$$R(i,j) = \frac{1 - S(i,j)}{2}, \quad |L(j) - L(i)| \le r_R$$



(Optional) Grouping Constraints for Seeded Segmentation

Optional initial seeds can be added through a constraint matrix U: If pixels a and b are known to belong to the same region (e.g. from a background mask), we have one constraint $X(a,:) = X(b,:)$, i.e. $U(a,k) = 1$, $U(b,k) = -1$ as the k-th constraint in matrix U.

Criterion

$$\max \varepsilon = \frac{\text{within-group } A}{\text{total degree of } A} + \frac{\text{between-group } R}{\text{total degree of } R}$$

Formulation

$$\begin{aligned} &\text{maximize} && \varepsilon(X) = \sum_{g=1}^{2} \frac{X_g^T W X_g}{X_g^T D X_g} \\ &\text{subject to} && X \in \{0,1\}^{n \times 2}, \ X 1_2 = 1_n \\ &&& U^T X = 0 \\ &\text{where} && W = A - R + D_R, \\ &&& D = D_A + D_R \end{aligned}$$

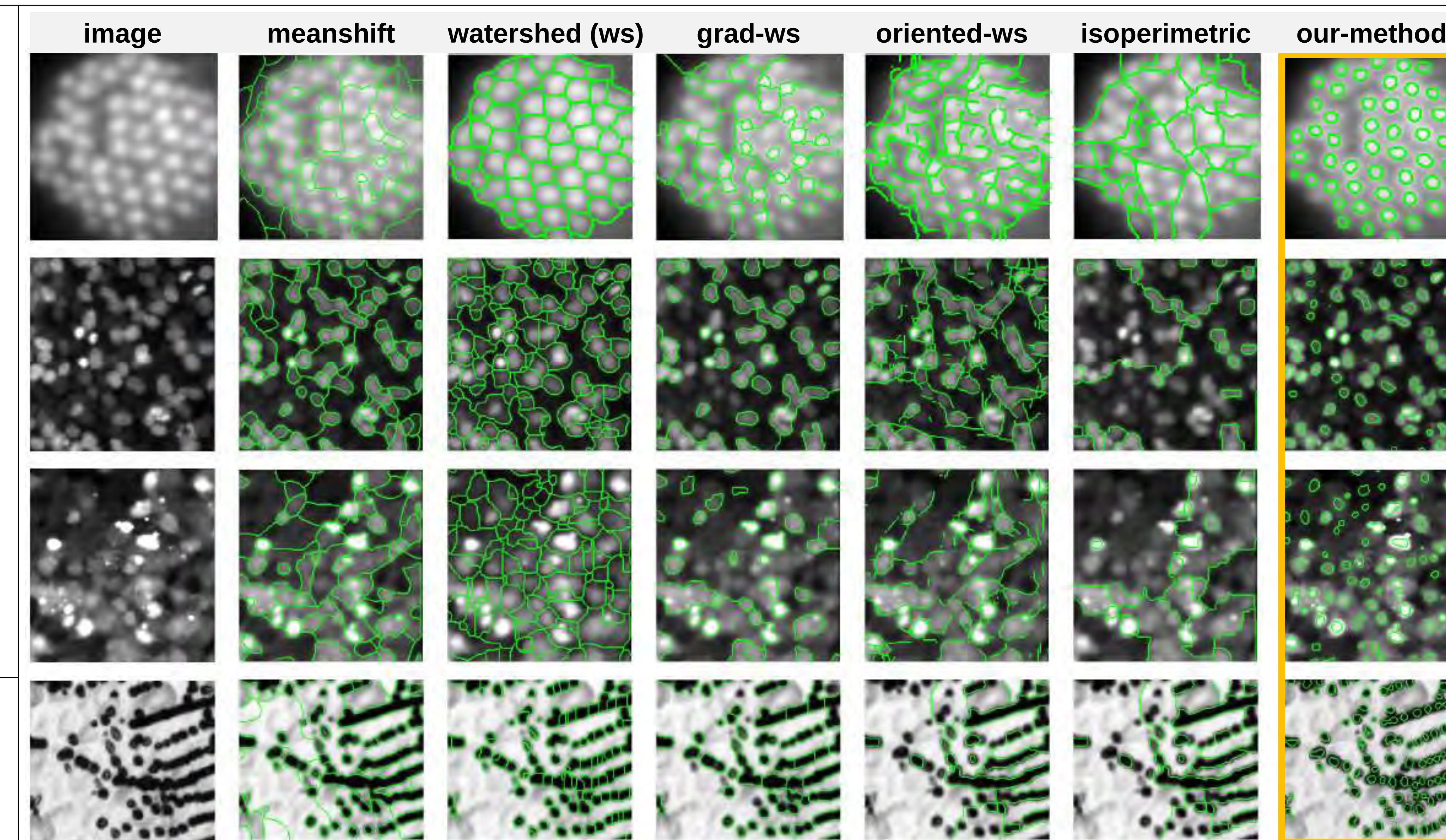
X = grouping indicator
A = attraction
R = repulsion
U = pairwise constraint matrix
D_W = diagonal *degree* matrix
1_n = $n \times 1$ vectors of 1's

Solution

A near-global optimum to this constrained normalized cuts problem is computed by finding the eigenvectors of QPQ, where

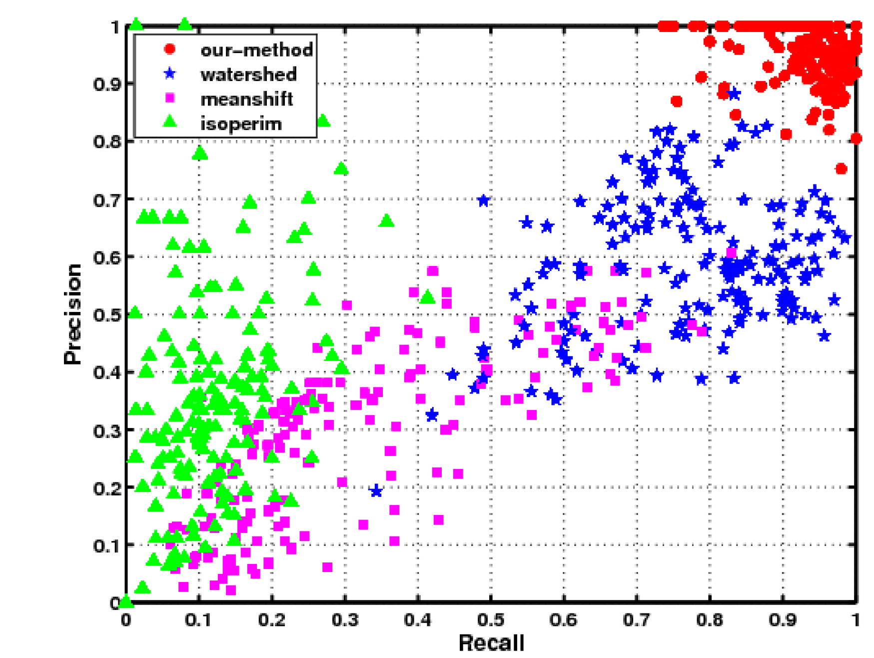
$$P = D^{-1} W$$

$$Q = I - D^{-1} U (U^T D^{-1} U)^{-1} U^T$$



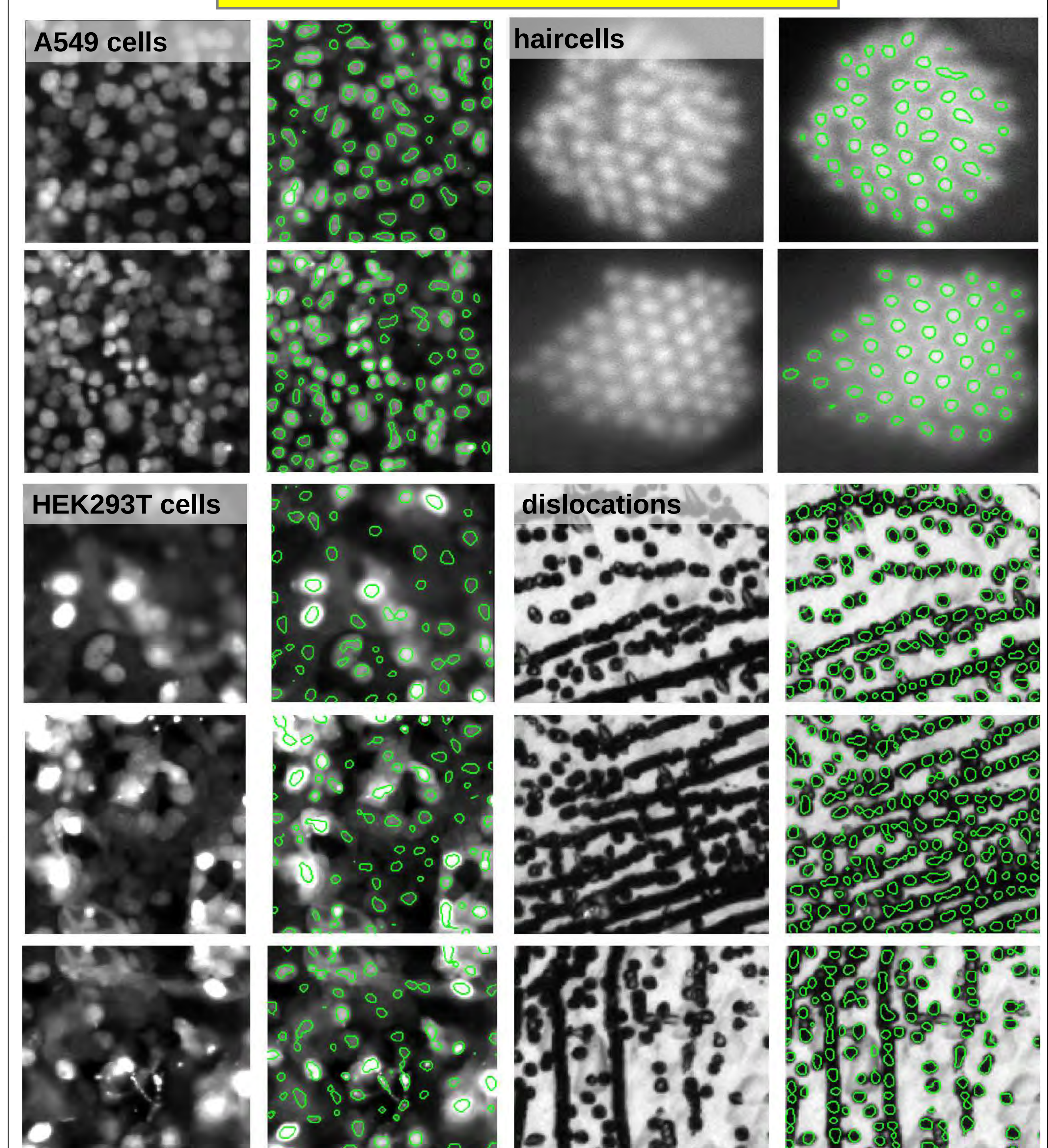
Statistics and Comparisons

Mean Shift: enhances intensity difference; scale sensitivity
Watershed methods: over-fragmented in the presence of local intensity fluctuations (standard); under-segmented if weak contrast (gradient); limited by Pb (oriented) [Arbalaez et. al., 2009]
Isoperimetric: recursively partitions image; initial seeds chosen from minimal intensity pixels; under-segmented. [Grady et. al., 2006]

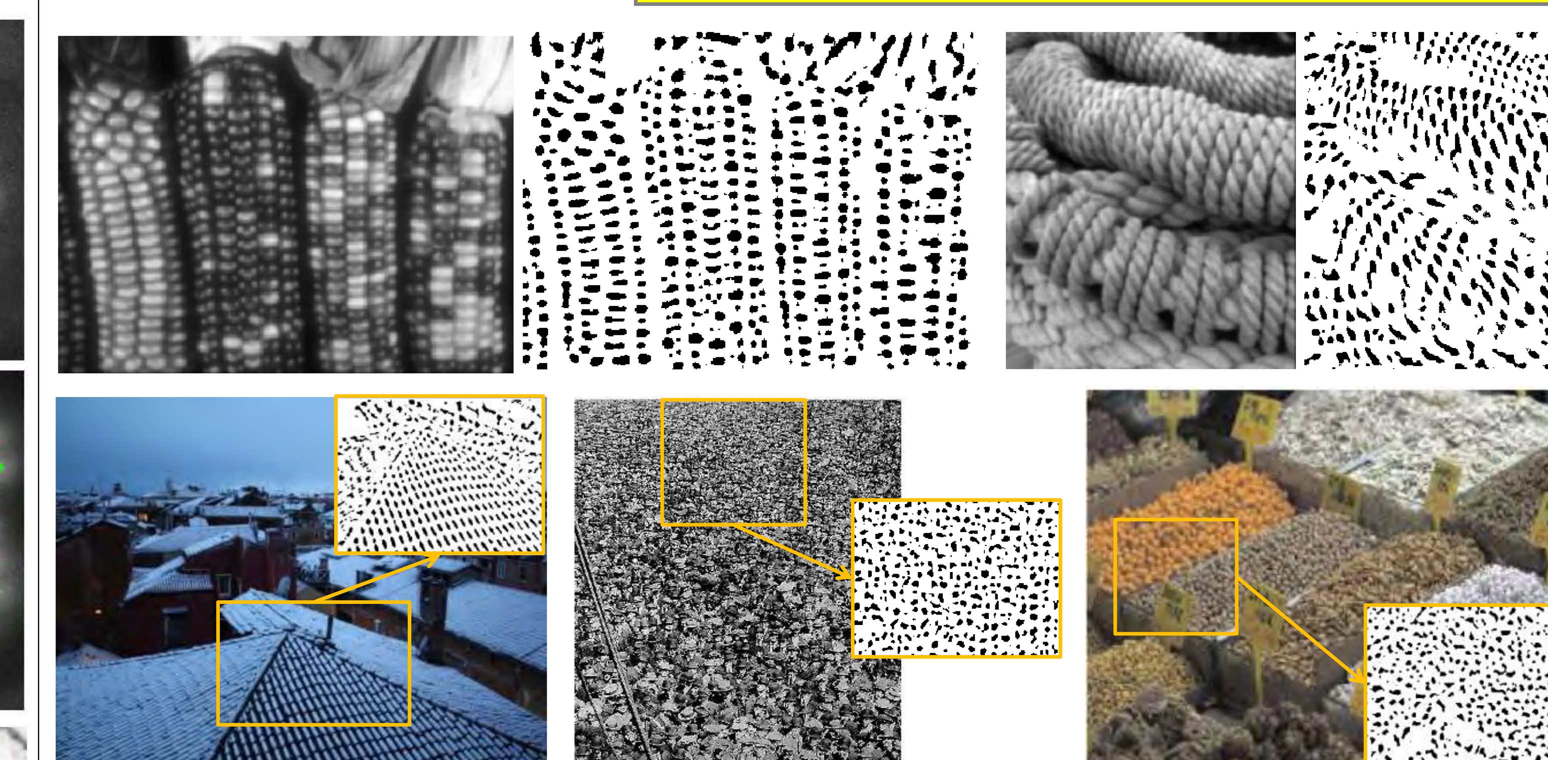


Precision: true dots picked out in the segmentation
Recall: segmented dots which are true dots

Our Results



Future: Shape from Texture



Conclusions

We successfully extract dots in a two-way segmentation by:

- Viewing boundaries as a flexible region of their own
- Encoding geometry (convexity) in a pixel-centric relational representation
- Having grouping cues that represent short-range attraction and long-range repulsion.

Dots are extracted as many disconnected components in the foreground, and no further post-processing is needed. The same set of parameters is used for all images.

Future work will include extending the model beyond convex shapes, e.g. tubular structures, and for possible shape from texture applications.

Acknowledgements

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