

Segmentation with Pairwise Attraction and Repulsion

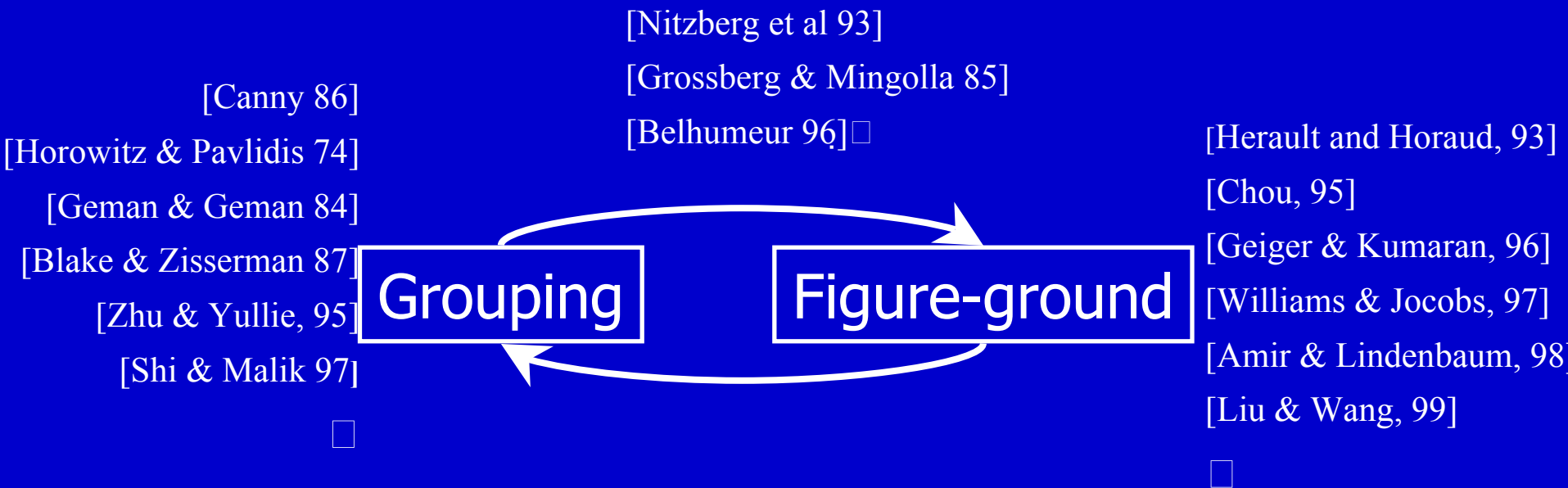
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- Grouping: decomposition into regions of coherent properties
- Figure-ground: decomposition into foreground and background

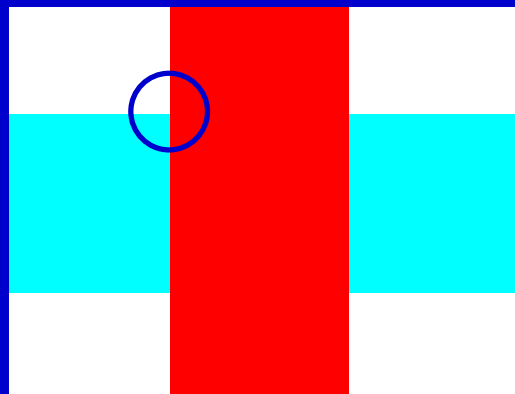
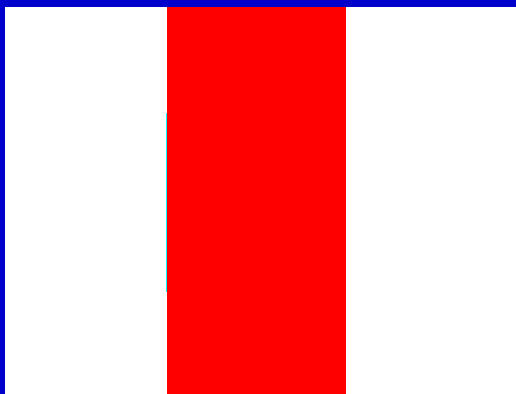
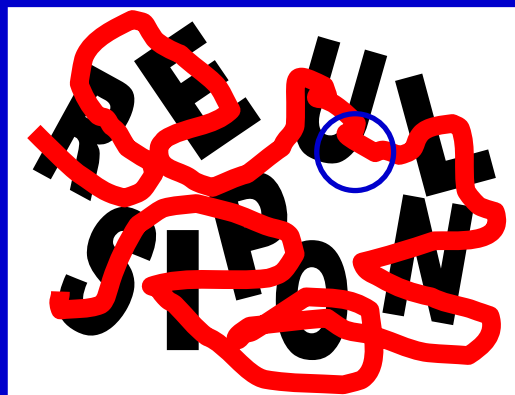
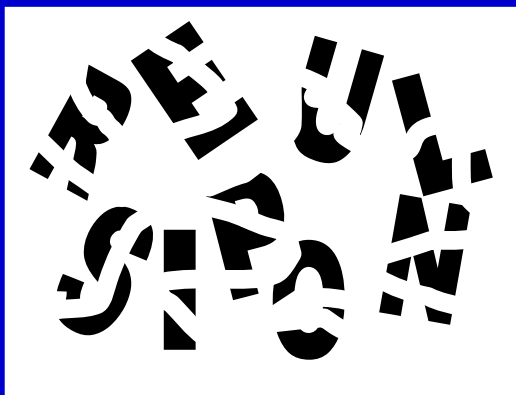


- Issues

- ➔ Fundamental: segmentation and figure-ground reasoning is circular
- ➔ Practical: lack of efficient computational techniques

Figure-ground cues for segmentation

- Figure-ground organization □ Segmentation + Figure-ground labelling
- Between-region relations can influence the internal organization of a region



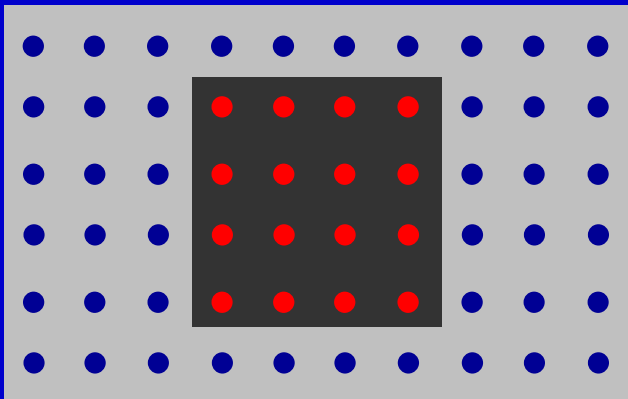
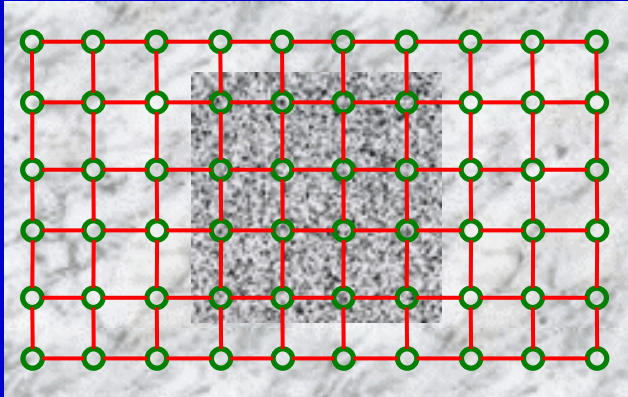
Roles of figure-ground cues:

- ✓ Link incoherent background or foreground together
- ✓ Global binding through local cues

Talk overview

- Segmentation in a graph framework
 - Ordered graph partitioning
- Representing pairwise relationships
 - Attraction and repulsion
- Criteria
 - Optimize global configuration of figure vs ground
- Energy formulation
 - Rayleigh quotient of Hermitian matrices
- Efficient solution technique
 - Sparse matrix eigendecomposition
- Results

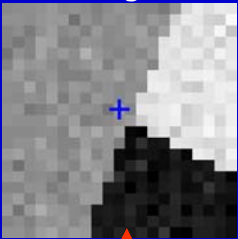
Segmentation in a graph framework



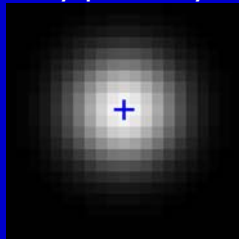
- $G=(V, E, W)$
 - V : each node denotes a pixel
 - E : each edge denotes a pixel-pixel relationship
 - W : each weight measures pairwise affinity
- Segmentation = vertex partitioning
 - break V into disjoint sets V_1, V_2
- Pairwise affinity, W :
 - similarity of pixel attributes
 - relative order of figure-ground
- Goal: ordered partitioning
 - V_1 = figure, V_2 = ground
- Criteria:
 - within-region similarity: high
 - between-region similarity: low
 - order from figure to ground: high

Generalized affinity: attraction and repulsion

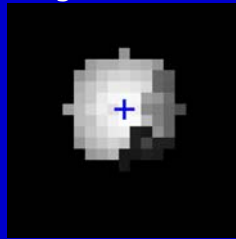
image



A by proximity



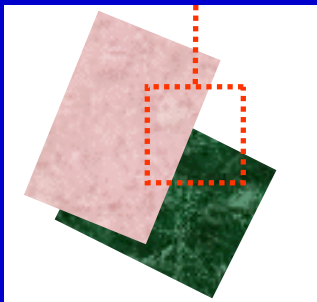
A by brightness similarity



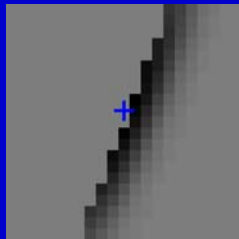
■ Attraction A

- feature similarity
- feature = location, brightness, texture, motion, ...
- the larger the A_{jk} , the more likely j and k in one region

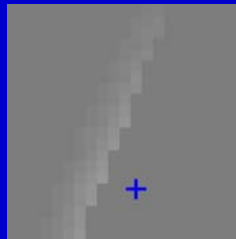
Relative depth from T-junctions



R for a figure pixel



R for a ground pixel

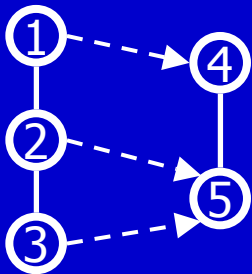


■ Directional repulsion R

- relative order of figure-ground
- the larger the $|R_{jk}|$, the more likely j and k in different regions

■ Generalized Affinity $W = A + \lambda R$

- A 5-node graph example
- W is Hermitian



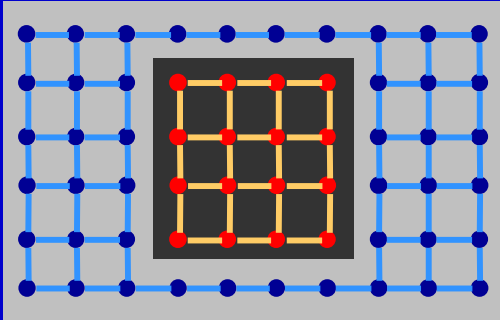
A is symmetric

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

R is skew-symmetric

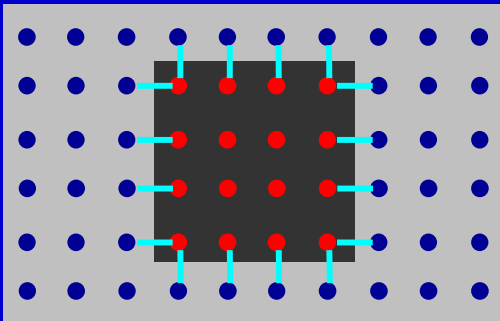
$$R = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & -1 & 0 & 0 \end{bmatrix}$$

Criteria: cuts, associations and difference flows



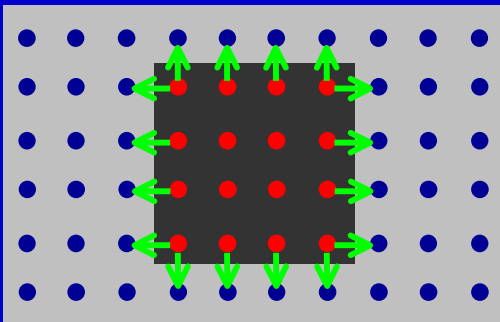
- within-region similarity
= within-group attraction
= associations

$$assoc(P) = \sum_{u \in P, v \in P} A(u, v)$$



- between-region similarity
= between-group attraction
= cuts

$$cut(P, Q) = \sum_{u \in P, v \in Q} A(u, v), \quad P \cap Q = \Phi$$



- order from figure to ground
= figure-to-ground repulsion
= difference flow

$$diffflow(P, Q) = \sum_{u \in P, v \in Q} R(u, v), \quad P \cap Q = \Phi$$

Criteria: generalized normalized association

- Maximize within-region similarity and figure-to-ground order

$$N_{assoc} = \frac{\text{within figure similarity}}{\text{total figure affinity}} + \frac{\text{within ground similarity}}{\text{total ground affinity}} + \frac{\text{figure} \sim \text{ground order}}{\text{average total affinity}}$$

$$N_{assoc}(V_1, V_2) = \frac{assoc(V_1)}{deg(V_1)} + \frac{assoc(V_2)}{deg(V_2)} + \frac{2 \cdot difflo\omega(V_1, V_2)}{\sqrt{deg(V_1) \cdot deg(V_2)}}$$

Criteria: generalized normalized cuts

- Minimize between-region similarity and ground-to-figure order

$$N_{cut} = \frac{\text{figure-ground similarity}}{\text{total figure affinity}} + \frac{\text{figure-ground similarity}}{\text{total ground affinity}} + \frac{\text{ground-figure order}}{\text{average total affinity}}$$

$$N_{cut}(V_1, V_2) = \frac{cut(V_1, V_2)}{\deg(V_1)} + \frac{cut(V_2, V_1)}{\deg(V_2)} + \frac{2 \cdot diff\text{low}(V_2, V_1)}{\sqrt{\deg(V_1) \cdot \deg(V_2)}}$$

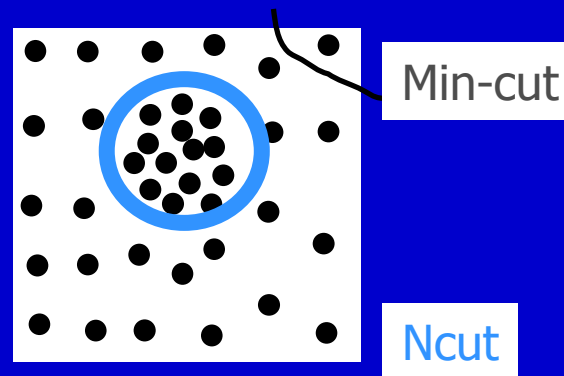
Properties of the criteria

- Duality to achieve both goals at the same time

$$N_{cut} + N_{assoc} = \text{constant}$$

$$\arg \min N_{cut} = \arg \max N_{assoc}$$

- Normalization for global structures



Energy formulation

- Variables:
group indicators

$$X_l(u) = \begin{cases} 1, & u \in V_l \\ 0, & u \notin V_l \end{cases}$$

$$X_1 = \begin{bmatrix} 1_{n_1 \times 1} \\ 0_{n_2 \times 1} \end{bmatrix}, \quad X_2 = \begin{bmatrix} 0_{n_1 \times 1} \\ 1_{n_2 \times 1} \end{bmatrix}$$

- Energy functions of indicator variables

$$\begin{bmatrix} 1 & 0 \\ & \begin{bmatrix} \text{yellow} & \text{grey} \\ \text{grey} & \text{grey} \end{bmatrix} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 1 \\ & \begin{bmatrix} \text{grey} & \text{grey} \\ \text{grey} & \text{yellow} \end{bmatrix} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 \\ & \begin{bmatrix} \text{grey} & \text{green} \\ \text{grey} & \text{grey} \end{bmatrix} \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$Nassoc(X_1, X_2) = \frac{X_1^T A X_1}{X_1^T D X_1} + \frac{X_2^T A X_2}{X_2^T D X_2} + \frac{2 X_1^T R X_2}{\sqrt{X_1^T D X_1 \cdot X_2^T D X_2}}$$

Energy formulation

$$Nassoc(X_1, X_2) = \frac{X_1^T A X_1}{X_1^T D X_1} + \frac{X_2^T A X_2}{X_2^T D X_2} + \frac{2 X_1^T R X_2}{\sqrt{X_1^T D X_1 \cdot X_2^T D X_2}}$$

$$y = \sqrt{1-k} X_1 - i \sqrt{k} X_2, \quad k = \frac{\deg(V_1)}{\deg(V)}$$

$$Nassoc(y) = \frac{y^H (A + i \cdot R) y}{y^H D y}$$

$$s.t. \quad y^{2T} D 1 = 0$$

- Change of variables
- Rayleigh quotient

Three aspects of solutions

- Efficient solutions in the continuous domain:

- Eigenvector corresponding to the largest eigenvalue of $(A+iR, D)$

$$y_{opt} = \arg \max \frac{y^H (A + i \cdot R)y}{y^H D y} \Rightarrow (A + i \cdot R)y_{opt} = \lambda_1 D y_{opt}$$

- Little increase in complexity

- Hermitian matrices preserve the most important properties of real symmetric matrices in eigendecomposition.

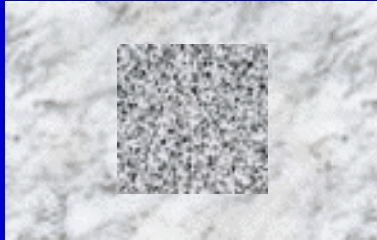
- Sparse matrix eigendecomposition $O(n^{3/2})$, $n = \#$ of pixels

- Interpretation of complex-valued solutions

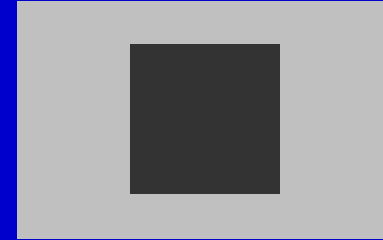
- Separation in phase plane indicates the separation of groups

- Relative phase advance indicates figure-ground ordering

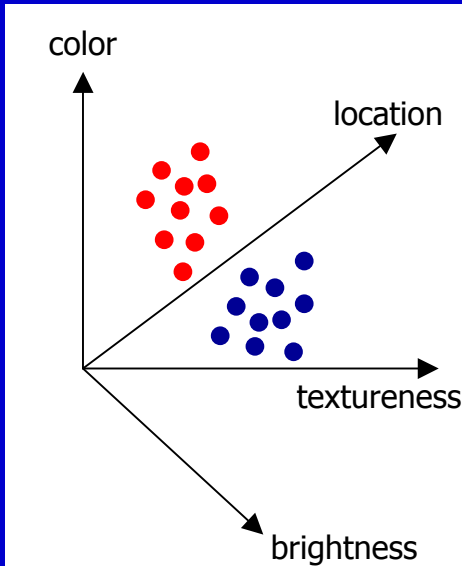
Segmentation as embedding



Assign region identity.



Every pixel corresponds to a point in a high dimensional feature space.



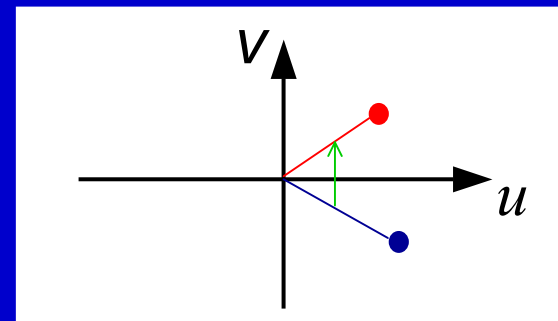
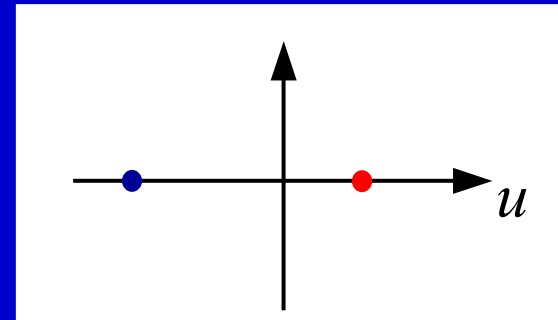
$$y_{opt} = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}$$

grouping

figure-ground

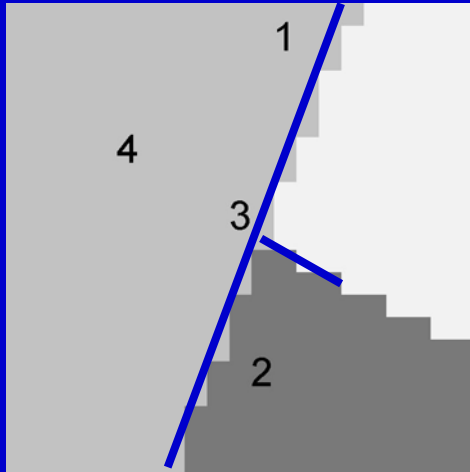
$$y_{opt} = \begin{bmatrix} u_1 + i \cdot v_1 \\ \vdots \\ u_n + i \cdot v_n \end{bmatrix}$$

Segmentation is about finding an embedding of manifolds into some 1D or 2D space.

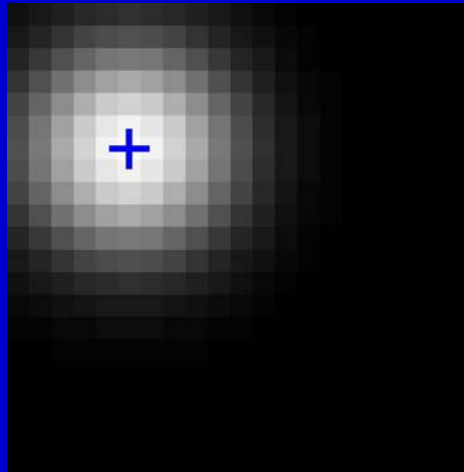


Interaction of attraction and repulsion

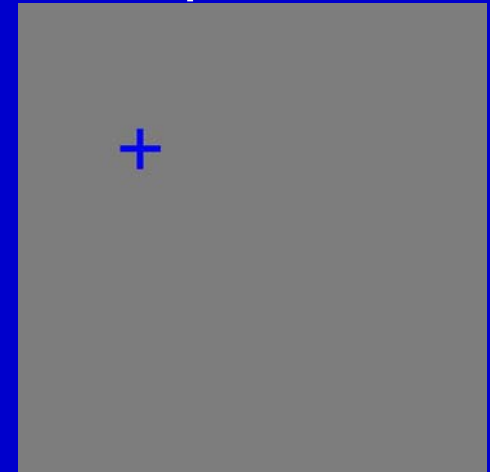
Image



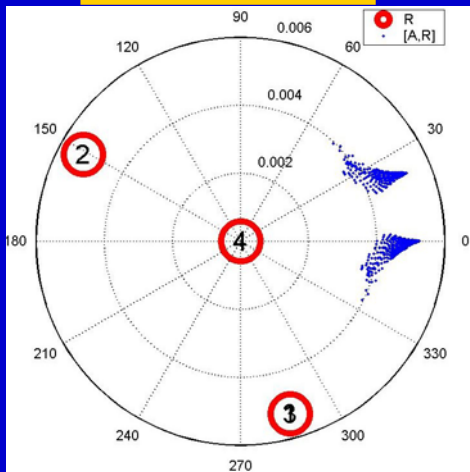
Attraction



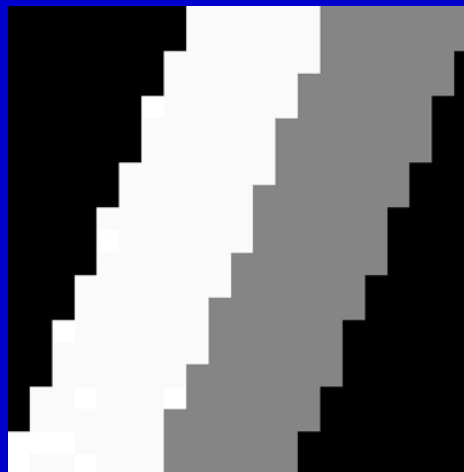
Repulsion



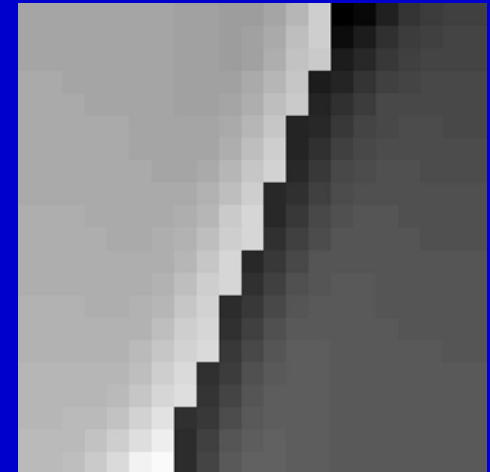
Phase Plot



Result: R



Result: A and R



Objects ordered in depth

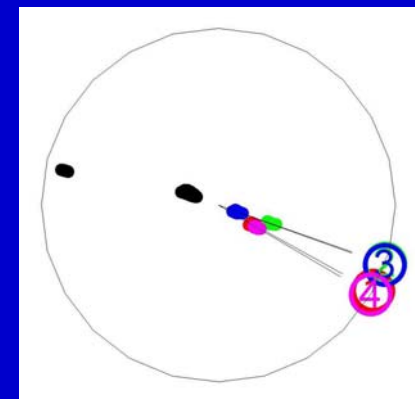
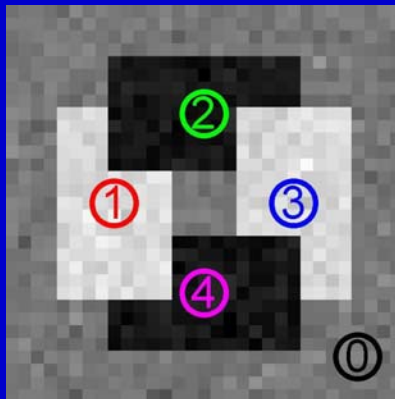
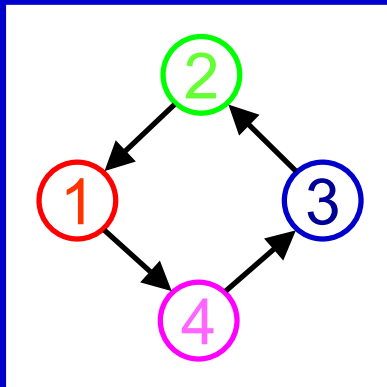
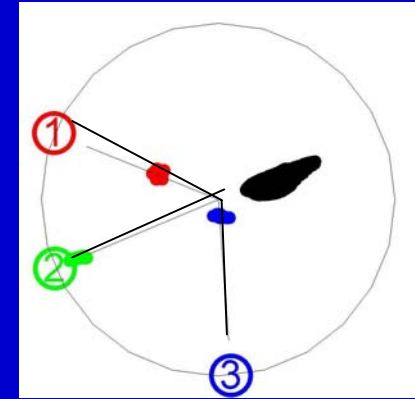
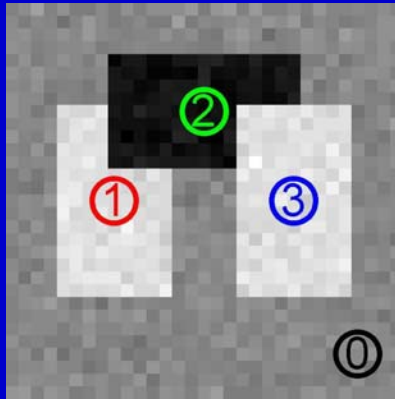
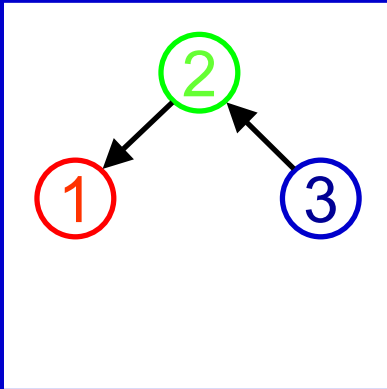
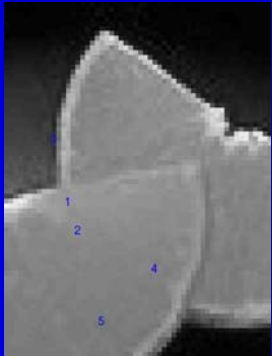
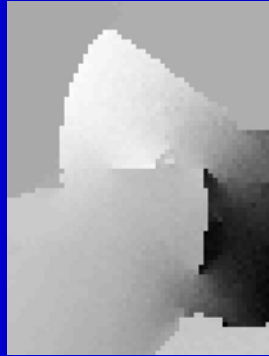


Figure-ground example

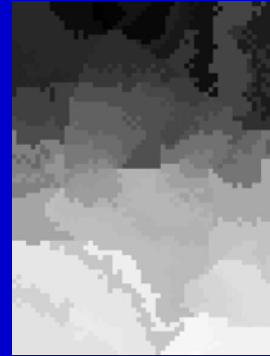
Image



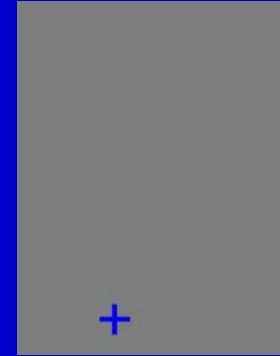
Solutions: A



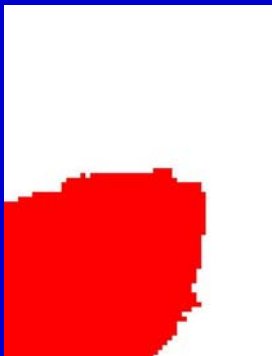
Oversegmentation based on A



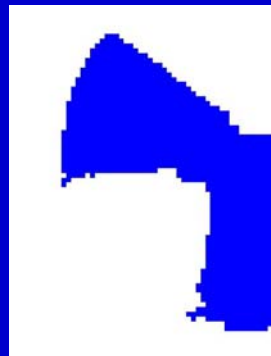
R



Figure



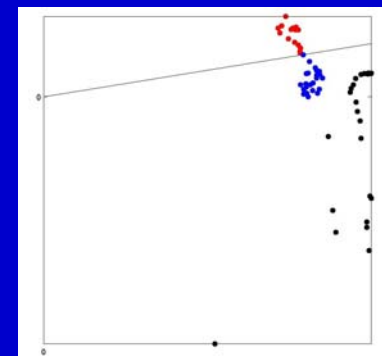
Ground 1



Ground 2



Phase plot



Conclusions

- Representation
 - Attraction + directional repulsion
- Formulation
 - Ordered graph partitioning for figure and ground
 - Rayleigh quotient of Hermitian matrices
- Solution
 - Efficient algorithm by eigendecomposition
 - Embedding in the phase plane of complex numbers
- Benefits
 - Grouping and figure-ground in one step
 - Computational efficiency