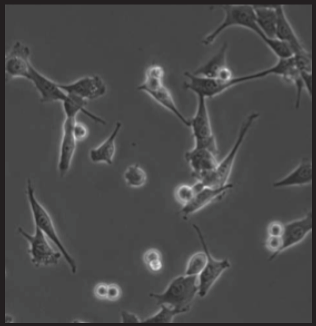
Multilevel Space-Time Aggregation for Cell Microscopy Segmentation and Tracking



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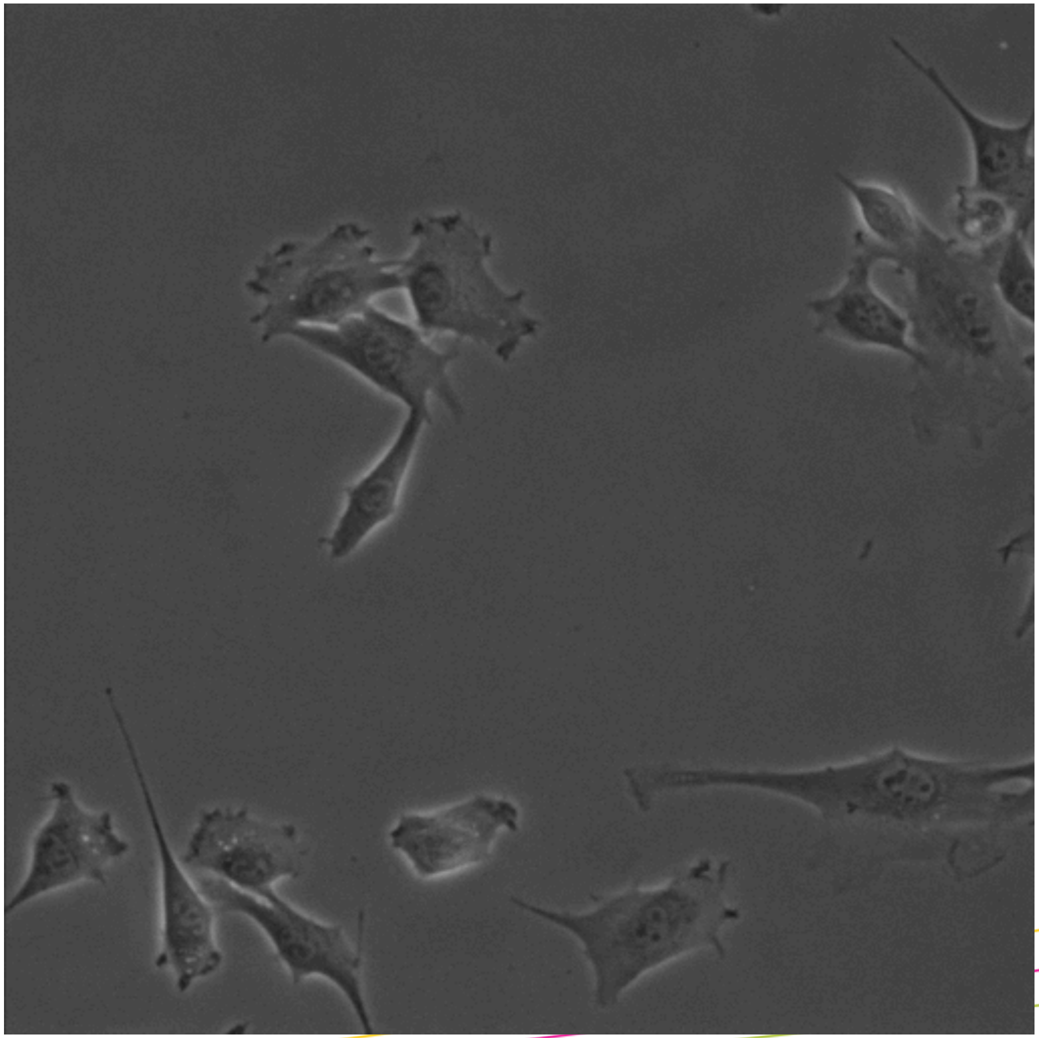
1. cell segmentation

- segment and track individual cells
- bright circular cells
- touching and overlapping cells
- cell divisions



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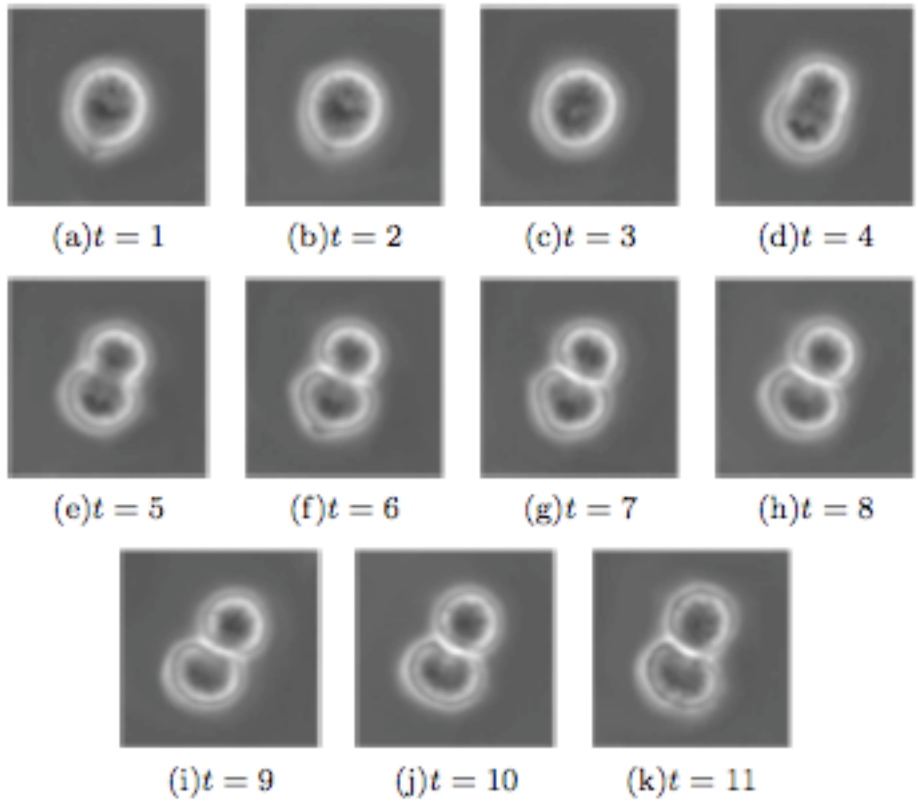
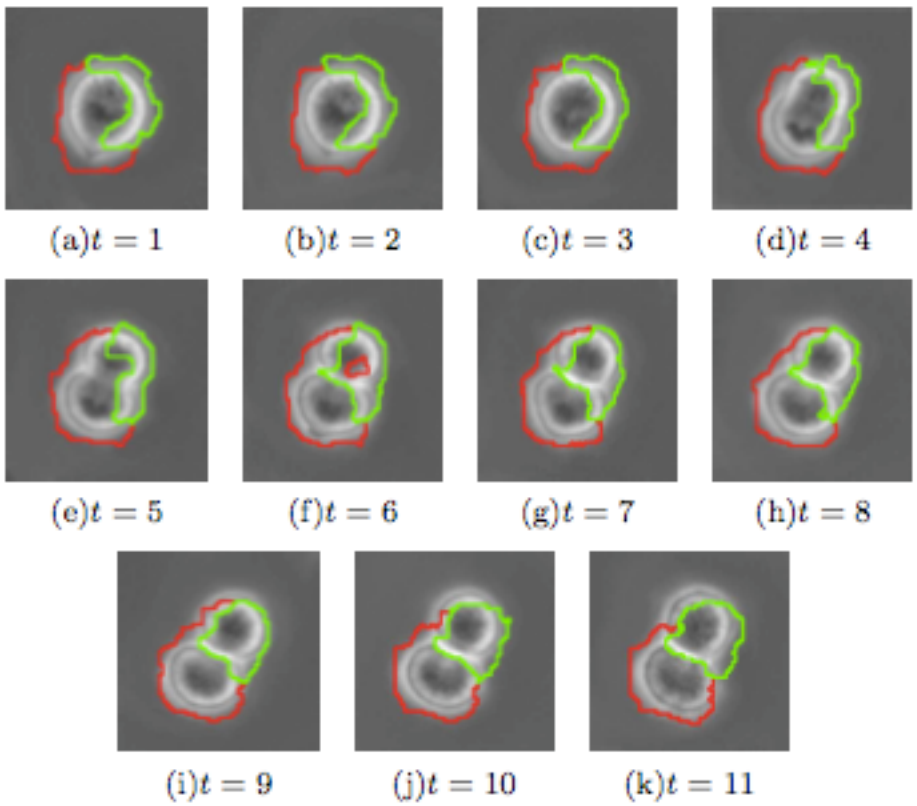
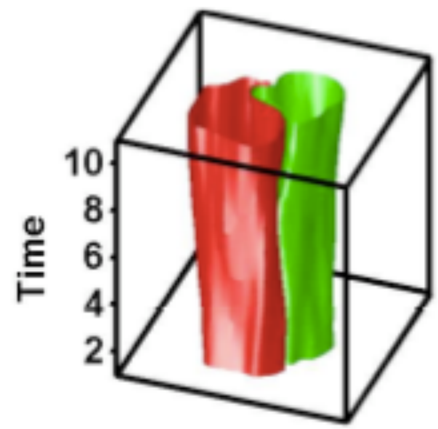
cell segmentation



cell segmentation





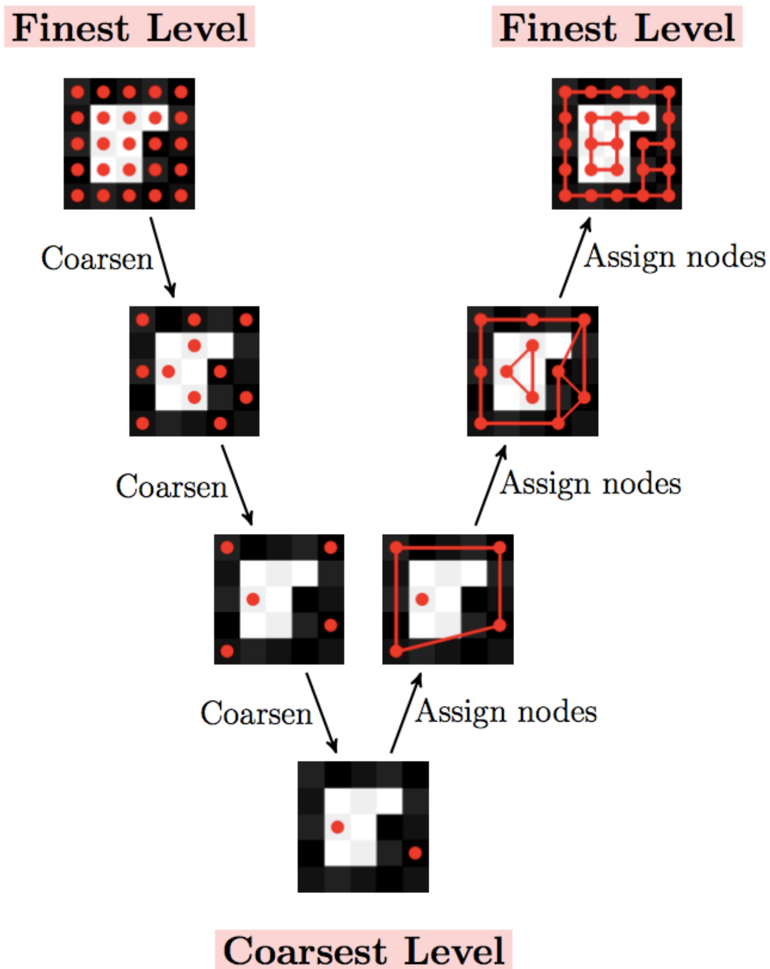
2. multilevel aggregation approach

[17] Eitan Sharon, Achi Brandt, and Ronen Basri. Fast multi-scale image segmentation. In *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 70–71, 2000.

[19] Eitan Sharon, Meirav Galun, Dahlia Sharon, Ronen Basri, and Achi Brandt. Hierachy and adaptivity in segmenting visual scenes. *Nature*, 442:810–813, 2006.

- we applied the ‘segmentation by weighted aggregation’ (SWA) algorithm to this problem
- we adapted the algorithm to our problem (in particular, new scale-invariant saliency measure)

3. multilevel aggregation



- weights between neighbouring fine-level pixels based on intensity similarity (undirected graph)
- coarsen the graph (group fine-level pixels and calculate new weights)
- adjust weights based on coarse-level features (average intensity, intensity variance, shape, orientation, ...)

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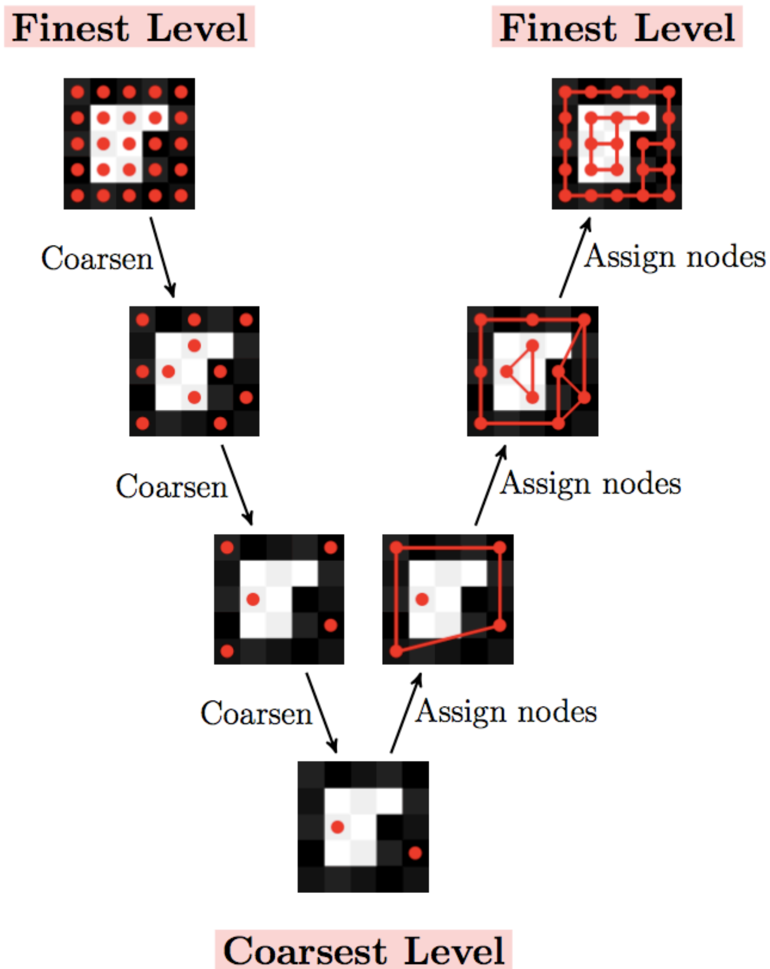
multilevel aggregation



- coarse-level nodes are overlapping groups of fine-level nodes
- coarse-level node not connected to any other nodes ➔ 'salient' segment!
- stop coarsening when all nodes are salient
- upward phase: assign nodes on all levels to segments (remove overlap between groups)

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4. some algorithmic details

- fine-level coupling matrix

$$A_{ij}^{[1]} = \begin{cases} e^{-\alpha|I_i^{[1]} - I_j^{[1]}|} & \text{if } i,\ j \text{ are horizontal or} \\ & \quad \text{vertical neighbours,} \\ 0 & \text{otherwise.} \end{cases}$$

- aggregate pixels using first pass of classical Ruge-Stueben AMG coarsening algorithm (strength of connection in coupling matrix)

  (first step in graph coarsening)

some algorithmic details

- interpolation from coarse to fine level

$$P_{ij}^{[1,2]} = \begin{cases} 1 & \text{if } i \in C^{[1]},\ i = C_j^{[1]}, \\ 0 & \text{if } i \in C^{[1]},\ i \neq C_j^{[1]}, \\ \dfrac{A_{iC_j^{[1]}}^{[1]}}{\sum\limits_{k \in C^{[1]}} A_{ik}^{[1]}} & \text{if } i \notin C^{[1]}. \end{cases}$$

- calculate coarse-level weights (second step in graph coarsening)

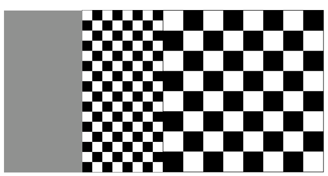
$$A^{[r+1]} = P^{[r,r+1]T} A^{[r]} P^{[r,r+1]}$$

some algorithmic details

- modify coarse-level weights:
  - average intensity (intensity similarity between coarse-level blocks)

$$A_{ij}^{[r+1]} \leftarrow A_{ij}^{[r+1]} e^{-\tilde{\alpha}|I_i^{[r+1]} - I_j^{[r+1]}|}$$

  - multilevel variance (as a measure of texture)



$$var(X) = E((X - E(X))^2) = E(X^2) - E(X)^2$$

$$A_{ij}^{[r+1]} \leftarrow A_{ij}^{[r+1]} e^{-\beta||\mathbf{s}_i^{[r+1]} - \mathbf{s}_j^{[r+1]}||_2}$$

5. saliency measure

- when is a coarse-level node sufficiently decoupled from other nodes on the same level to make it (the representative of) a salient segment?

- SWA: energy functional

$$\Gamma^{[r]}(u^{[r]}) = \frac{\sum_{i>j} A_{ij}^{[r]} (u_i^{[r]} - u_j^{[r]})^2}{\sum_{i>j} A_{ij}^{[r]} u_i^{[r]} u_j^{[r]}}$$

saliency measure

- SWA: energy functional

$$\Gamma^{[r]}(u^{[r]}) = \frac{\sum_{i>j} A_{ij}^{[r]} (u_i^{[r]} - u_j^{[r]})^2}{\sum_{i>j} A_{ij}^{[r]} u_i^{[r]} u_j^{[r]}}$$

- seek segments (boolean vectors $u^{[r]}$) that yield low values of the energy functional (equivalent to normalized cut formulation, on finest level) (but: multilevel in SWA)

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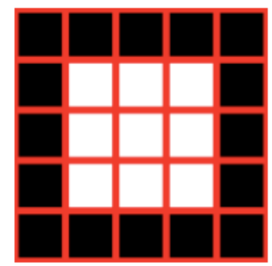
saliency measure

- low saliency Γ indicates segment

$$\Gamma^{[r]}(u^{[r]}) = \frac{\sum_{i>j} A_{ij}^{[r]} \left(u_i^{[r]} - u_j^{[r]}\right)^2}{\sum_{i>j} A_{ij}^{[r]} u_i^{[r]} u_j^{[r]}}$$

- numerator
  = sum of coupling coefficients along boundary
  = boundary length, weighted by similarity
- denominator
  = sum of coupling coefficients in interior
  = area, weighted by internal similarity



saliency measure

$$\Gamma^{[r]}(u^{[r]}) = \frac{\sum_{i>j} A_{ij}^{[r]} (u_i^{[r]} - u_j^{[r]})^2}{\sum_{i>j} A_{ij}^{[r]} u_i^{[r]} u_j^{[r]}} = \frac{u^{[r]T} L^{[r]} u^{[r]}}{\frac{1}{2} u^{[r]T} W^{[r]} u^{[r]}}$$

- graph Laplacian

$$L_{ij}^{[r]} = \begin{cases} -A_{ij}^{[r]} & \text{if } i \neq j, \\ \sum_{k \neq i} A_{ik}^{[r]} & \text{if } i = j, \end{cases}$$

- coupling matrix

$$W^{[r]} = A^{[r]}$$

- on coarse level

$$\Gamma_i^{[r]} = \Gamma(u^{[r],i}) = \frac{L_{ii}^{[r]}}{\frac{1}{2} W_{ii}^{[r]}}$$

$$\Gamma_i^{[r]} < \gamma.$$

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saliency measure

$$\Gamma_i^{[r]} = \Gamma(u^{[r],i}) = \frac{L_{ii}^{[r]}}{\frac{1}{2} W_{ii}^{[r]}} \qquad \Gamma_i^{[r]} < \gamma.$$

problems with shape-invariance and scale-invariance

(due to ratio length / area)

(a)Small L_{ii}, large W_{ii}. (b)Large L_{ii}, small W_{ii}.

saliency measure

$$L_{ij}^{[r]} = \begin{cases} -A_{ij}^{[r]} & \text{if } i \neq j, \\ \sum_{k \neq i} A_{ik}^{[r]} & \text{if } i = j, \end{cases}$$

$$W^{[r]} = A^{[r]}$$

$$\Gamma_i^{[r]} = \Gamma(u^{[r],i}) = \frac{L_{ii}^{[r]}}{\frac{1}{2} W_{ii}^{[r]}} \qquad \Gamma_i^{[r]} < \gamma.$$

- unweighted coupling matrix (boundary length)

$$V_{ij}^{[1]} = \begin{cases} 0 & \text{if } A_{ij}^{[1]} = 0, \\ 1 & \text{if } A_{ij}^{[1]} \neq 0. \end{cases}$$

- unweighted Laplacian (area)

$$\Gamma_i^{[r]} = \frac{L_{ii}^{[r]} / G_{ii}^{[r]}}{W_{ii}^{[r]} / V_{ii}^{[r]}}$$

$$G_{ij}^{[1]} = \begin{cases} -V_{ij}^{[1]} & \text{if } i \neq j, \\ \sum_{k \neq i} V_{ik}^{[1]} & \text{if } i = j. \end{cases}$$

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saliency measure

$$\Gamma_i^{[r]} < \gamma.$$

similarity-weighted boundary length /
similarity-weighted area

$$\Gamma_i^{[r]} = \frac{L_{ii}^{[r]}}{\frac{1}{2} W_{ii}^{[r]}}$$

➔ normalize boundary length and area

average similarity along boundary /
average internal similarity

$$\Gamma_i^{[r]} = \frac{L_{ii}^{[r]} / G_{ii}^{[r]}}{W_{ii}^{[r]} / V_{ii}^{[r]}}$$

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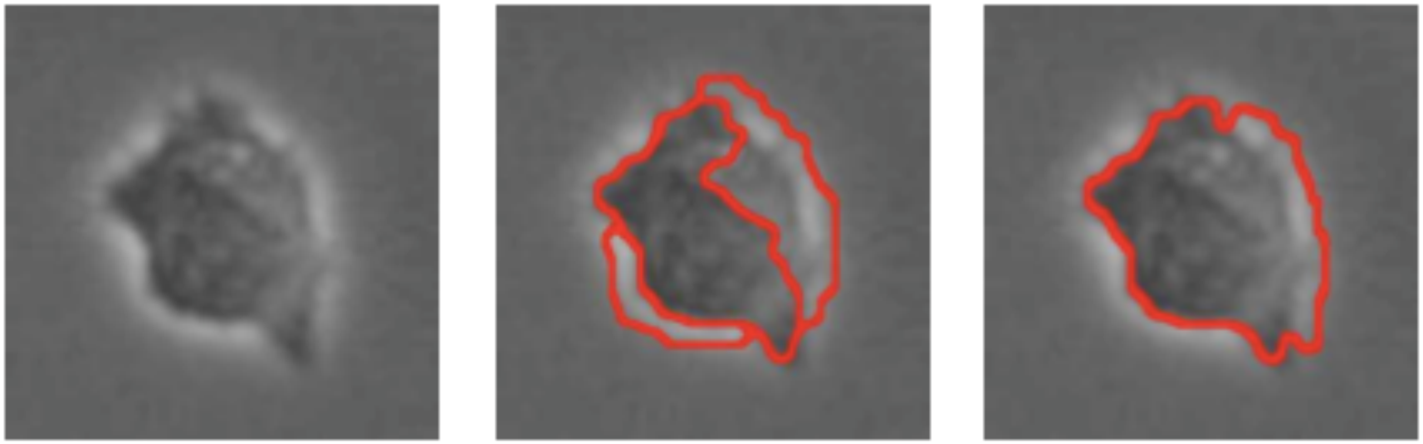
6. cell segmentation

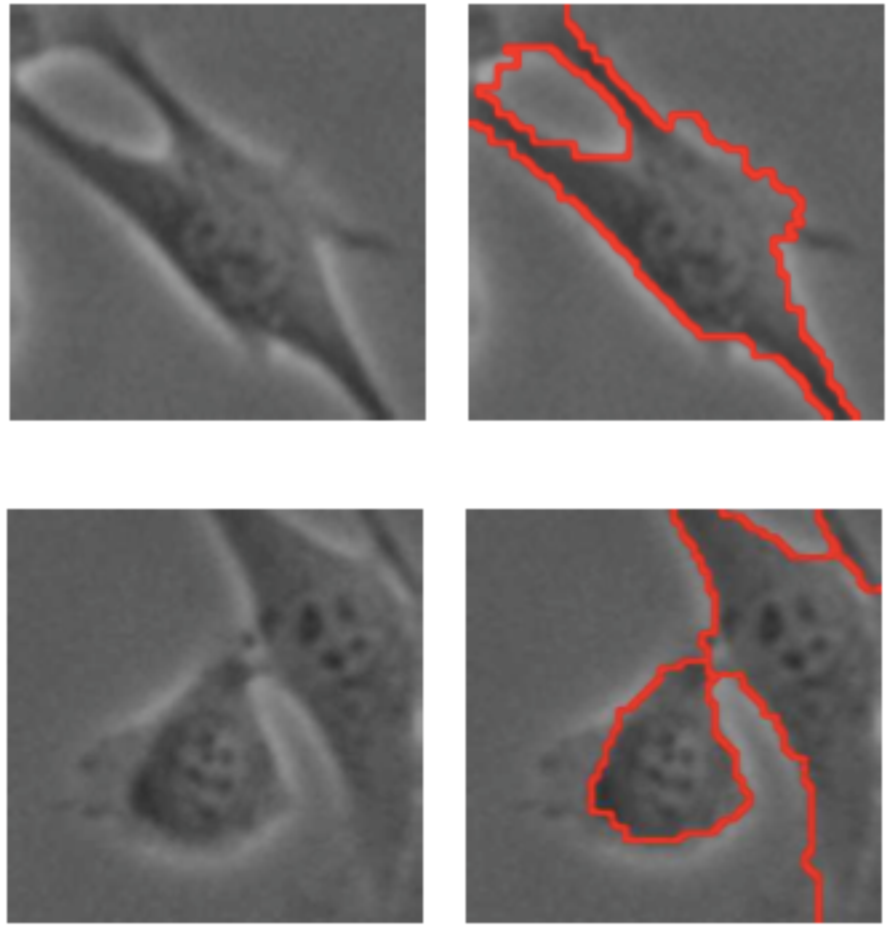


(a) Original image

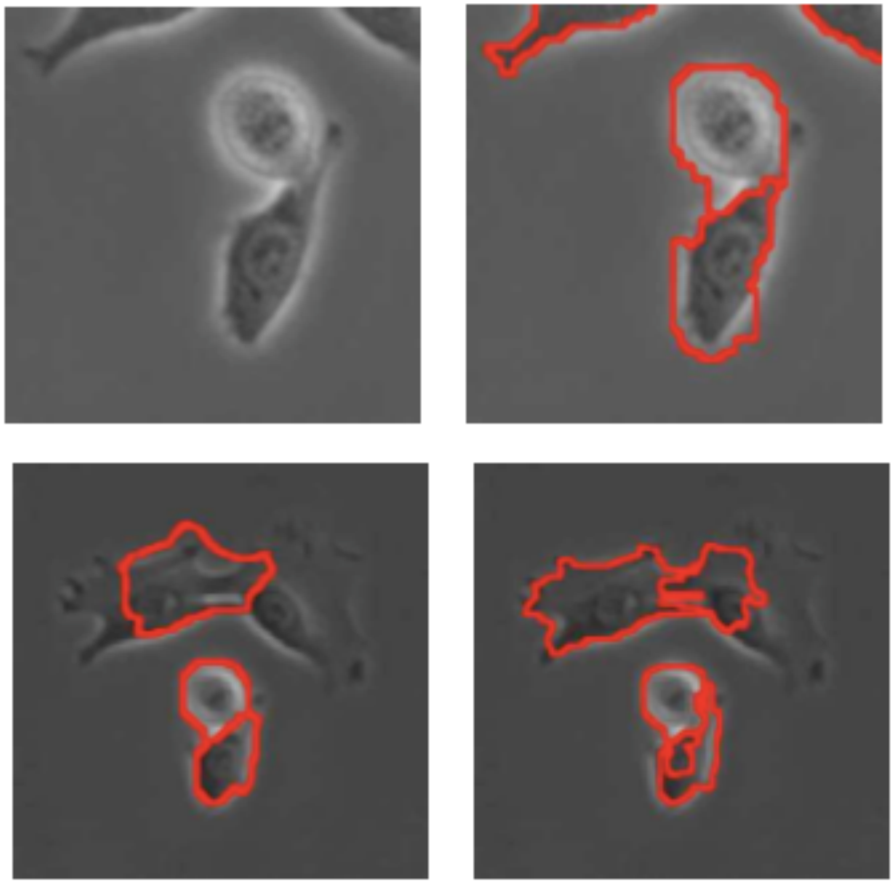
(b) 4 segments found (including the background segment), not using variance

(c) 2 segments found (including the background segment), using variance

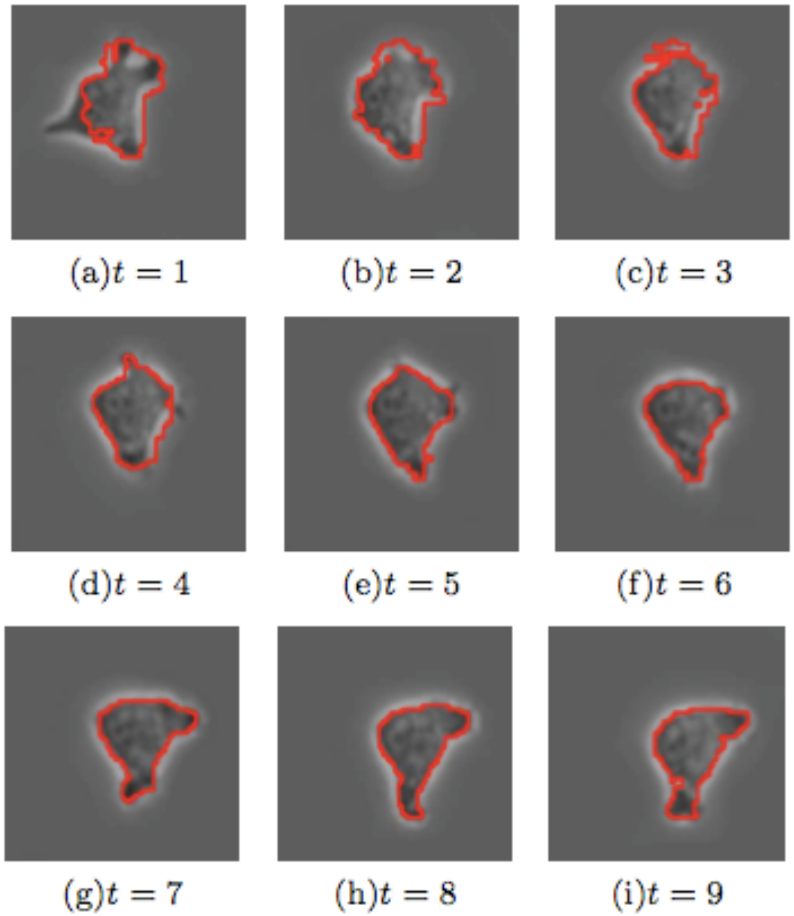
cell segmentation

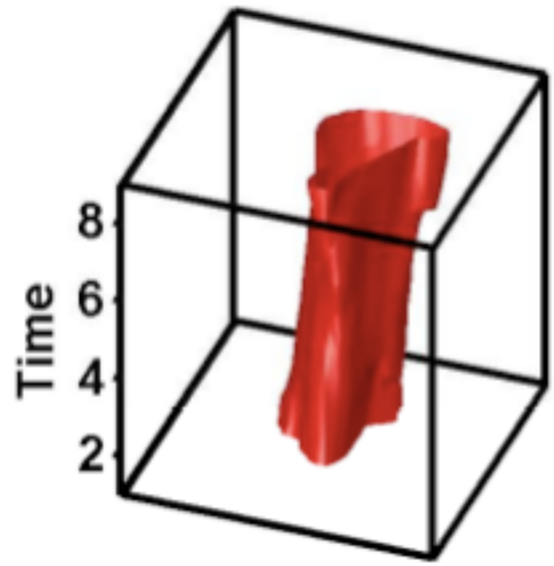


cell segmentation



7. cell tracking in space-time





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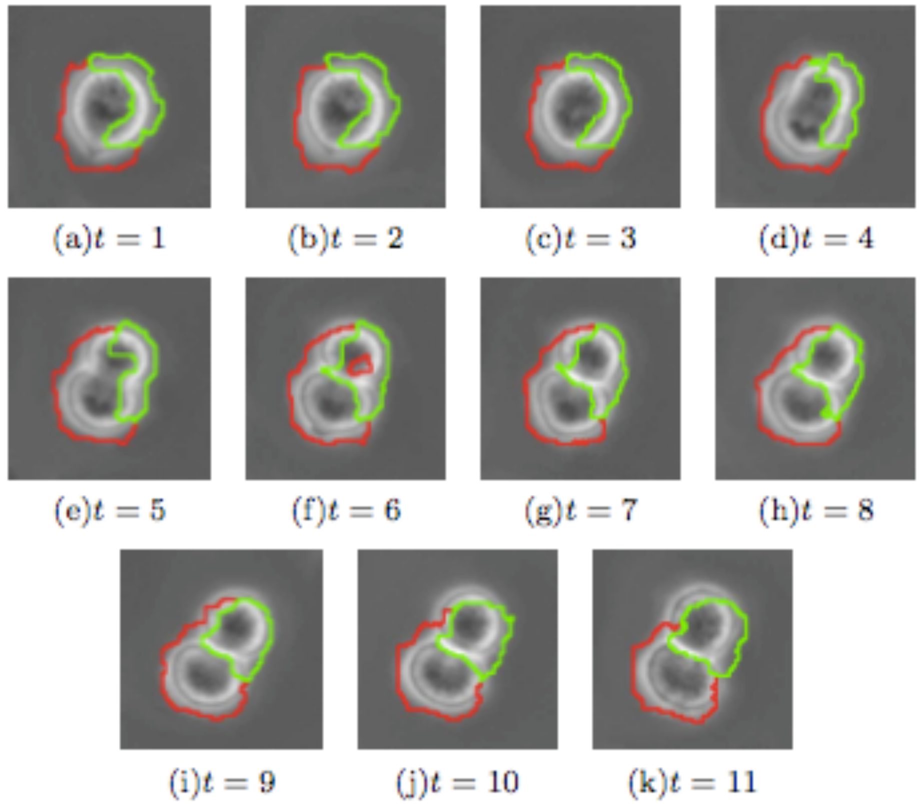
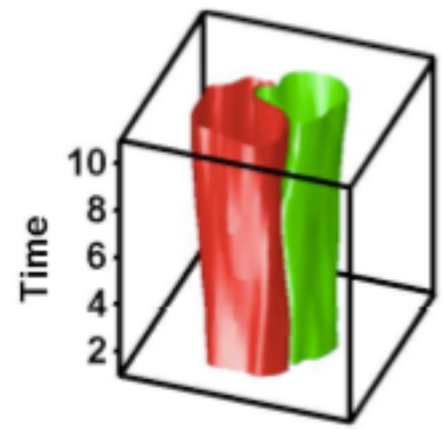
cell tracking in space-time





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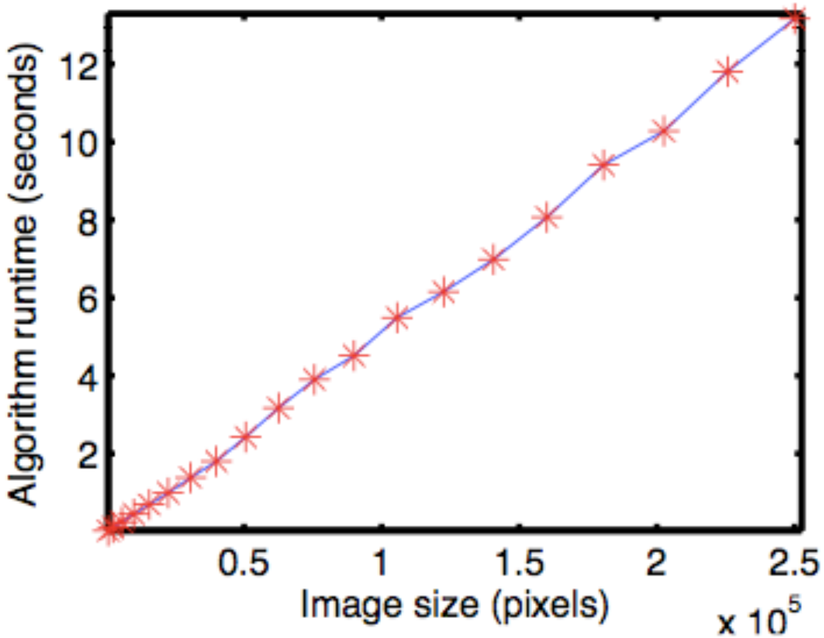
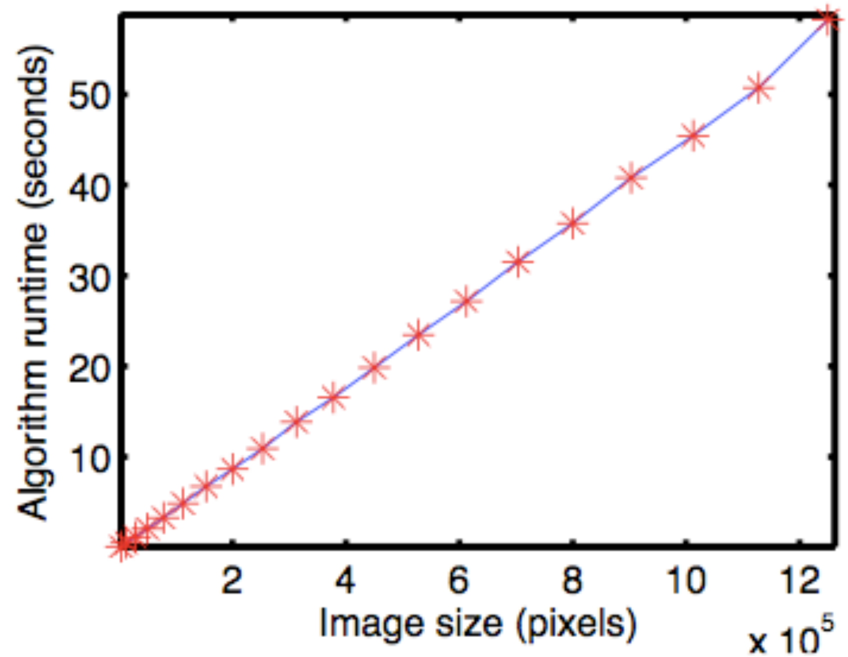
8. performance





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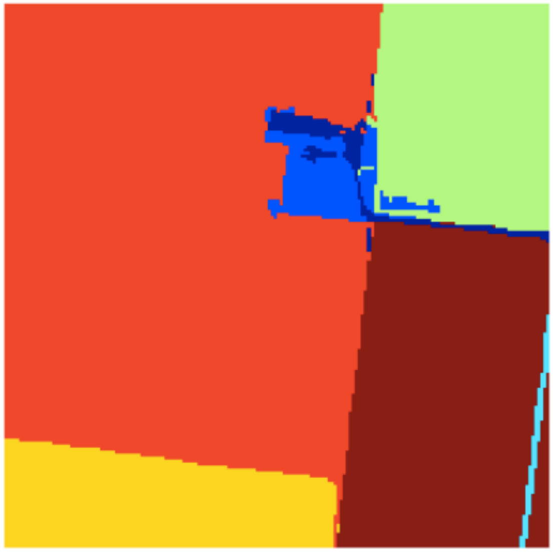
9. satellite segmentation

Figure 5.1: RGB image of a farm (180x180).



satellite segmentation

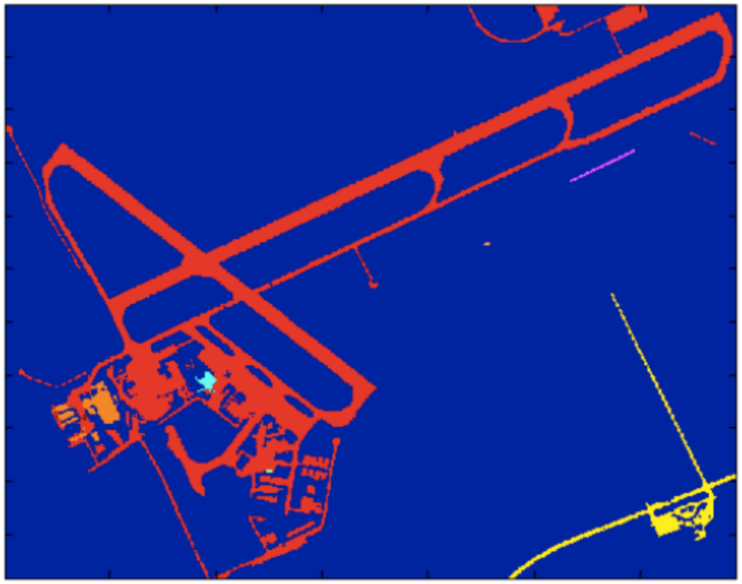


Figure 5.5: RGB image of the Region of Waterloo airport taken by Ikonos (2301x1801).

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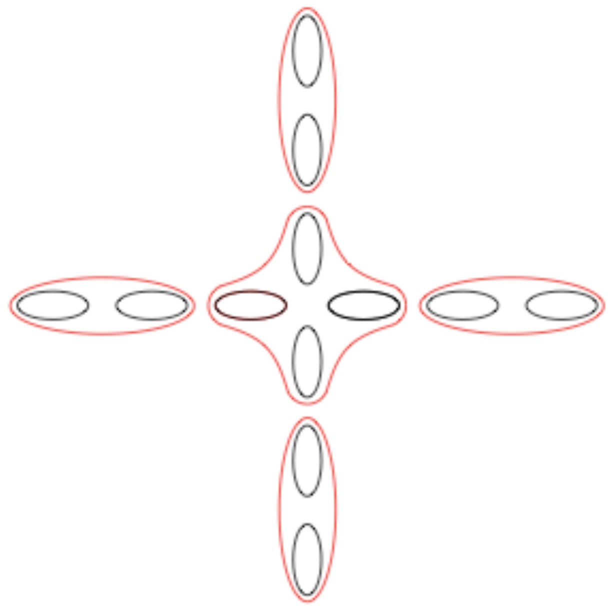
satellite segmentation: multilevel elongation

$$\Lambda_k = \begin{bmatrix} (\overline{x^2})_k - (\overline{x})_k^2 & (\overline{xy})_k - (\overline{x})_k(\overline{y})_k \\ (\overline{xy})_k - (\overline{x})_k(\overline{y})_k & (\overline{y^2})_k - (\overline{y})_k^2 \end{bmatrix}$$

$$R_k = \frac{\min(\omega)}{\max(\omega)}$$



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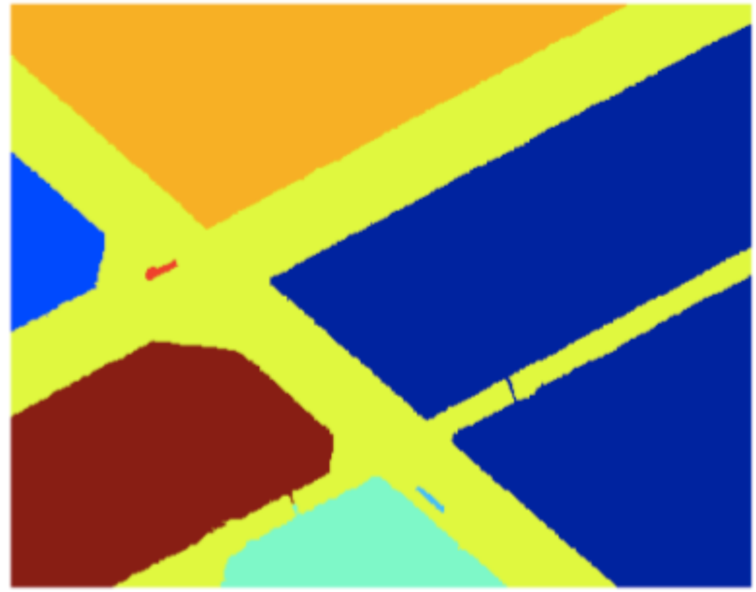
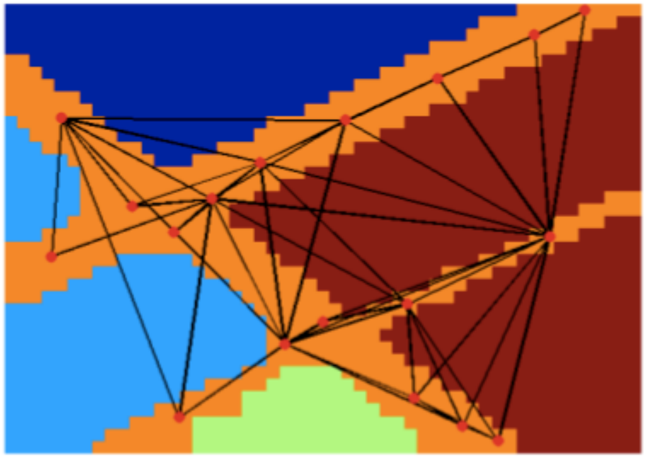
satellite segmentation

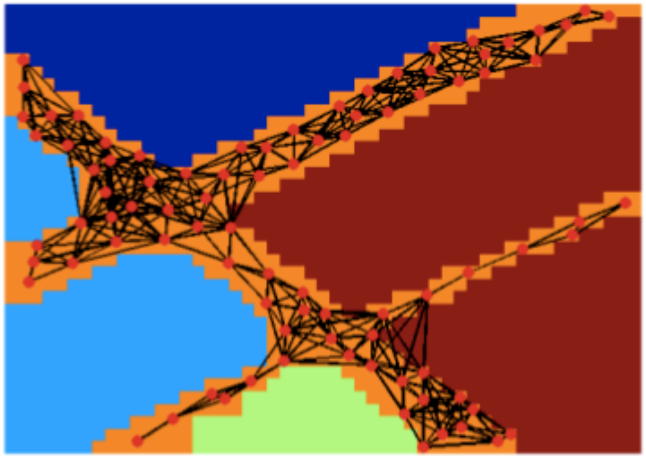
Figure 5.7: RGB image of the Region of Waterloo airport runway (501x351).



satellite segmentation

Figure 5.9: Scaled runway image (51x36).





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10. collaborators

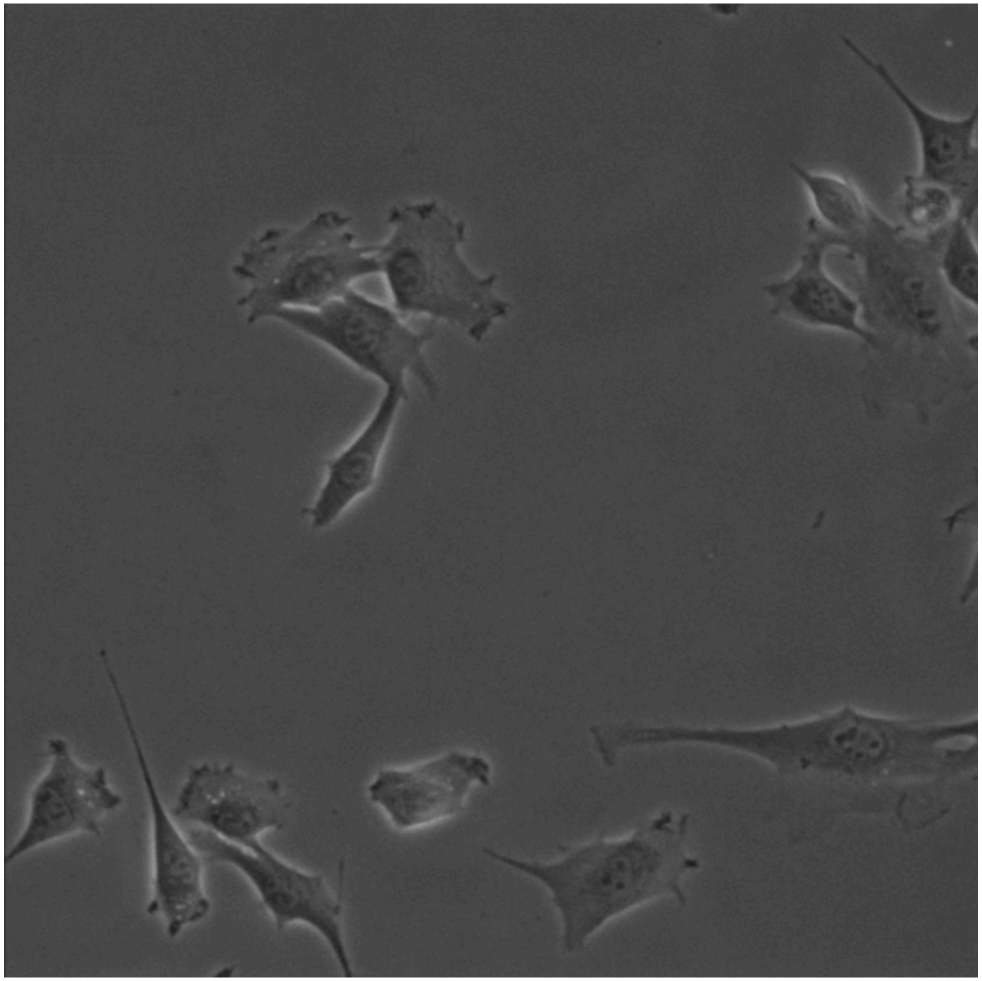
- my Master's students at Waterloo:
  - Tiffany Inglis (cell application)
  - Adley Au (satellite application)
- Geoff Sanders (Boulder)
- Haig Djambazian, Robert Sladek, and Saravanan Sundarara (McGill University and Genome Quebec Innovation Centre, Montreal) and Thomas J. Hudson (Ontario Institute for Cancer Research, Toronto)

11. conclusions

- multilevel aggregation (SWA) appears promising for cell segmentation and tracking, and satellite segmentation
- we propose a new scale-invariant and shape-invariant saliency measure for SWA
- problem: too many free parameters (‘ideal’ solution: include more coarse-level features up to the point that parameters can be fixed for a whole class of images)

conclusions

- powerful (multilevel features), efficient (linear complexity)
- space-time aggregation automatically uses temporal information (touching, overlapping cells)
- advantage: multilevel hierarchy contains extensive feature information about segments (cell (part) classification, road extraction, ...)
- commercial application: search for famous people in online movies



questions?

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