How I Learned to Stop Worrying and Love the SOM

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TECHNISCHE FAKULTÄT

Motivation

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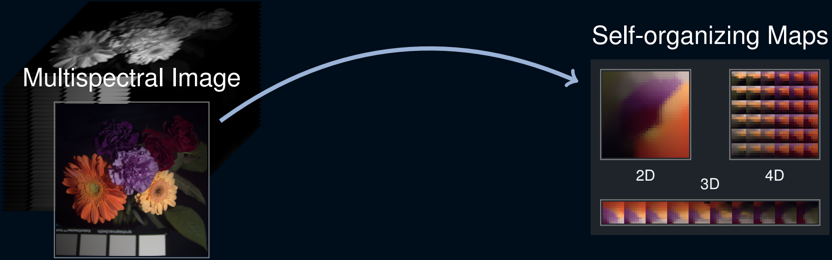

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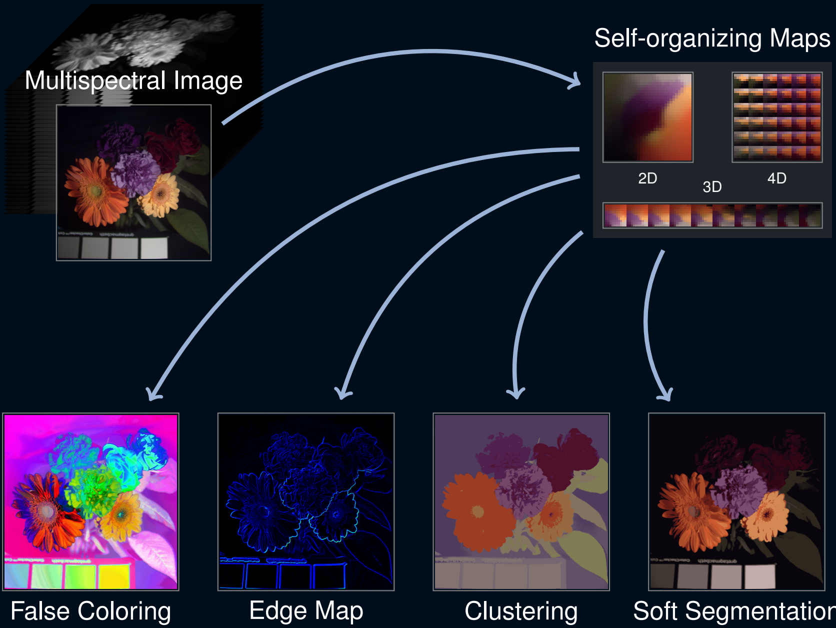
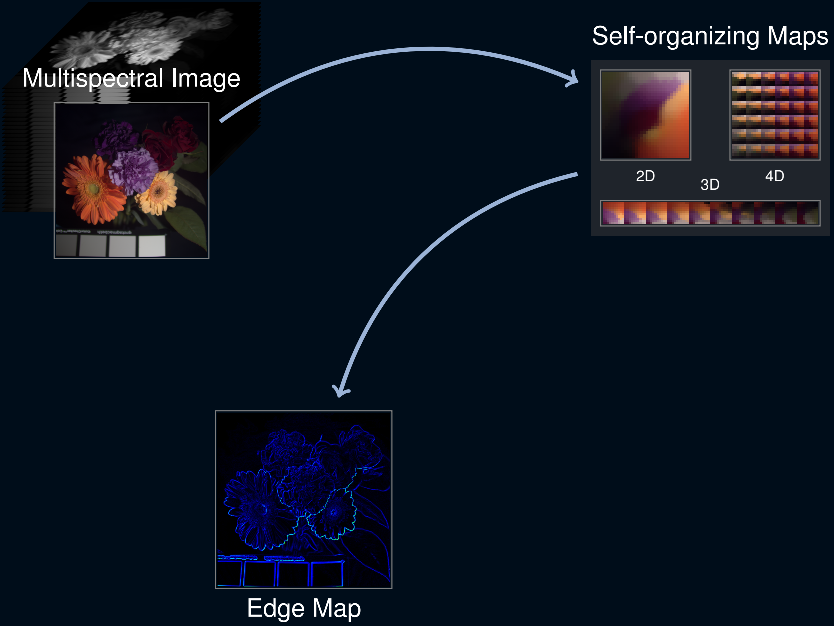


Multispectral Image
Self-organizing Maps
2D
3D
4D
False Coloring
Edge Map
Clustering
Soft Segmentation

Motivation



Multispectral Gradient Calculation

True-color rendering

False-color rendering

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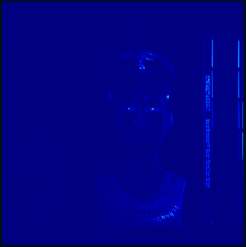
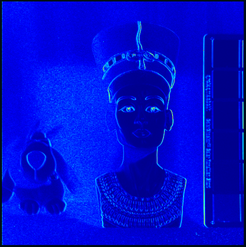
Established measures for spectral vector distance: ∇_x



Euclidean Distance



Spectral Angle

Spectral Information Divergence (SID)

Multispectral Gradient Calculation

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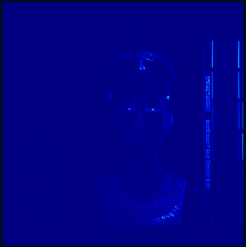

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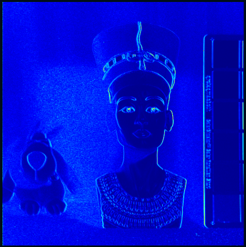

Spectral Angle

Spectral Information Divergence (SID)

Observations:

1. Euclidean distance misses crucial details
2. Spectral Angle and SID are prone to noise in dark regions

Multispectral Edge Detection

Canny: 1986, Gradient-based

1. Sobel / Gaussian filter
2. Non-maximum suppression
3. Edge tracking with double threshold

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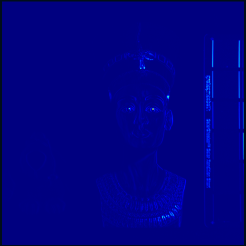
Vector Order Statistics: 1993, 2003

- Local R-ordering: *see RCMG*
- Global Ordering (SOM):
  Ordering is flawed
  False edges appear

Challenges

True color



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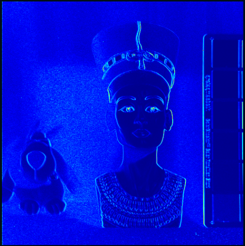

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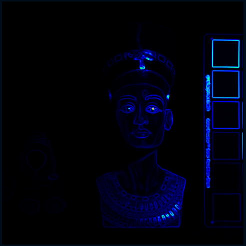
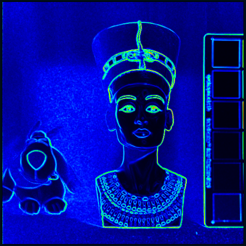


RCMG on L_2



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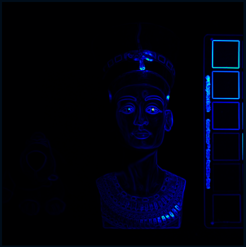

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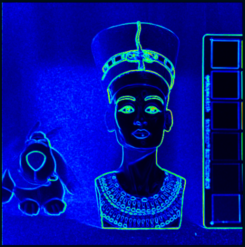

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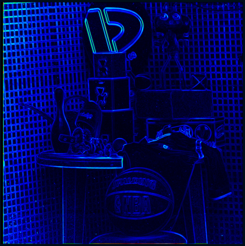
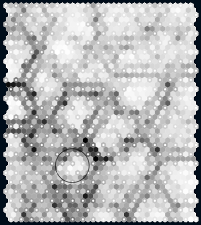


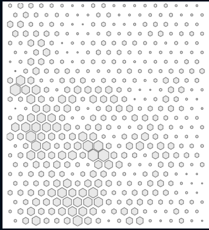
RCMG on L_2

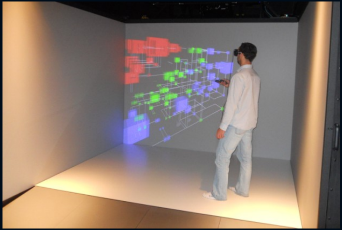
RCMG on Spectral Angle

Self-organizing Map

The Self-organizing Map (SOM) is a tool for data visualization:







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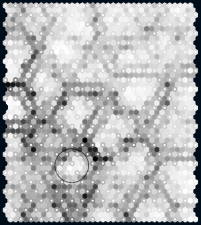
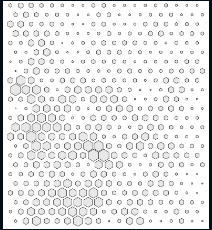
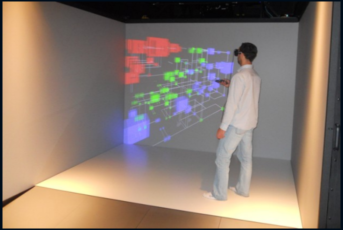




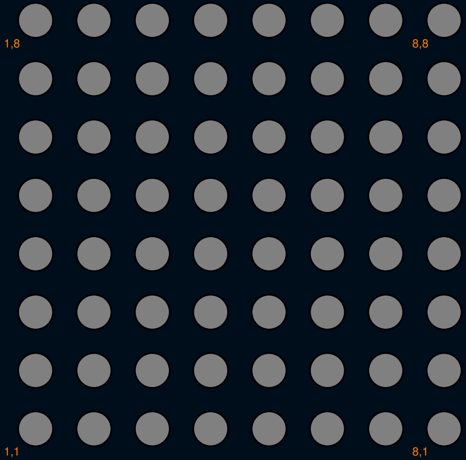
SOM design:

- n-dimensional mesh of *model vectors (neurons)*
- Mapping: spectral vector $\mathbf{x} \rightarrow$ model vector $\mathbf{m}_i$ (L_2 distance)
- Topological representation of original spectral distribution
  Typical topology: hexagon lattice

Learning

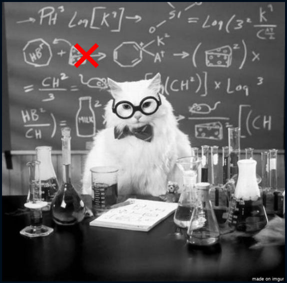
Input Image (Multispectral)

Initial State: Random



Self-organizing Map (8x8 Lattice)

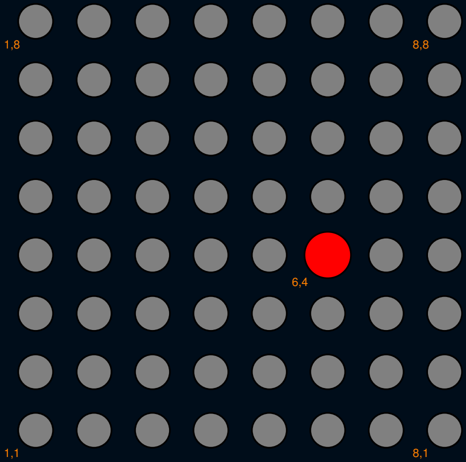
Learning



Input Image (Multispectral)

First Iteration

1. Find best match (BMU)



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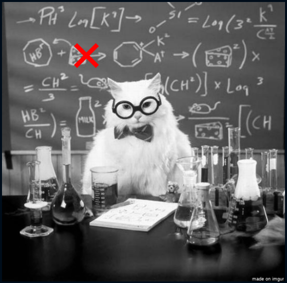
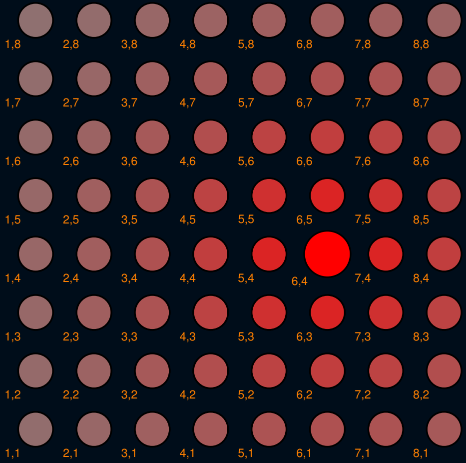


Input Image (Multispectral)

First Iteration

2. Update neighborhood



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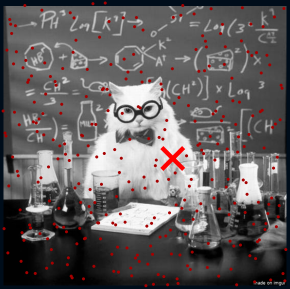

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Iteration at 33%

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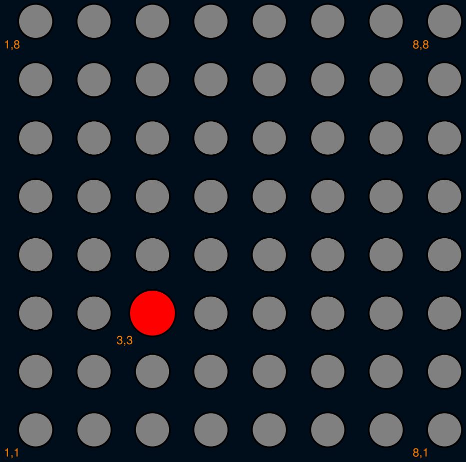

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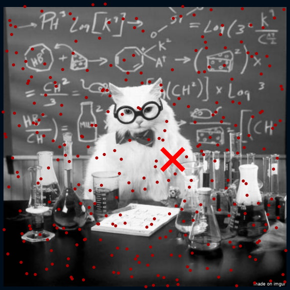

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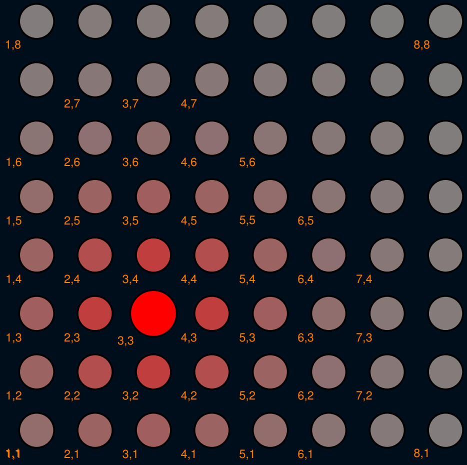

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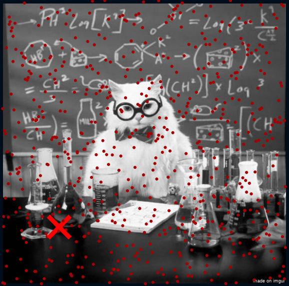

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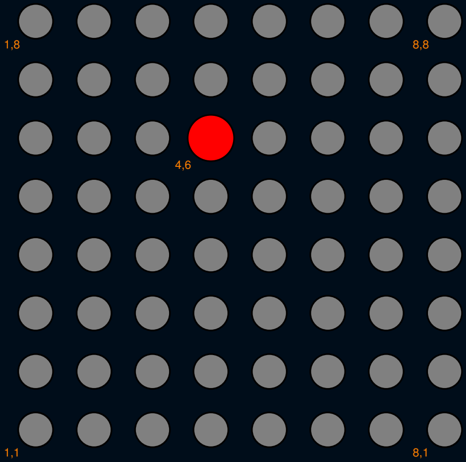

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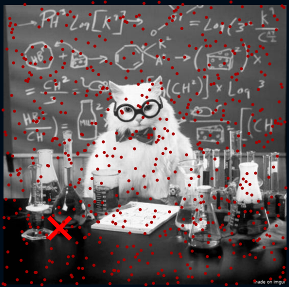

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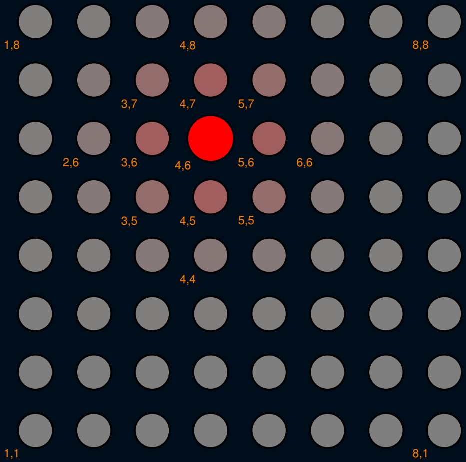

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Learning

Input Image (Multispectral)

Last Iteration

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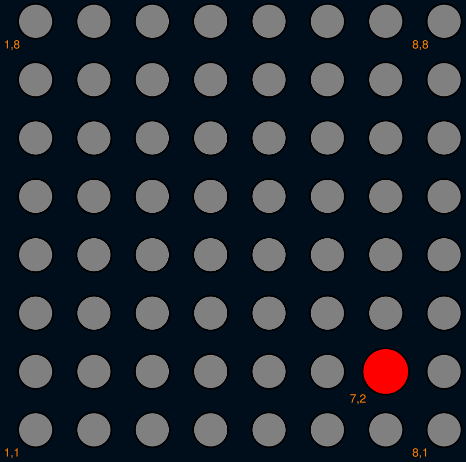

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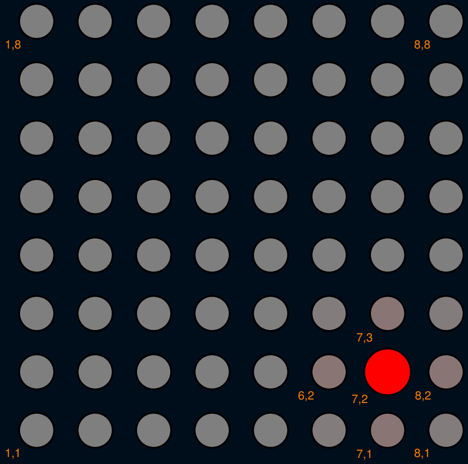

Self-organizing Map (8x8 Lattice)

Pushing the SOM further

We adapt the SOM for new purposes:

1. Increase size: typically 64 to 256 neurons, now 1000 to 4000 neurons
   $\rightarrow$ reduces quantization problem
2. Increase dimensionality: Train cubes and tesseracts
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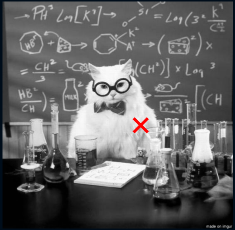

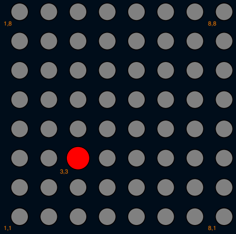

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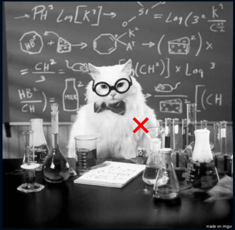

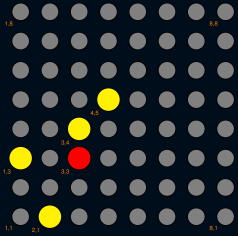

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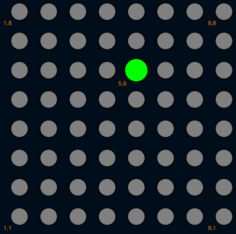
But how does it help edge detection?

SOM Edge Detection – Sniper Approach

Case I: Gradient



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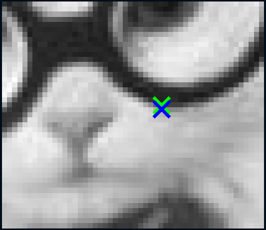

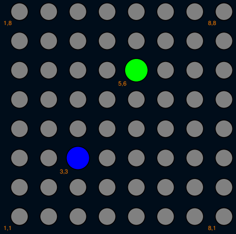

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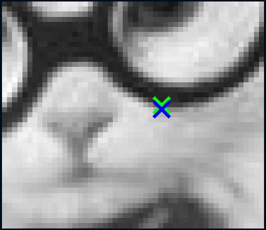

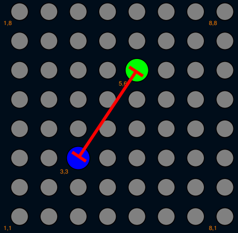

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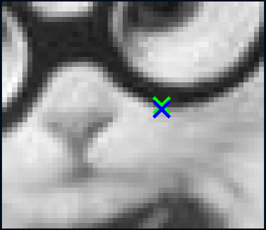
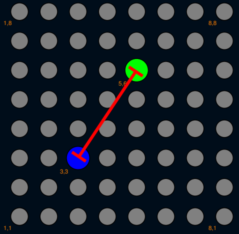
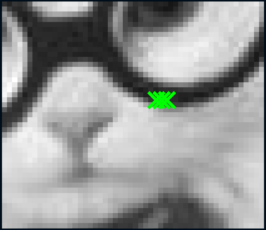
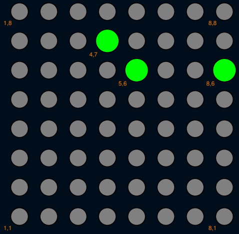




Case II: Sobel





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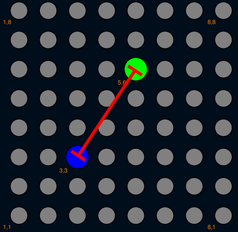

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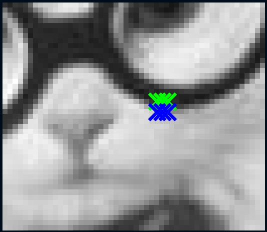

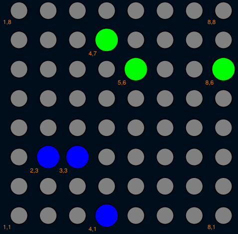

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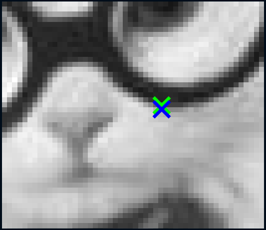

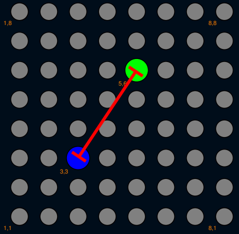

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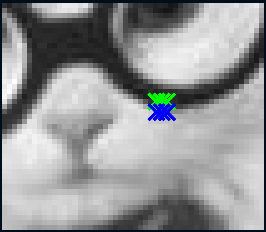

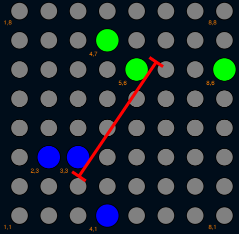

Case II: Sobel

Problems with the sniper approach

Material representation in the SOM:

- depends on #pixels in the scene
- depends on material variation (noise!)

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$\rightarrow$ Distances in the SOM are not robust

Gradient Magnitude

Canny Binary Map

Solution: Shotgun Approach

Exploit more information in the SOM!

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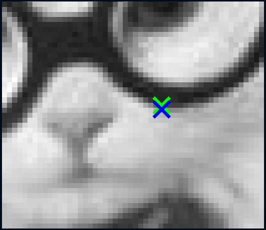

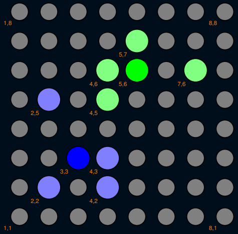

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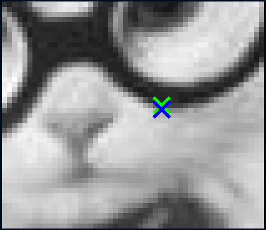

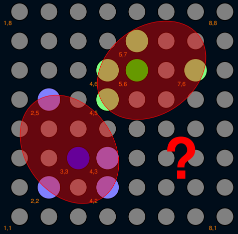

Case I: Gradient

Comparing Coordinate Sets

Idea: Coordinate set distance as a minimization problem

1. Pair coordinates from each set
2. Calculate sum of pair distances
3. Find optimal pairings w.r.t sum of pair distances

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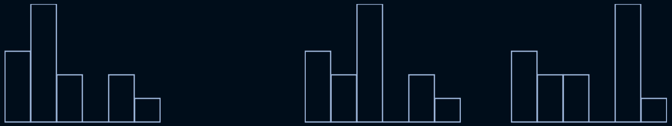
- Each lab member needs a specific time for each task
- We need to assign each member to a task
- We minimize the total time spent on tasks
- Matching in a bi-partite graph with weighted edges
- **Solution:** Hungarian Algorithm $O(n^3)$ ☹

Comparing Coordinate Sets (2)

The Earth Mover's Distance:

Comparing Coordinate Sets (2)

The Earth Mover's Distance:



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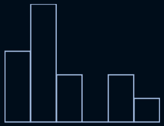
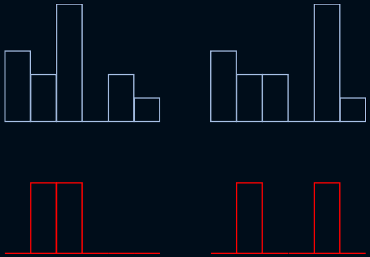
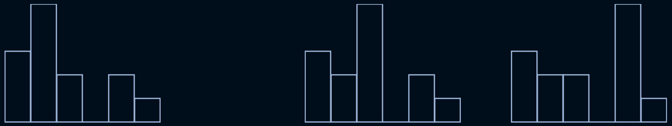




Element-wise comparison:

Comparing Coordinate Sets (2)

The Earth Mover's Distance:



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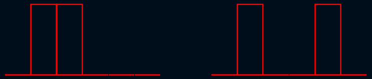
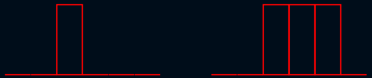


Earth Mover's Distance:



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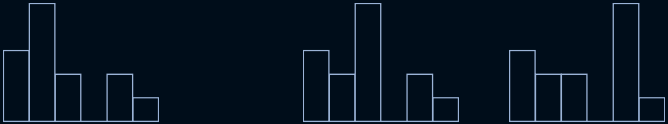
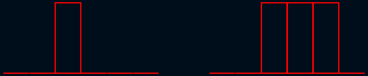


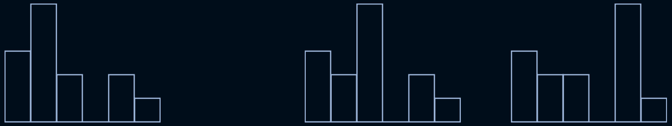
Earth Mover's Distance:



- **Solution:** Hungarian Algorithm

Comparing Coordinate Sets (2)

The Earth Mover's Distance:



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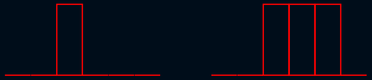
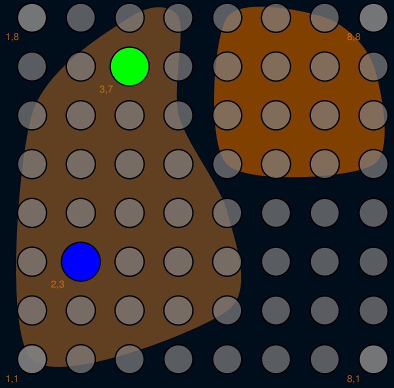


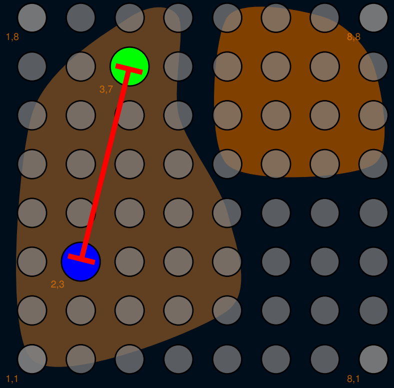
- **Solution:** Hungarian Algorithm
- Variant with $O(n^2)$
- Approximation using wavelets with $O(n)$

Sniper vs Shotgun



Case 1: No edge   Sniper

Sniper vs Shotgun



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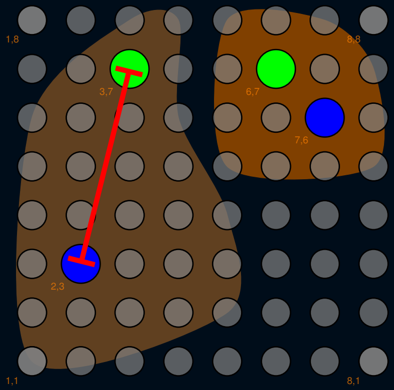

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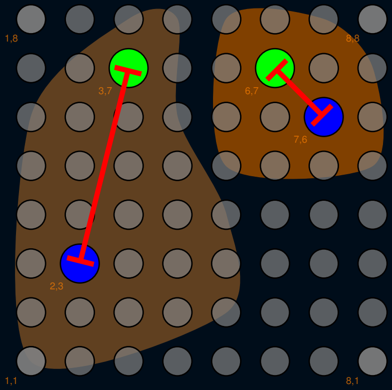

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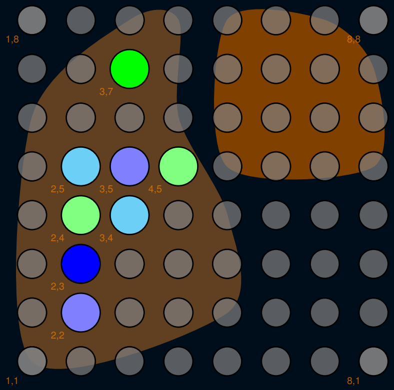

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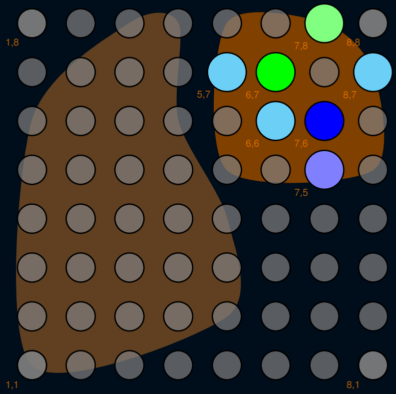
TECHNISCHE FAKULTÄT

Sniper vs Shotgun



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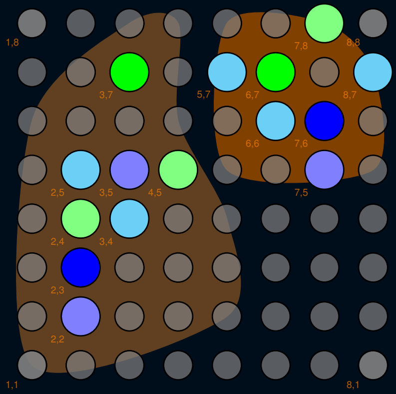

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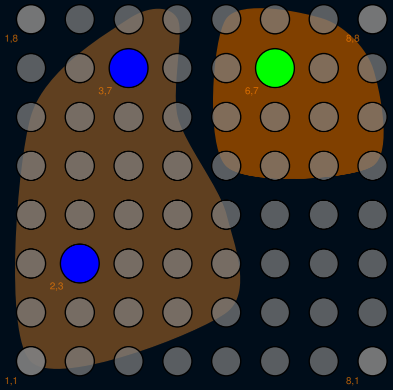
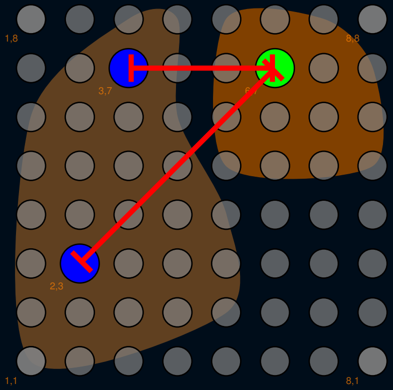


Case 2: Edge Sniper

Sniper vs Shotgun



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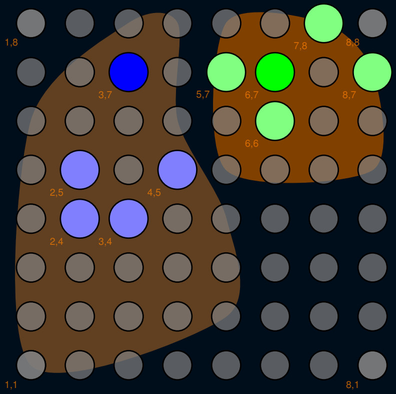

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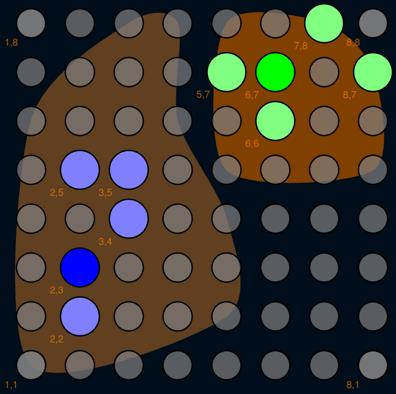
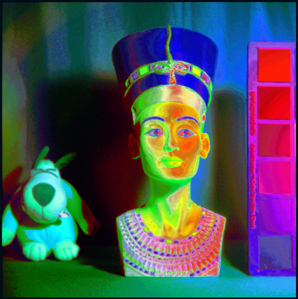
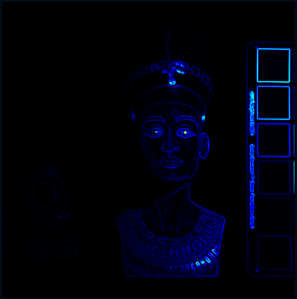


Case 2: Edge Shotgun

Evaluation: CAVE Egyptian Statue

False-color rendering





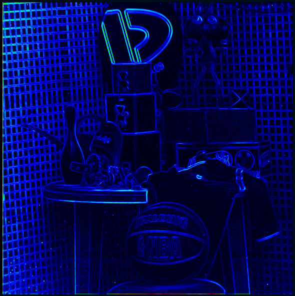
RCMG L_2

SOM Sniper

SOM Shotgun

Evaluation: Foster's Scene5 (2002)

True-color rendering

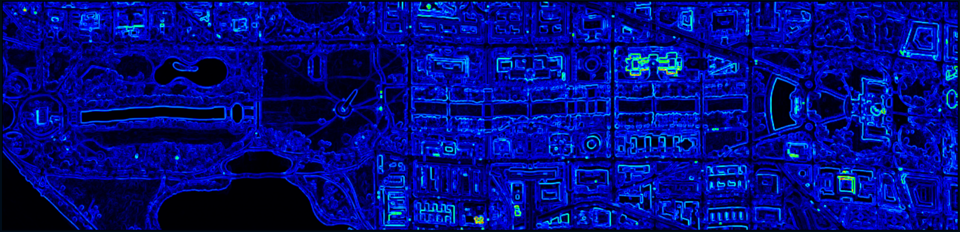


RCMG L_2

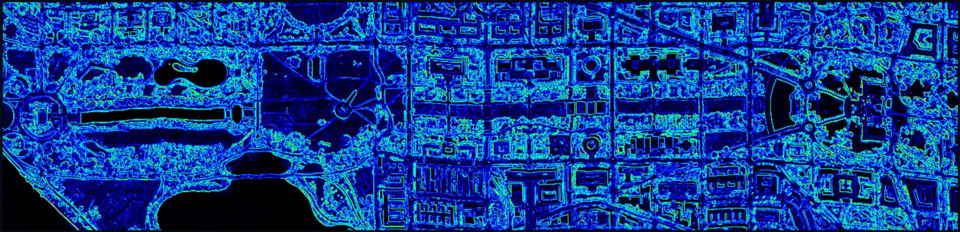
SOM Shotgun

SOM Shotgun RCMG

Evaluation: D.C. Mall



RCMG



SOM Shotgun 25

Conclusions

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- Adaptations of the Self-organizing map (SOM)

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$\rightarrow$ **The SOM is simple, yet powerful**

Thank you!