Robust Segmentation by Cutting Across a Stack of Gamma Transformed Images

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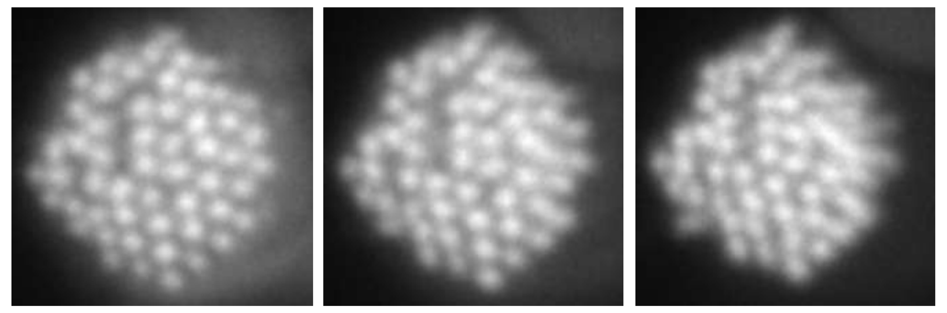
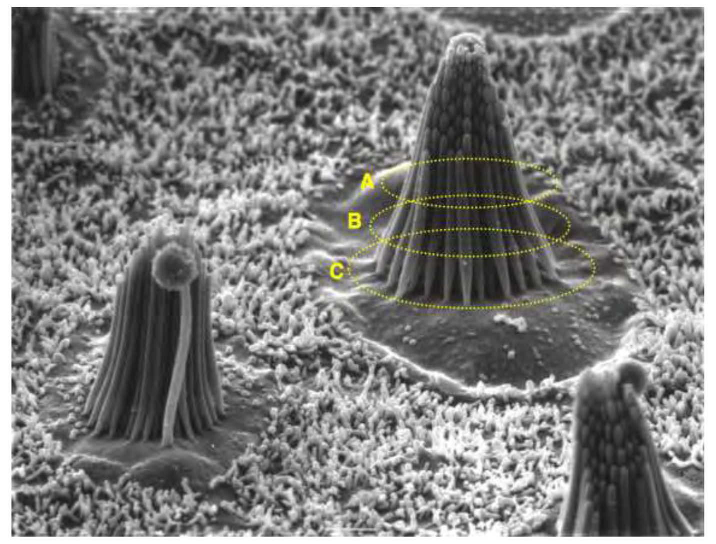
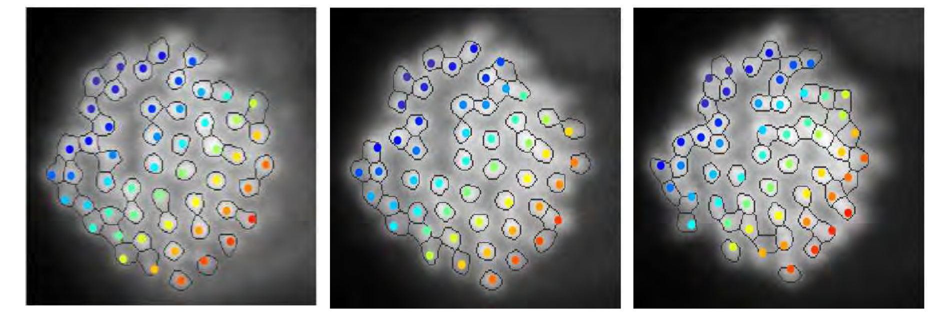
Input: medical images of low imaging quality such as 2D fluorescent slices of stereocillia

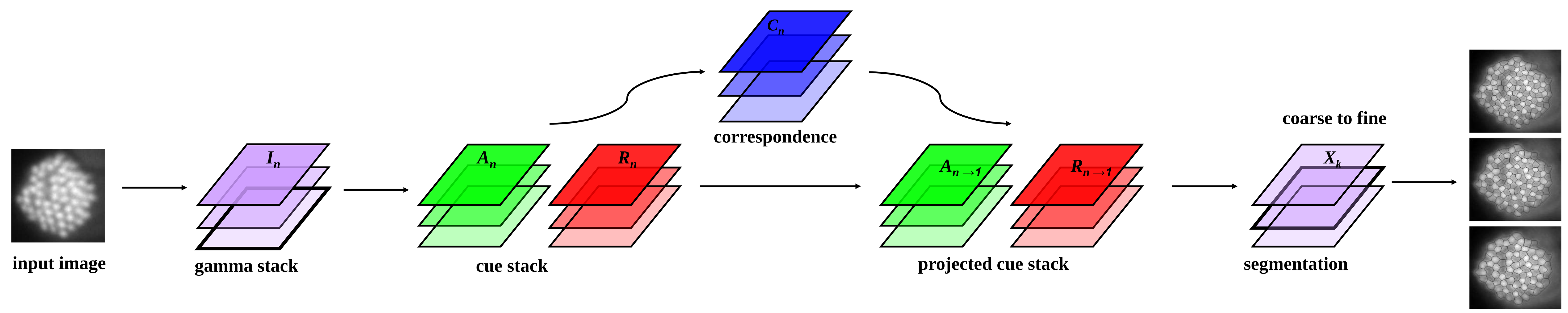




3D view of hair cells

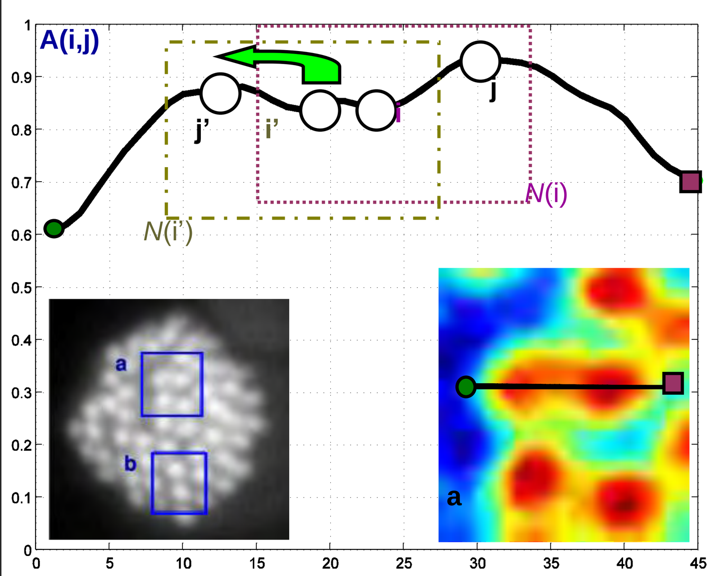
Output: segmentation from the global consensus of local cues from a stack of gamma images





Short-Range Attraction within Individual Peaks

A(i,j) inversely proportional to the maximal intensity difference M_{ij} between pixel i and any pixel on the line ij:

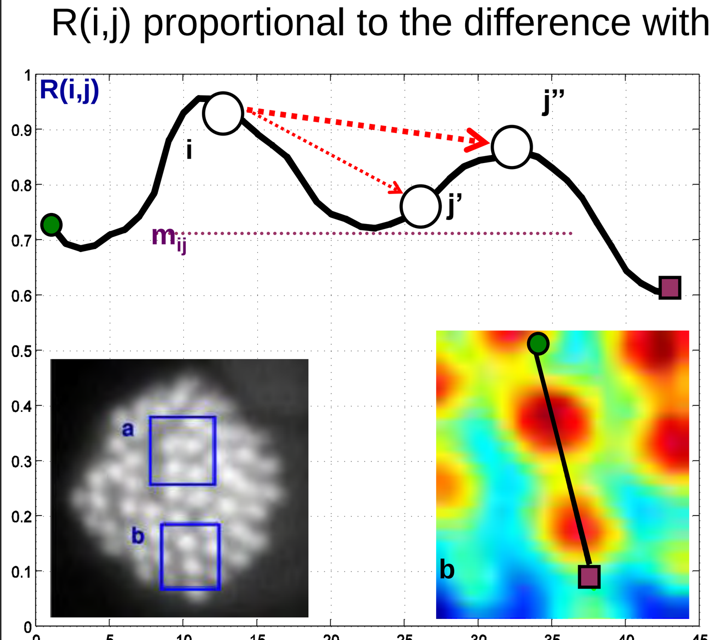


$$A(i,j) = e^{-\frac{\max_{t\in \text{line}(i,j)} |I_i - I_t|^2}{2\delta_i^2 \cdot \sigma_a^2}}$$
$$\delta_i = \max_{t\in\mathcal{N}(i)} I_t - \min_{t\in\mathcal{N}(i)} I_t$$

- δ(i) the local intensity range
- Asymmetric between I and j
- Adaptive scaling effectively enhances attraction within weak peaks
  Allows a single parameter setting for σ_a to work on a variety of images

Long-Range Repulsion between Peaks

R(i,j) proportional to the difference with the minimal intensity mij on the line ij:



$$R(i,j) = 1 - e^{-\frac{\min(|I_i - m_{ij}|, |I_j - m_{ij}|)}{\sigma_r}}$$
$$m_{ij} = \min_{t\in \text{line}(i,j)} I_t.$$

Repulsion R(i,j) is strongest for nearby peaks; decreases as pixels approach minimum intensity m_{ij}: $R(i, j) > R(i, j)$.

Pixel Correspondence and Cue Projection

Compute rough pixel correspondences C_n between adjacent gamma layers, and project cues at each layer to the reference layer I_1: $A_n \to 1$ and $R_n \to 1$.

Partial Grouping Constraints

Force background pixels to belong together through constraint matrix U. The mask is obtained by intensity thresholding the original image.

Criterion

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

Formulation

$$\begin{aligned} &\text{maximize} && \varepsilon(X) = \sum_{l=1}^{k} \frac{X_l^T W X_l}{X^T D X_l} \\ &\text{subject to} && X \in \{0,1\}^{N\times k},\ X1_k = 1_N \\ &&& U^T X = 0 \\ &\text{where} && W = A - R + D_R \\ &&& D = D_A + D_R \end{aligned}$$

X = grouping indicator
A = attraction
R = repulsion
U = pairwise grouping constraint
D_W = degree matrix of weights
1_n = n x 1 vector of all 1's

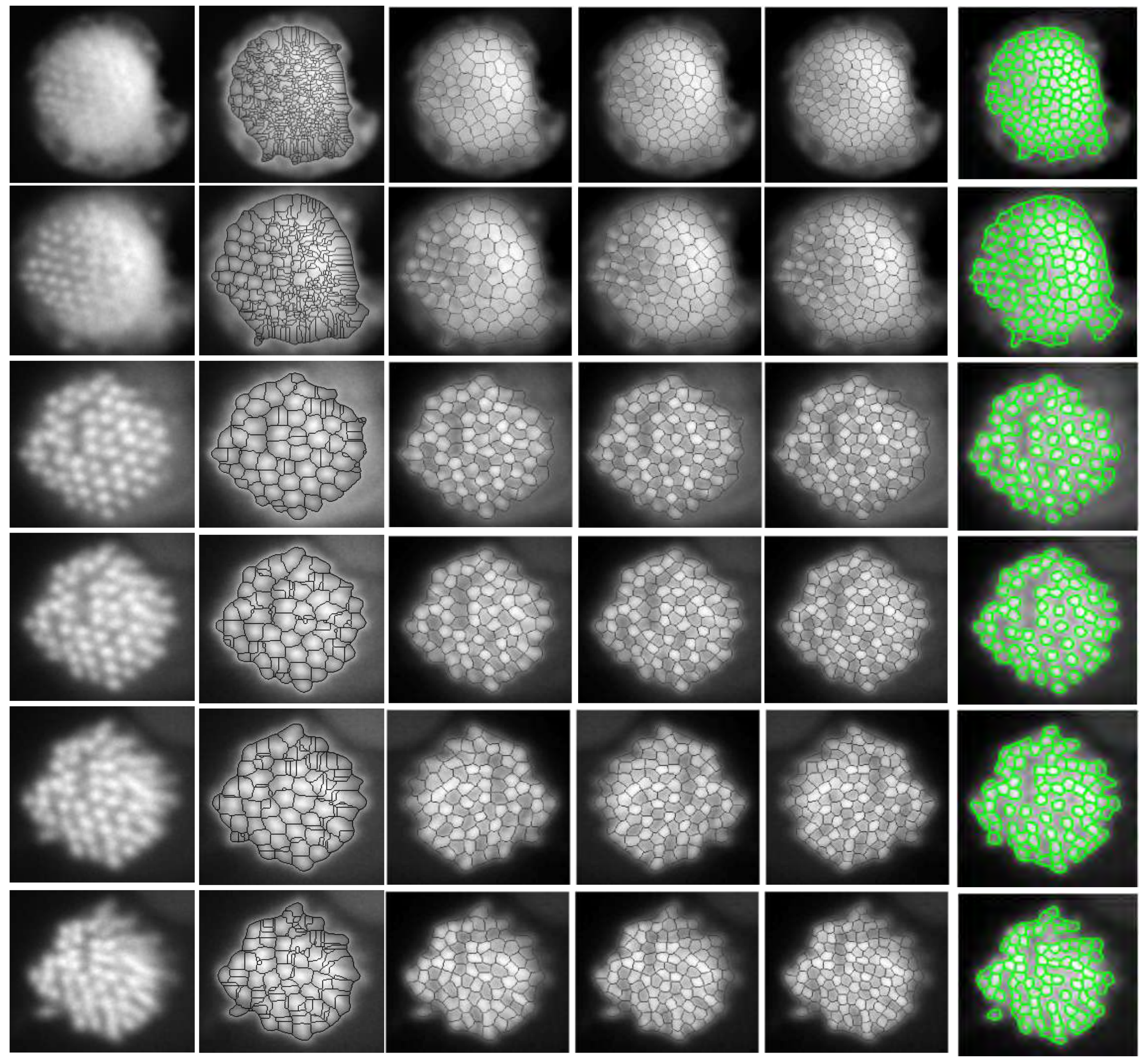
Solution

Discretize eigenvectors of QPQ for near-optimal global discrete segmentation; where

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

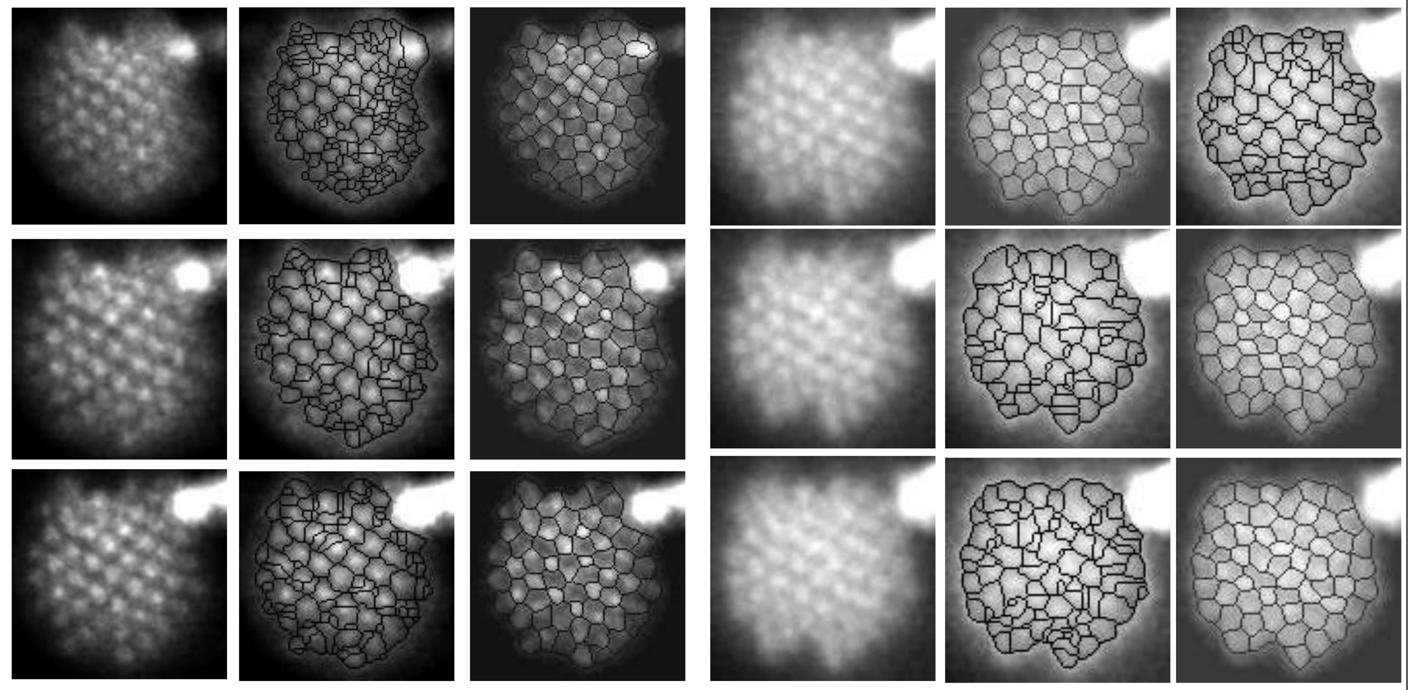
Cutting across the aligned cue stack produces a segmentation X_k invariant to gamma transformations, where k indicates the granularity of segmentation.

Coarse-to-fine stereocilia segmentations



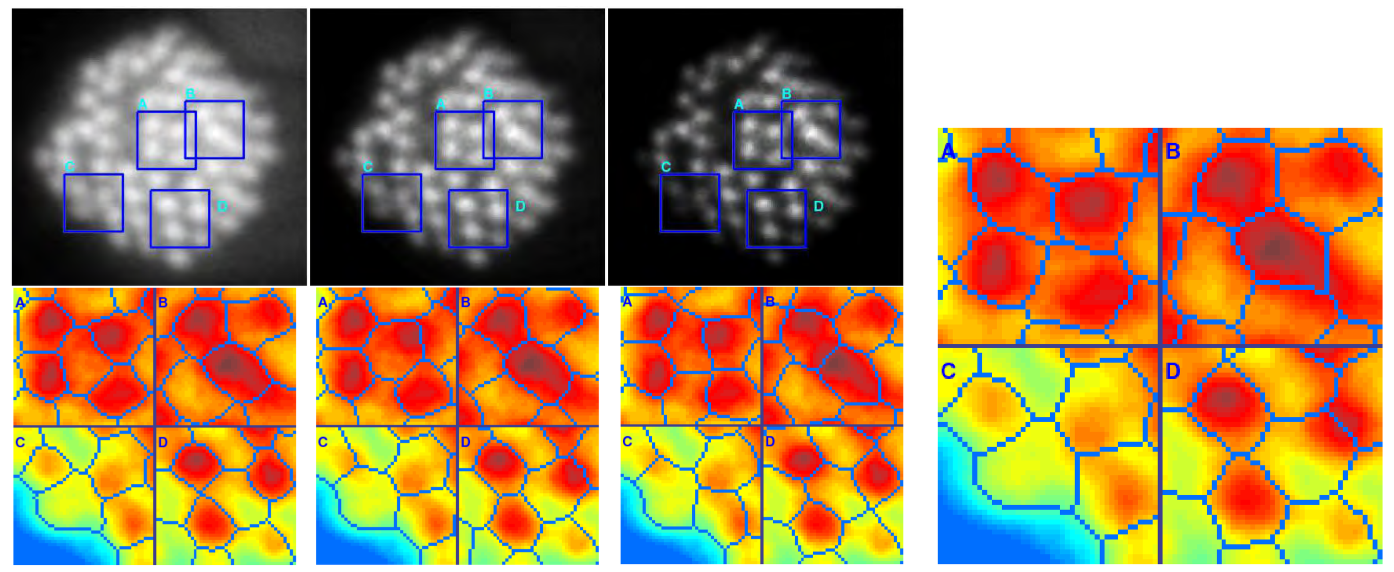
a: image | b: watershed | c: k = 80 | d: k = 100 | e : k = 120 | f: cells only

Low contrast image segmentation



a: image | b: watershed | c: ours | a: image | b: watershed | c: ours

Gamma stack improvement over single images



γ_0 | γ_1 | γ_2 | $\gamma_0, \gamma_1, \gamma_2$

Segmentation of medical images is governed by global intensity levels, yet imaging noise and local intensity fluctuations present many challenges.

Morphological methods (e.g. watershed methods)
- Local segmentation methods; efficient but prone to local noise
- Prescribe a computational procedure computationally

Energy-driven methods (e.g. active contours and level set methods)
- Minimization of an energy function based on either regions or contours
- Computationally costly and critically dependent on initial seed solutions.

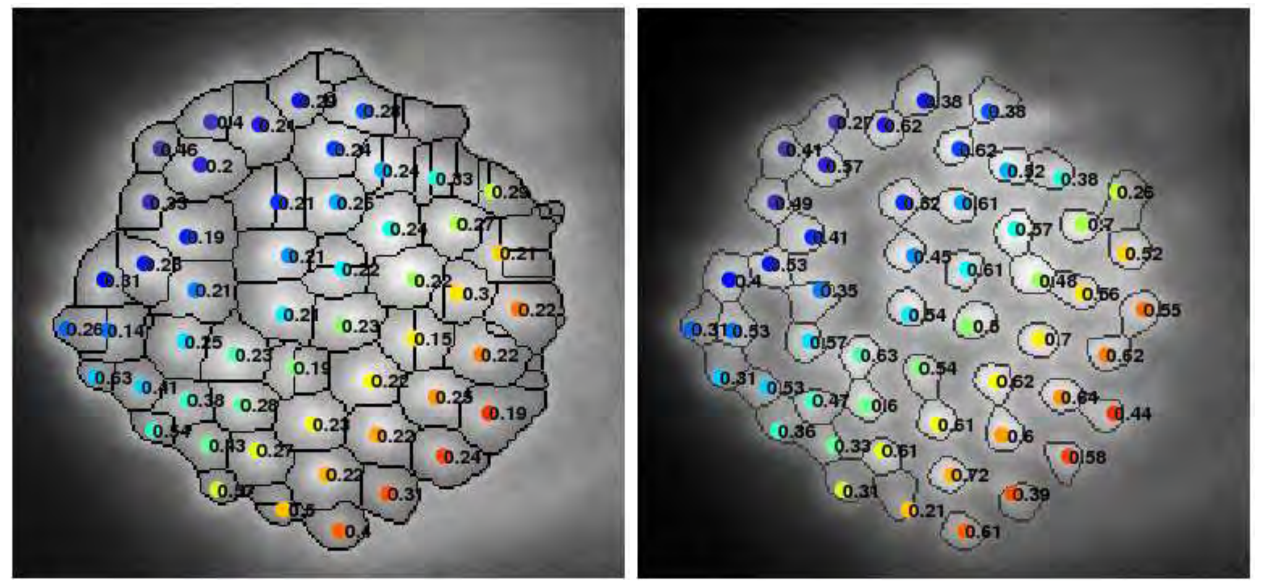
Hybrid methods (e.g. watersnakes and level sets for watershed)
- To combine benefits of morphological and energy-driven methods

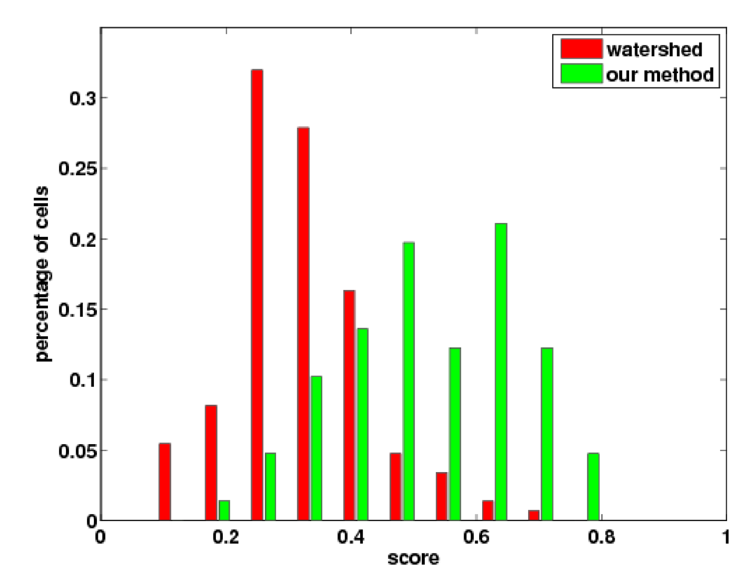
Graph cuts methods
- To overcome the limitations of watershed algorithms
- Segmenting a single connected component (e.g. isoperimetric graph partitioning) and thin structures with augmented banded graph cuts.

Our spectral graph cuts method
- Global segmentation approach based on local pairwise cues
- Combines attraction, repulsion and grouping constraints
- Few parameters and little tuning
- Successfully segments weak peaks even in noisy images

Improvement over Watershed

Goodness of segmentation is measured (in terms of the extent of overlap) by scoring it with respect to the ground-truth center locations of stereocilia.





We obtain more accurate and robust results than watershed on a variety of images with the same set of parameters, demonstrating the advantage of cutting across the entire gamma stack.

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