Automated Tracking for Alignment of Electron Microscope Images

Fernando Amat[1], Farshid Moussavi[1], Luis R. Comolli[3], Gal Elidan[2], Kenneth H. Downing[3], Mark Horowitz[1]

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1-Department of Electrical Engineering, Stanford University
2-Department of Computer Science, Stanford University
3-Life Sciences Division, Lawrence Berkeley National Laboratories

Motivation

One image is worth a thousand words…

Outline

- Correspondence between two images
- Global correspondence
- Results
- Future work
- Conclusions

Previous work

- Pre-align images
- Seed model
- Build projection model sequentially
- Find new candidates

Previous work

Advantages

- Runs very fast
- Works for high SNR

Disadvantages

- Depends on projection model
- Fails at low SNR
- Requires manual intervention to fix errors

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Correspondence between two images

- Key building block

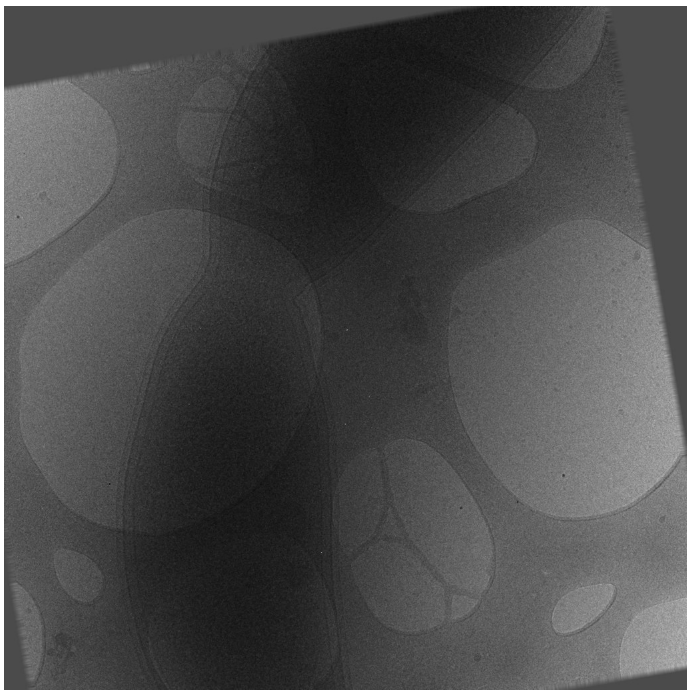


Image A

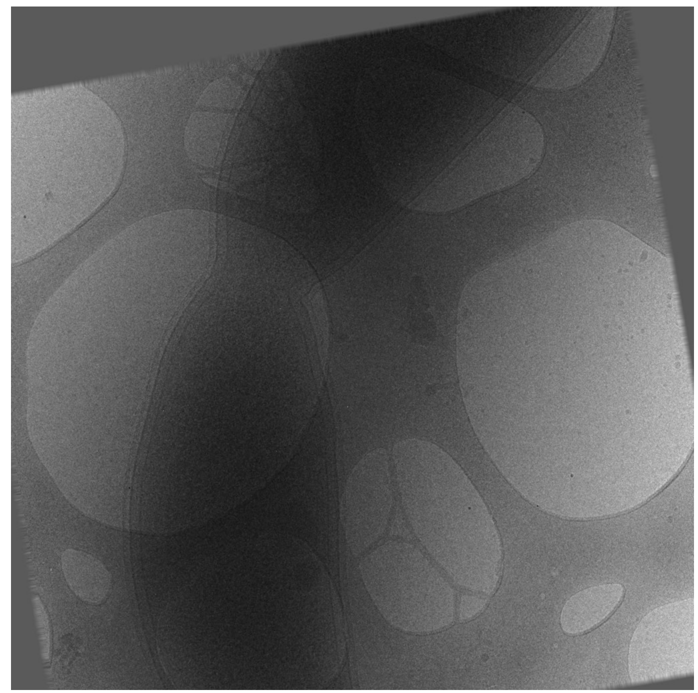


Image B

Images by Luis R. Comolli

Correspondence between two images

- Find point candidates in each image

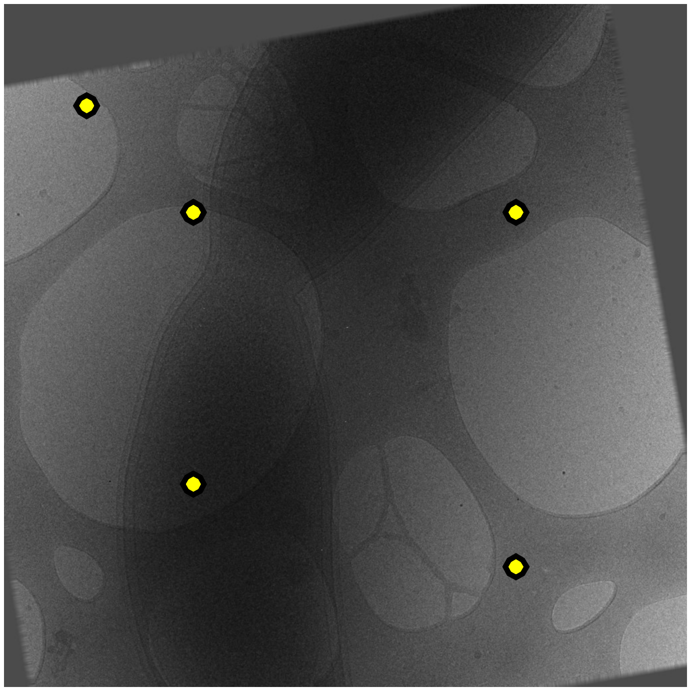


Image A

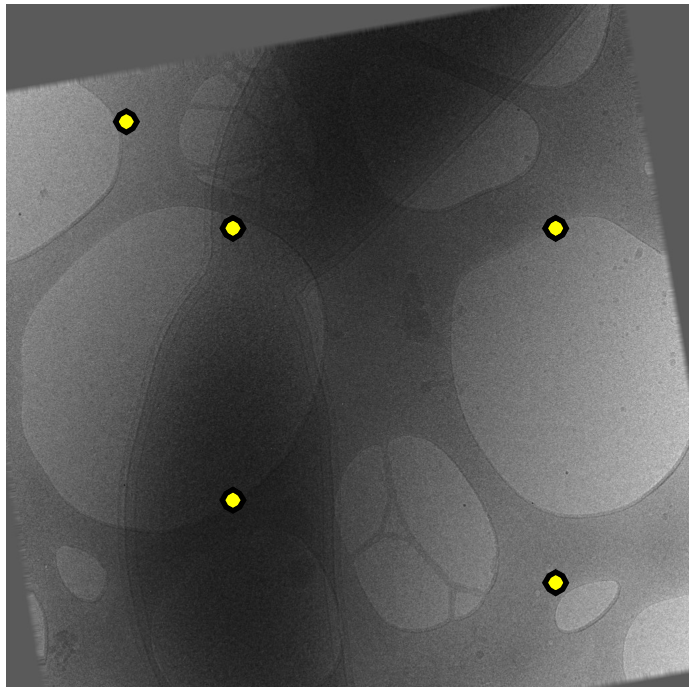


Image B

Images by Luis R. Comolli

Correspondence between two images

- Find correspondence between points

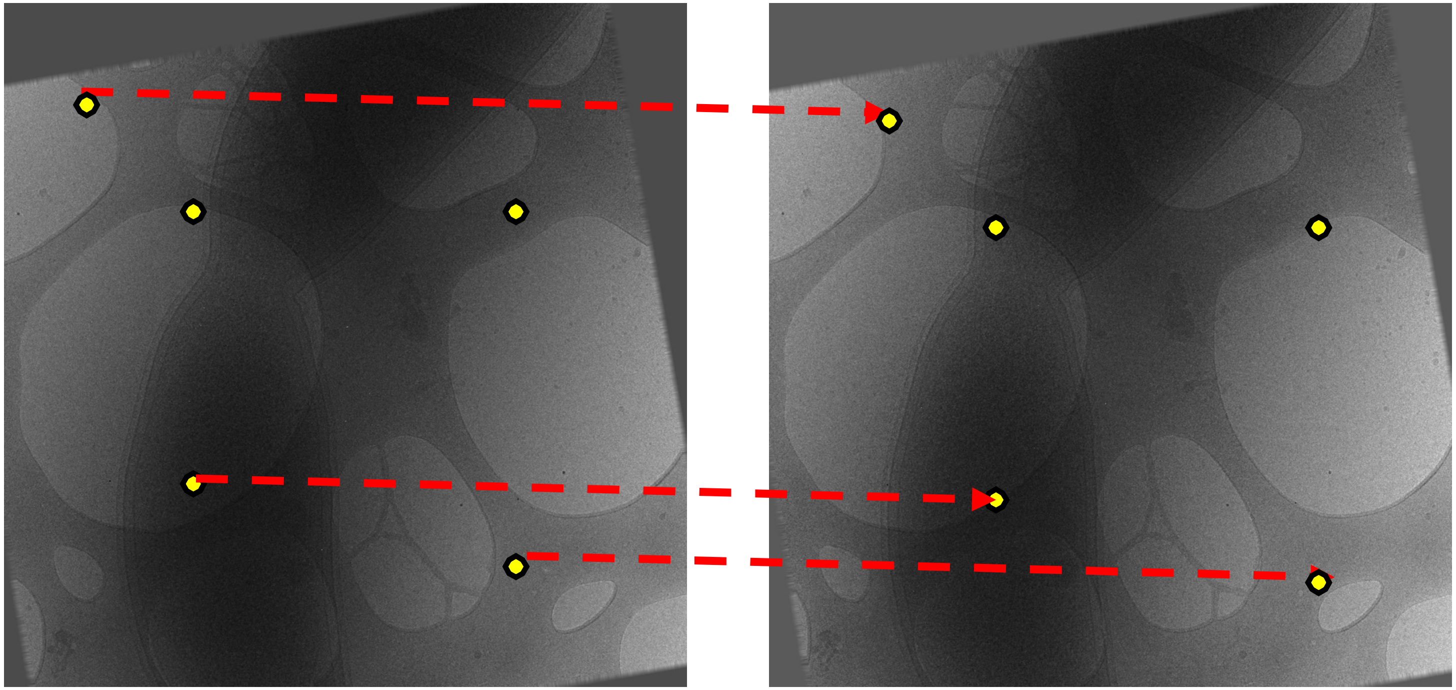
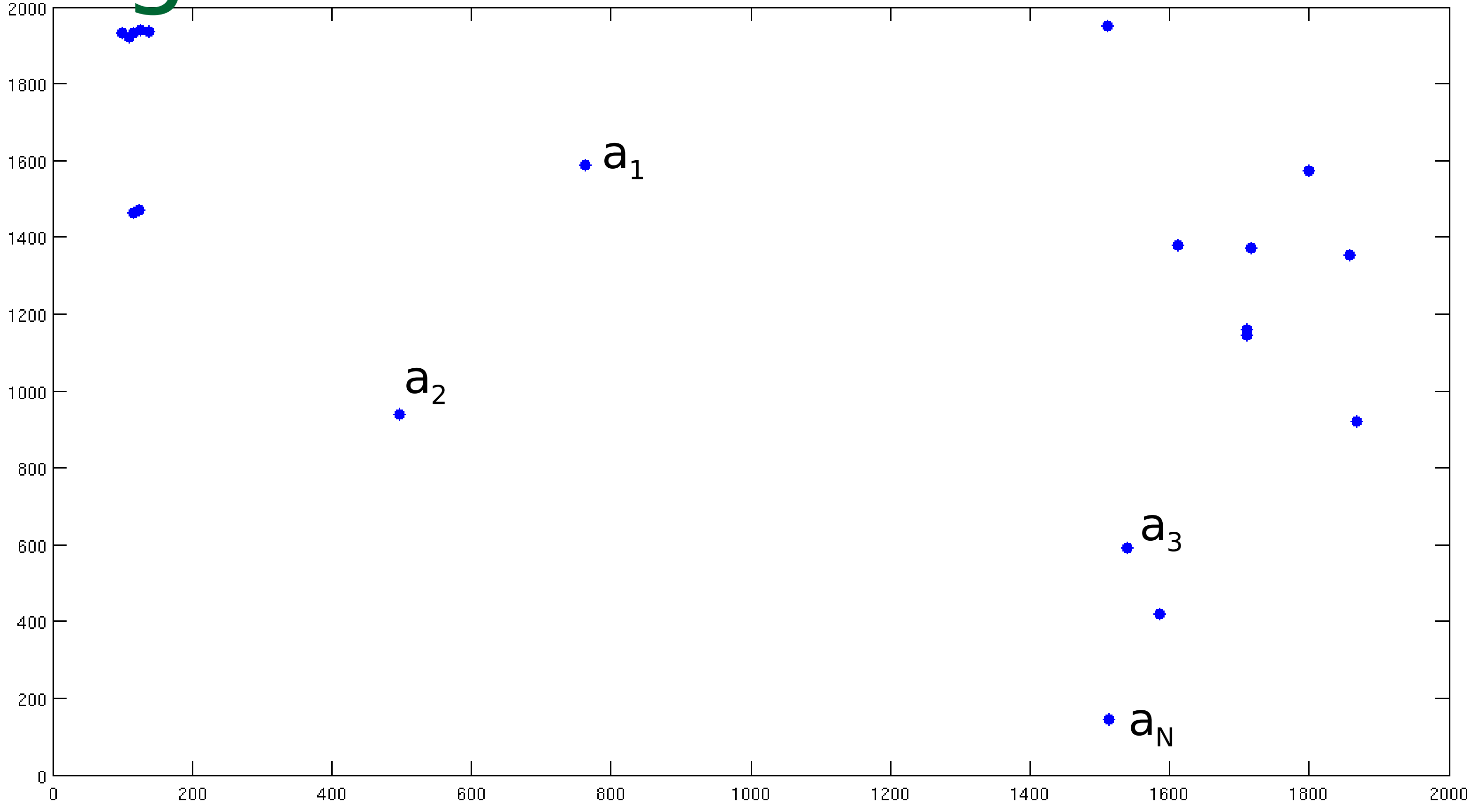


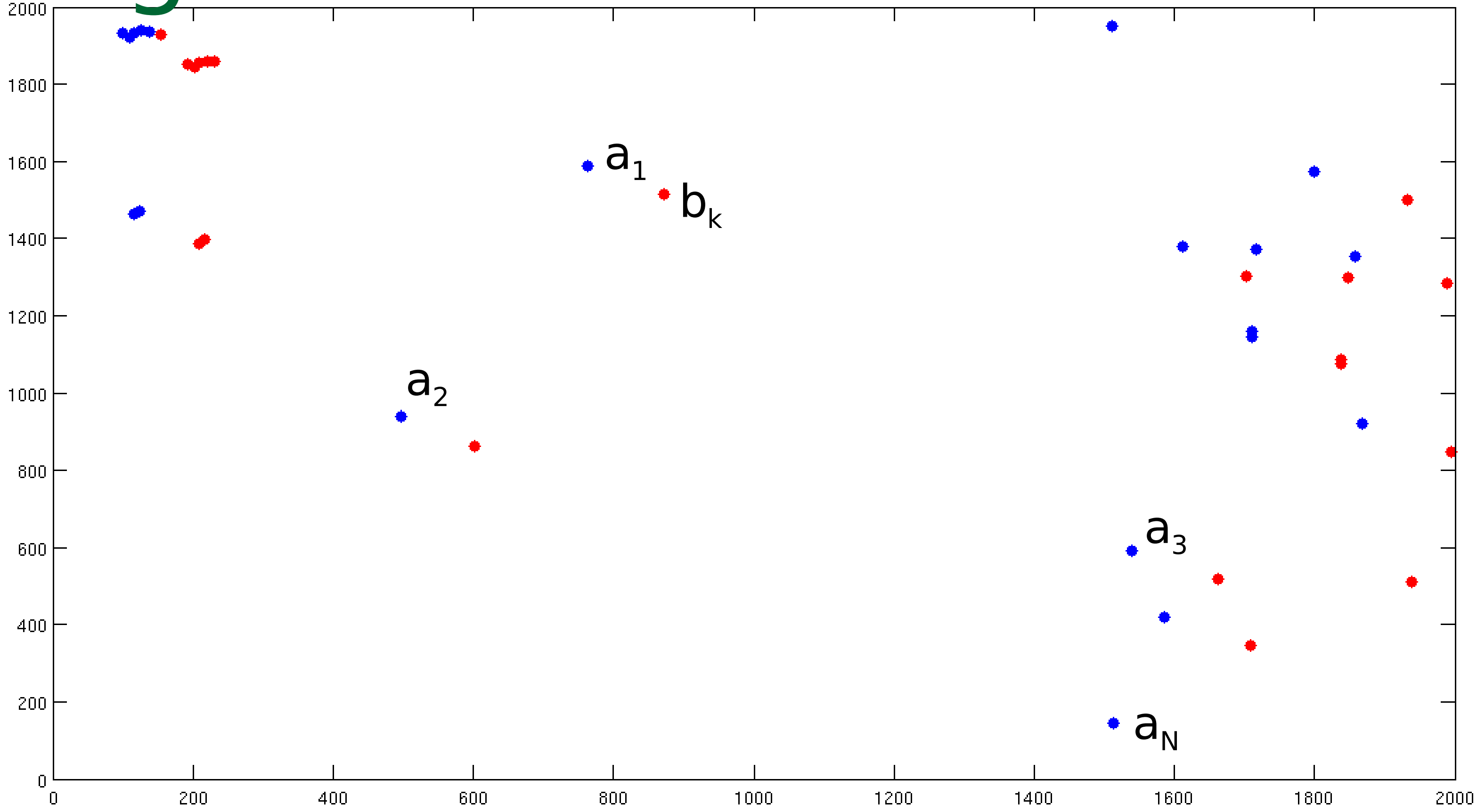
Image A Image B

Images by Luis R. Comolli

Correspondence between two images



Correspondence between two images

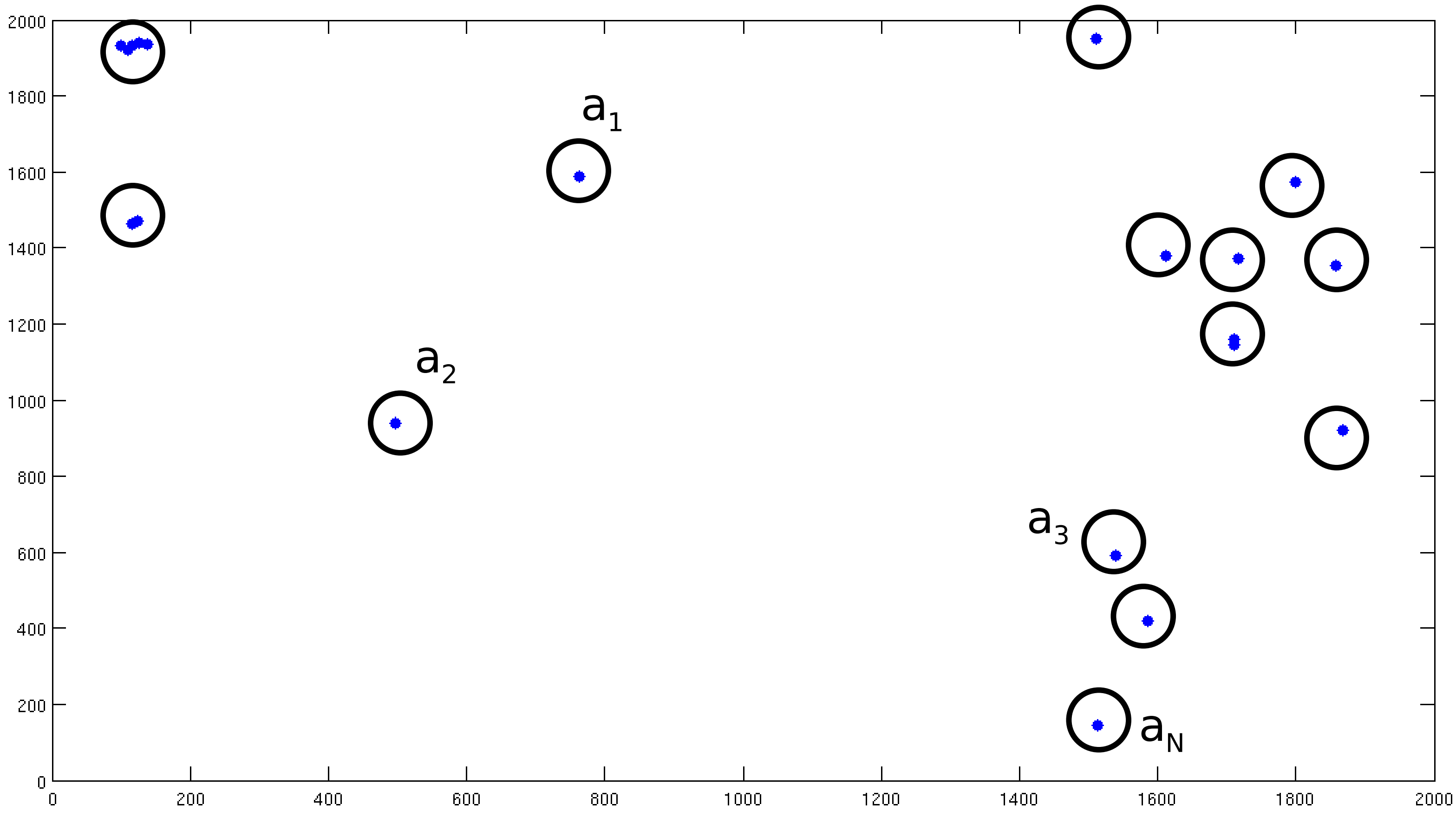


Probabilistic framework

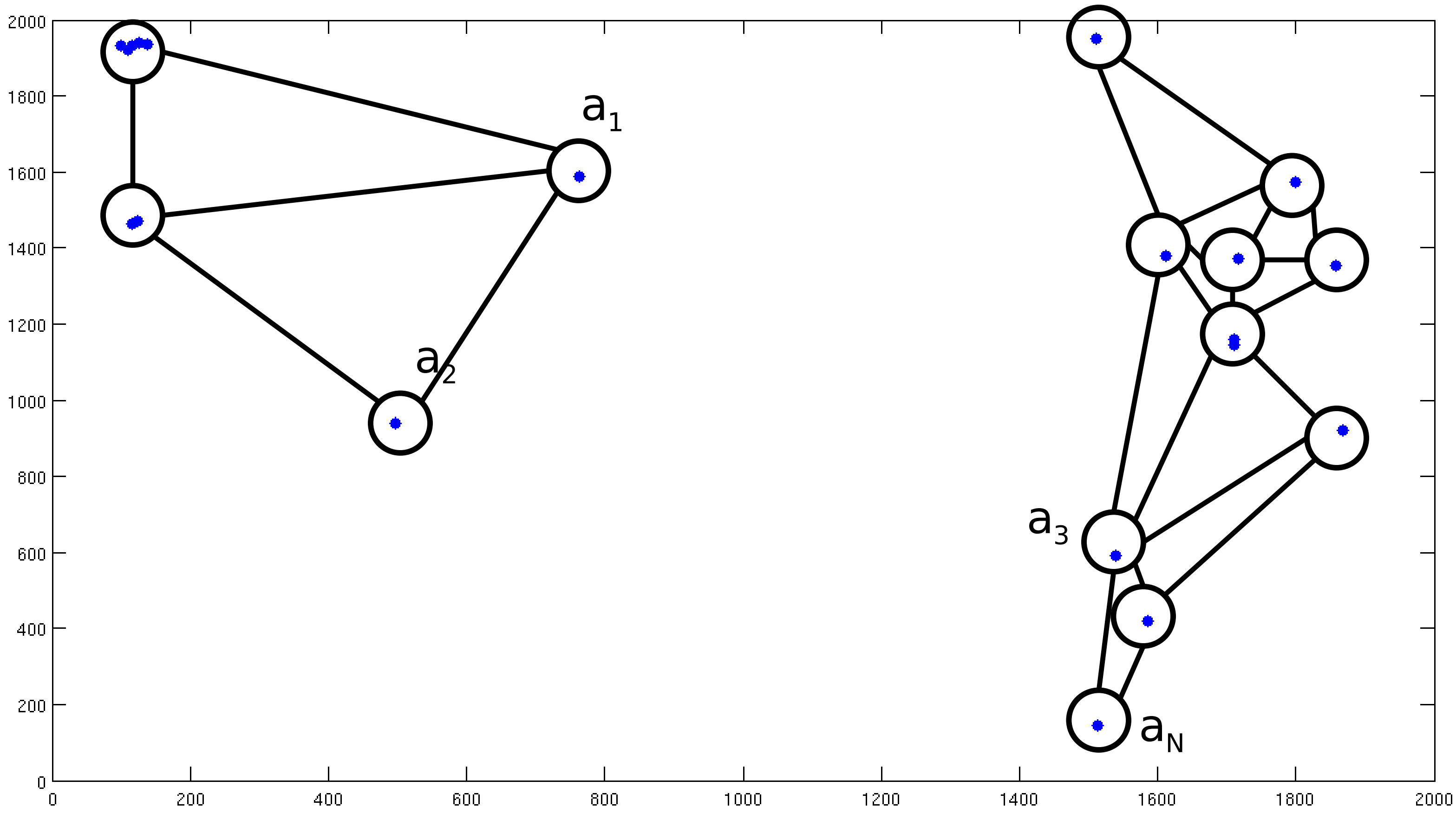
- Random variables $a_1, \ldots, a_N$
- Possible assignments $a_i = \{b_1, \ldots, b_K\}$
- Find joint distribution $p(a_1, \ldots, a_N)$
- Exponential complexity K^N is intractable

Exploit conditional independence

Graphical models



Graphical models



Graphical models

$$p(a_1, \ldots, a_n) \propto \prod_{i=1}^{n} \varphi_i(a_i) \prod_{i,j \in E} \varphi_{ij}(a_i, a_j)$$

φ_i: singleton factors

φ_{ij}: pairwise factors

$\boxed{\text{Solve combinatorial optimization problem}}$

Graphical models

- Complexity reduces to $O(K^2)$
- Spatial proximity determines the graph
- Image similarity determines singleton factors

$$\varphi_i(a_i = b_r) = NCC(patch(a_i), patch(b_r))$$

- Geometric similarity determines pairwise factors

$$\varphi_{ij}(a_i = b_r, a_j = b_s) = \exp\left(-\left\| vec(a_i a_j) - vec(b_r b_s) \right\|_2^2 \Big/ \sigma^2 \right)$$

Message passing

- Build table with initial beliefs

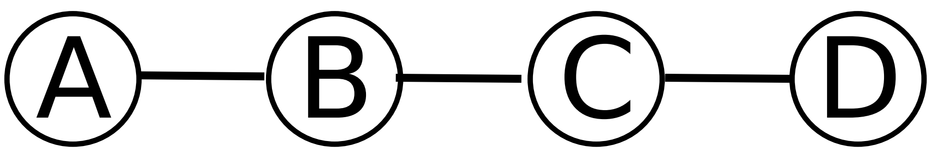
$a_i a_j$	b_1	b_2	…	b_K
b_1	0	0.8		0.2
b_2	0.3	0		0.1
…			0	0.4
b_K	0.1	0.7	0.2	0

- Calculate marginal distribution efficiently

$$p(a_k) \propto \sum_{i,j \neq k} \prod_{i=1}^{n} \varphi_i(a_i) \prod_{i,j \in E} \varphi_{ij}(a_i, a_j)$$

Message passing: inference

- Basic Idea
  - Calculate local marginals (beliefs) from “root”
  - Propagate up through graph
- Markov Chain example



$$P(A)= \sum P(A|B)P(B|C)P(C|D)P(D)$$

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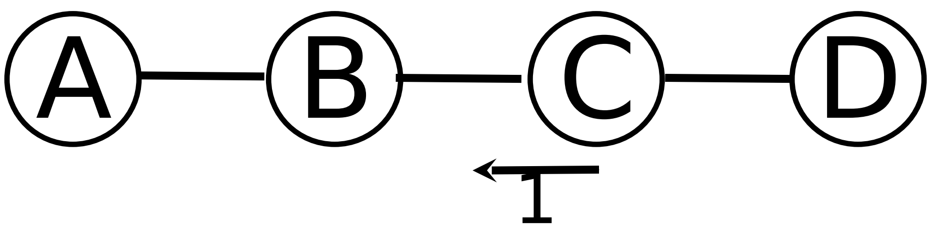

$$P(A) = \sum P(A|B) \sum P(B|C) \underbrace{\boxed{\sum P(C|D)P(D)}}_{1}$$

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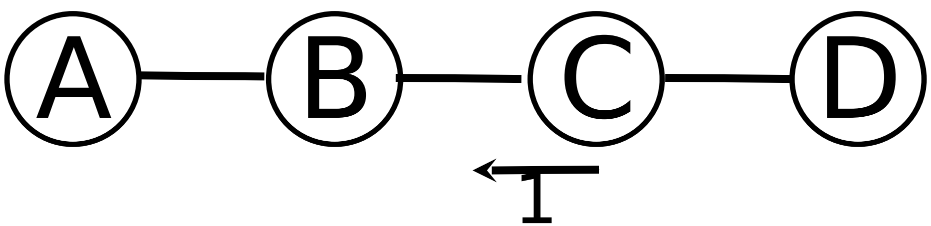

$$P(A) = \sum P(A|B) \sum P(B|C)\, \Psi(C)$$

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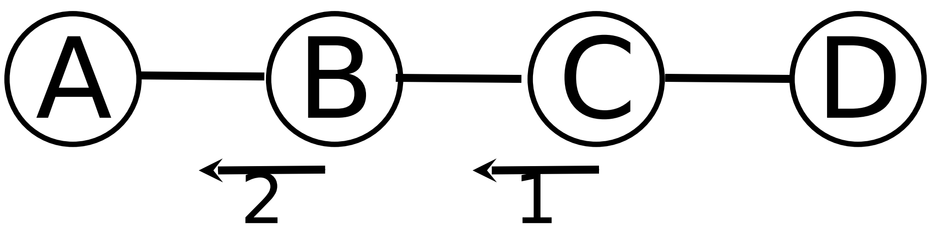

$$P(A)= \sum P(A|B) \underbrace{\sum P(B|C)\, \Psi(C)}_{\leftarrow 2}$$

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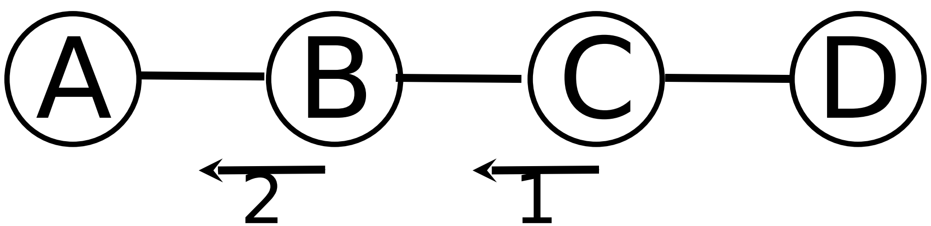

$$P(A) = \sum P(A|B)\,\Psi(B)$$

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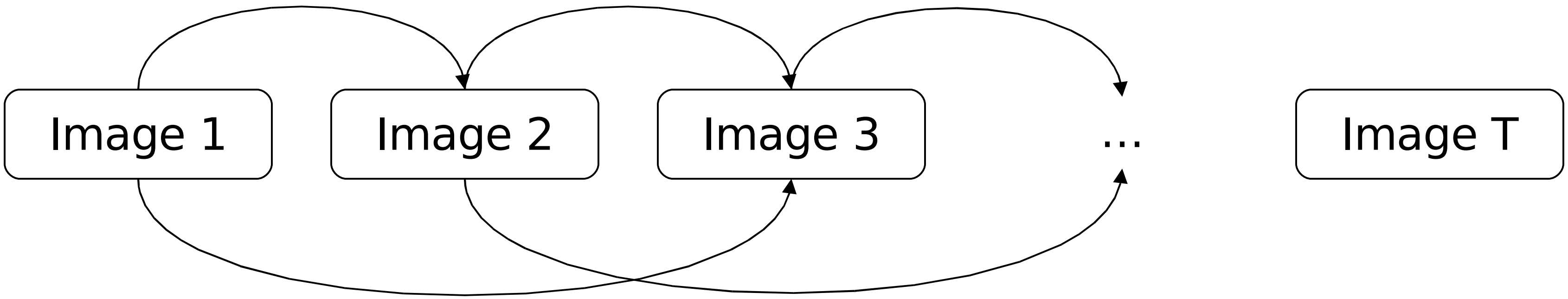
Global correspondence

- Combine pairwise correspondence



- Robust matrix decomposition to find outliers[1]

[1] Q. Ke and T. Kanade. *Robust L1 Norm Factorization in the Presence of Outliers and Missing Data by Alternative Convex Programming*. *CVPR*, 2005.

Summary

- Local/global trade-off approach
- Based on small angle change between images
- Independent of projection model
- Robust against errors

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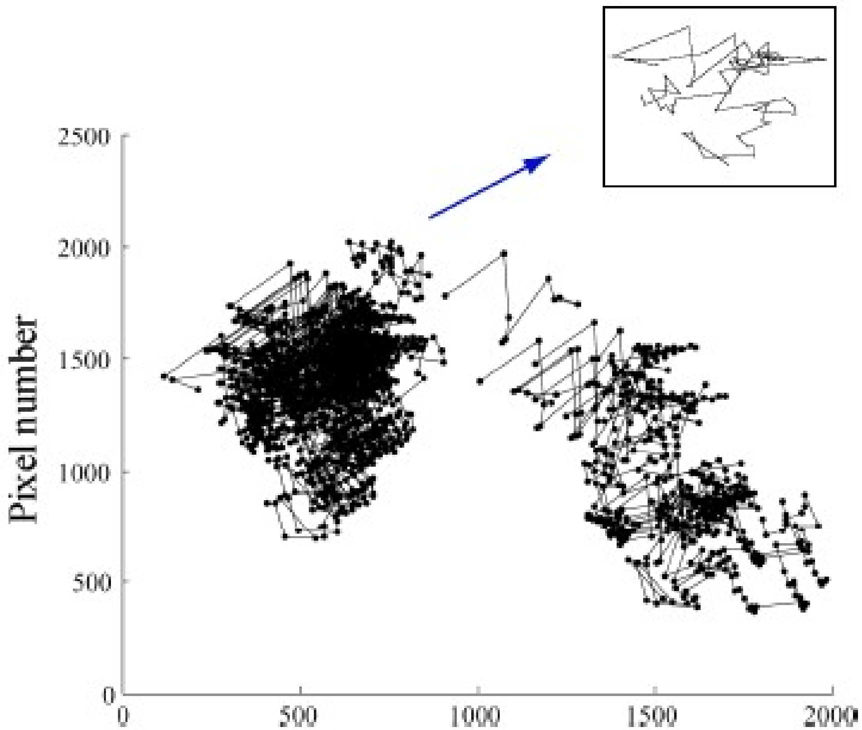
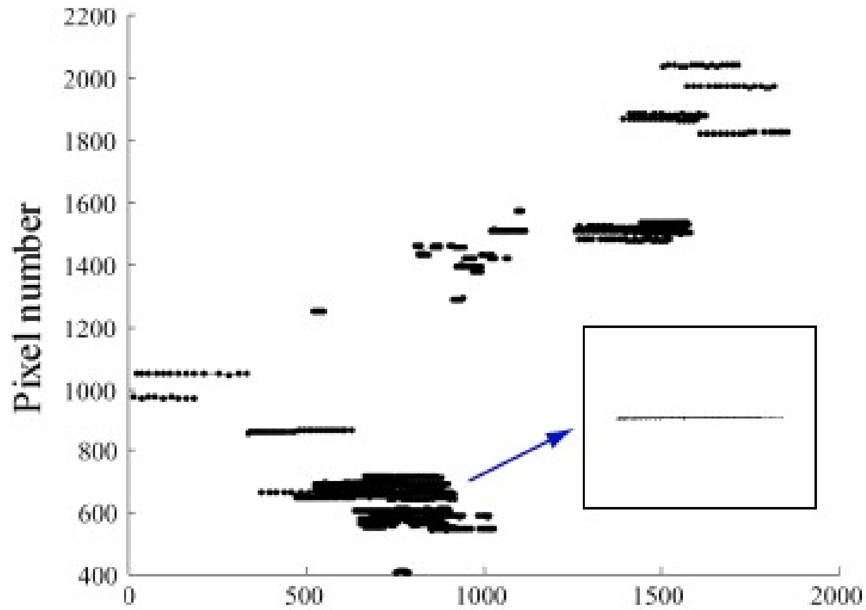
Results: tracked trajectories



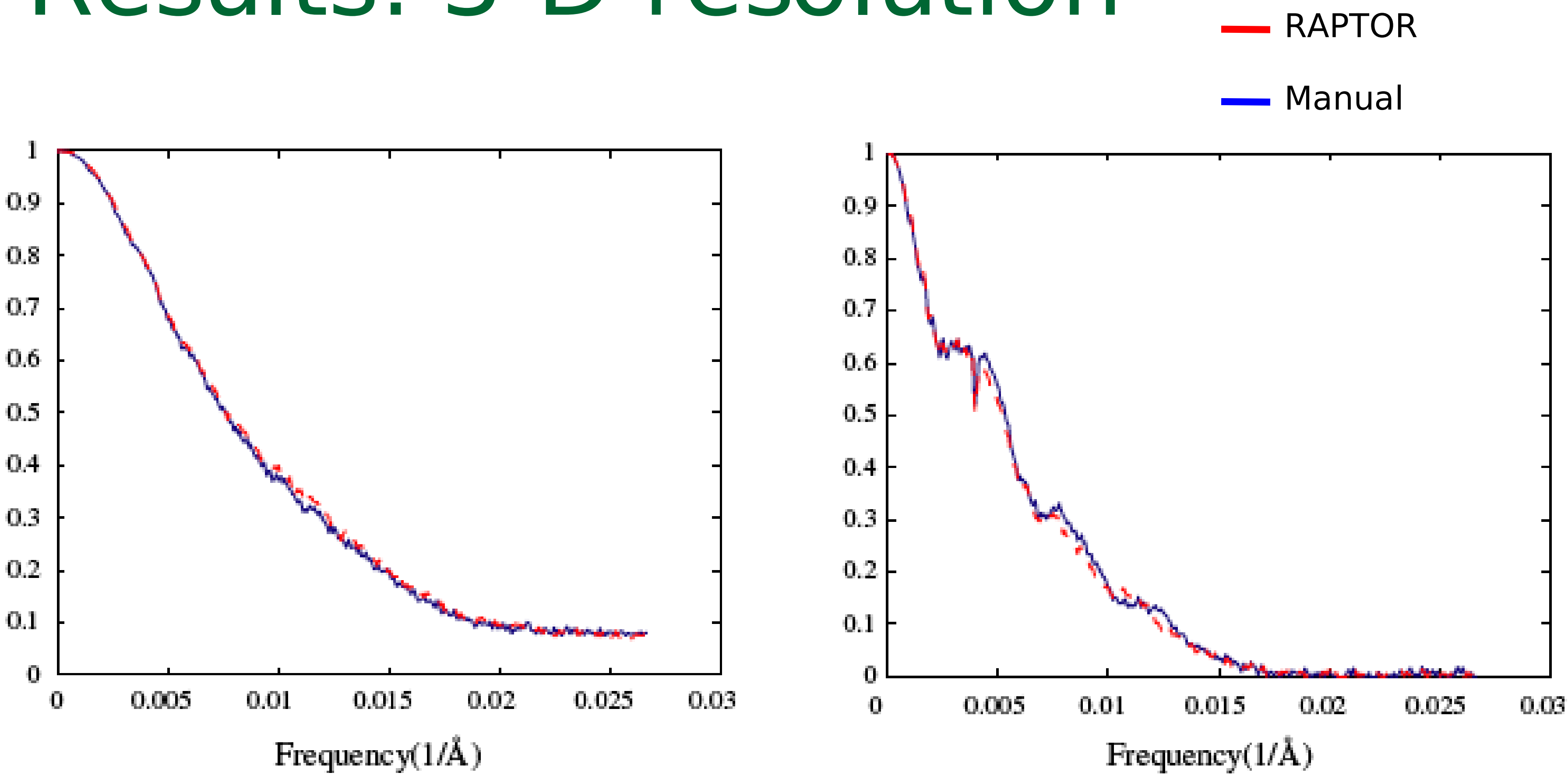
Before alignment



After alignment

Amat, F. et al., Markov random field based automatic image alignment for electron tomography, J. Struct. Biol. (2007)

Results: 3-D resolution



Amat, F. et al. Markov random field based automatic image alignment for electron tomography. J. Struct. Biol. (2007)

Cardone, G. et al. A resolution criteria for electron tomography based on cross-validation. J. Struct. Biol. 2005.

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Future Work

- Track multiple axis tomography
- Track images with hundreds of markers
- Improve local to global correspondence
- Parallelization

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Conclusions

- Graphical models: local/global compromise
- Probabilistic framework robust against noise
- Algorithms help high throughput data analysis
- Software available at http://www-vlsi.stanford.edu/TEM/software.htm

THANKS!

Message passing

- Efficient algorithm to calculate marginals
- (a_i, a_j) share an edge in the graph

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$$\psi_{ij}(a_i, N(i)\ j) = \prod_{k \in N(i)\ j} \varphi_{ik}(a_i, a_k)\,\delta(a_k \rightarrow a_i)$$

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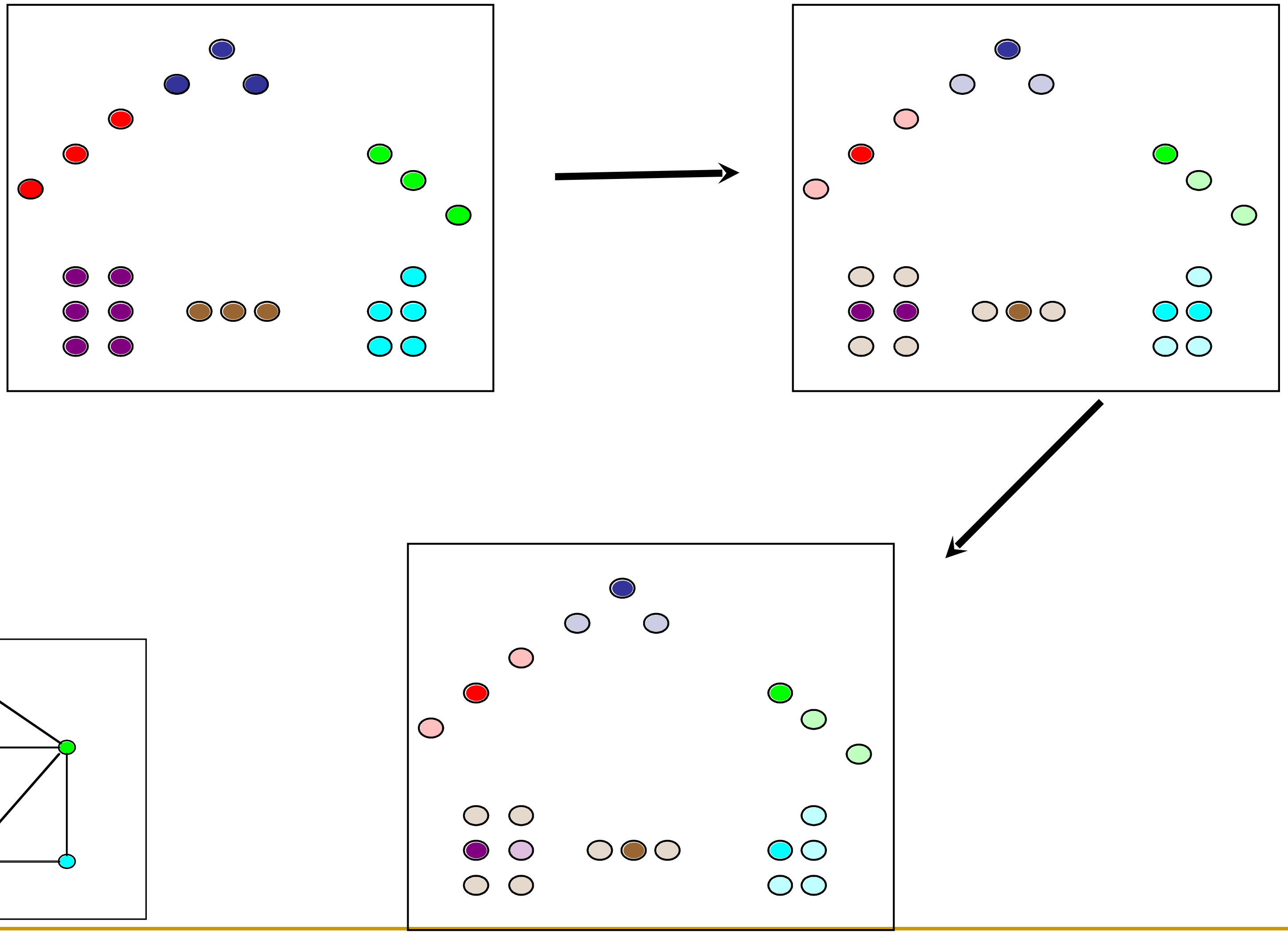
$$\delta(a_i \rightarrow a_j) = \varphi_i(a_i) \sum_{N(i)\ j} \psi_{ij}(a_i, N(i)\ j)$$

Message passing



Ground Truth