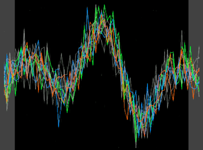
# Edge Detection in Multispectral Images Using the N-Dimensional Self-Organizing Map

September 14, 2011



**Johannes Jordan**
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Friedrich-Alexander-University Erlangen-Nuremberg

# Motivation

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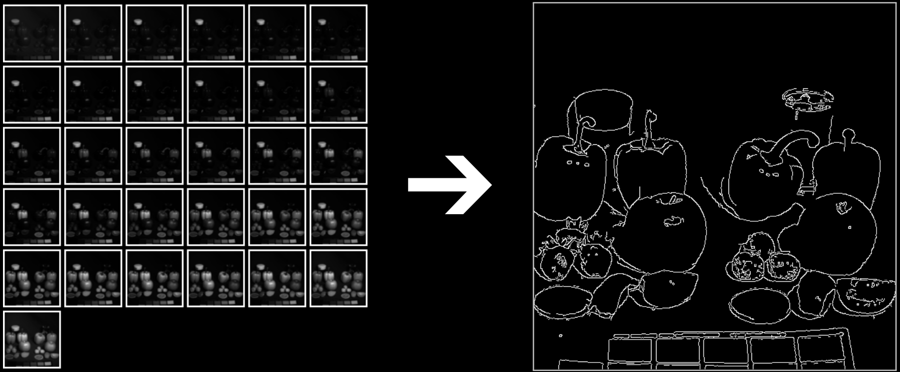

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**Problem:** Traditional edge detection works on monochromatic images.

- Multispectral images: vectors of 7 to 200 dimensions per pixel
- Reducing dimensionality not trivial
- No extensive research on edge-detection in this domain

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**Our contribution:**

- Examine Toivanen's method on recent data
- A new method with improved performance

# Self Organizing Map

The *Self Organizing Map (SOM)* is an artificial neural network that reduces dimensionality.

- 1D array or 2D grid of *model vectors (neurons)*
- Mapping: spectral vector $\rightarrow$ model vector ($L_2$ distance)
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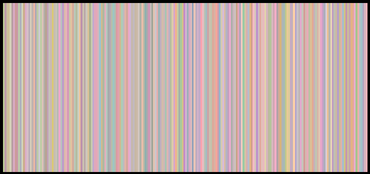
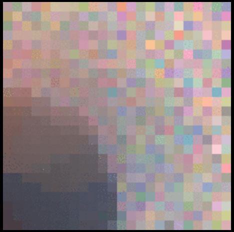
**Training:**





# SOM for Edge Detection 1D

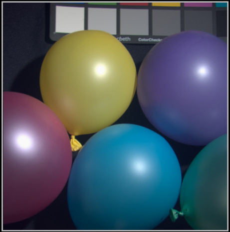
*Input image in sRGB*

- A 1D SOM is trained on the image
- Then, each image pixel is mapped to a neuron
- Neuron indices are interpreted as intensities
- Canny is applied on intensity map

*Trained SOM with 32 neurons in sRGB*

*Trained SOM with 256 neurons in sRGB*

# SOM for Edge Detection 1D



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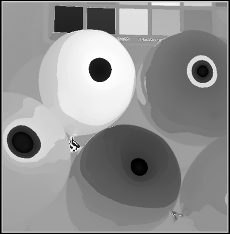


*Intensity map*

*Canny output*

# Problems with this approach

*Input image in sRGB*

*Intensity map (64 neurons)*

# Problems with this approach

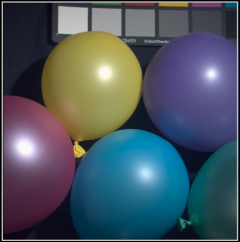
*Input image in sRGB*

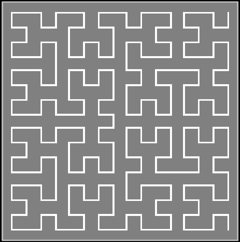
*Intensity map (64 neurons)*

*Trained SOM with 256 neurons in sRGB*

# SOM for Edge Detection 2D

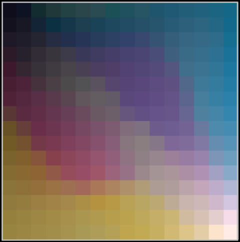
*Input image in sRGB*

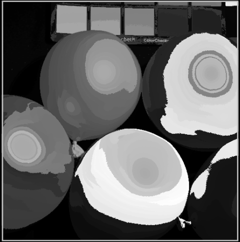




*Space filling curve (16x16)*

*Trained SOM in sRGB*

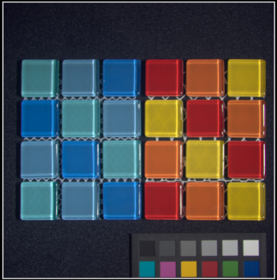




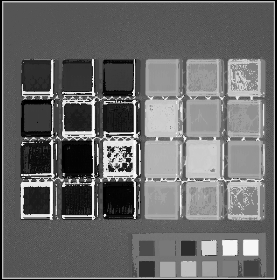
*Intensity map*

A 2D SOM is trained, then a 1D indexing is generated.

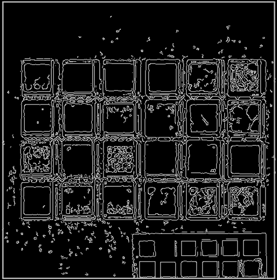
# Problems with this approach



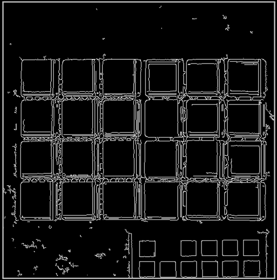
*Input image in sRGB*



*Intensity map (16x16 neurons)*



*Canny output, 2D SOM*

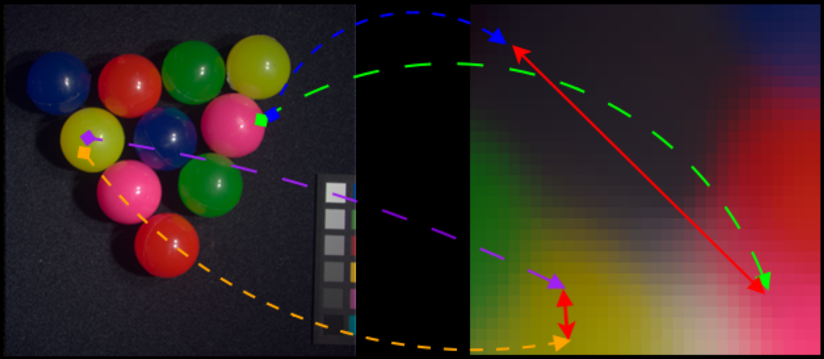


*Canny output, new method*

# New Method

**Observation:** For Canny to work, we only need differential data!

- We omit the creation of an intensity map, linearization
- Difference between pixels is defined by neuron distance ($L_2$)



# Method details

**Problem:**
Canny expects input from Sobel operator

$$\begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}$$

**Solution:** We compute weighted means from the neuron positions of adjoining pixels. From these we take the distance.

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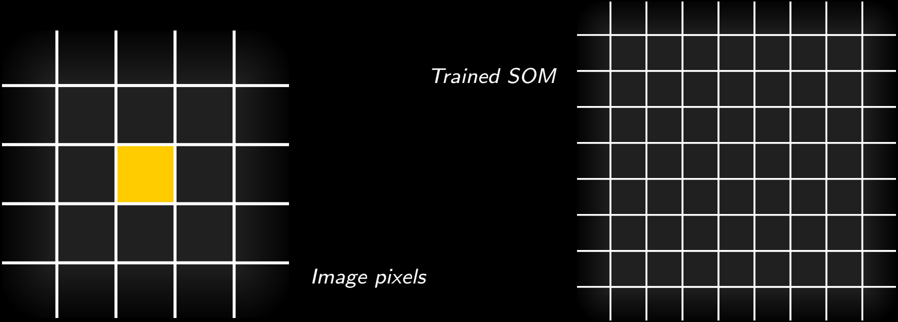

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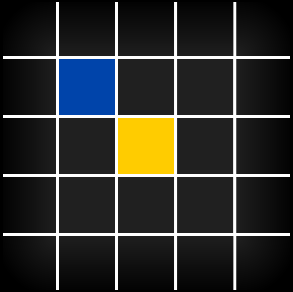


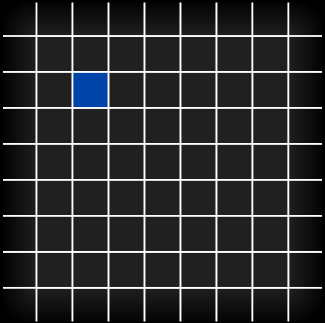

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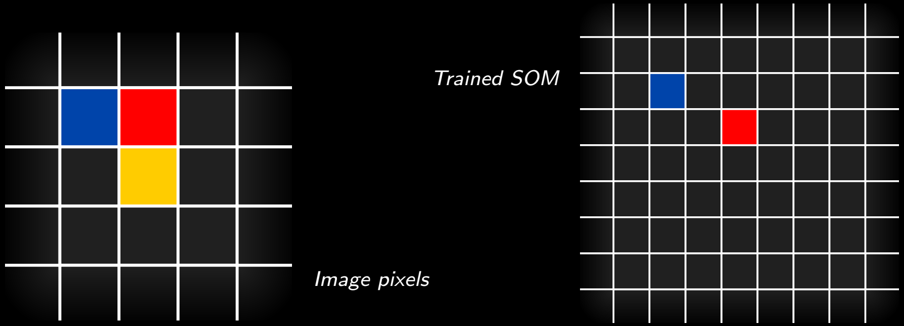

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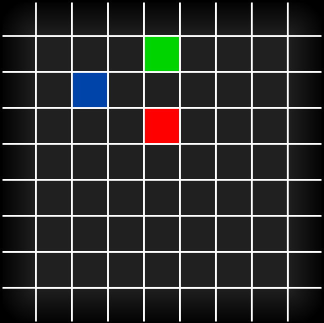
*Image pixels*

*Trained SOM*



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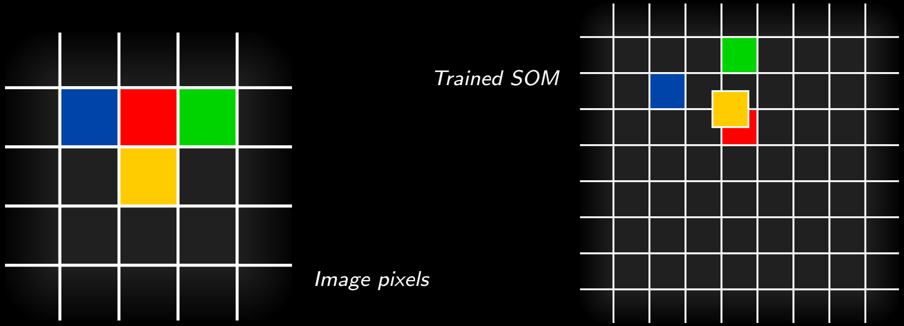

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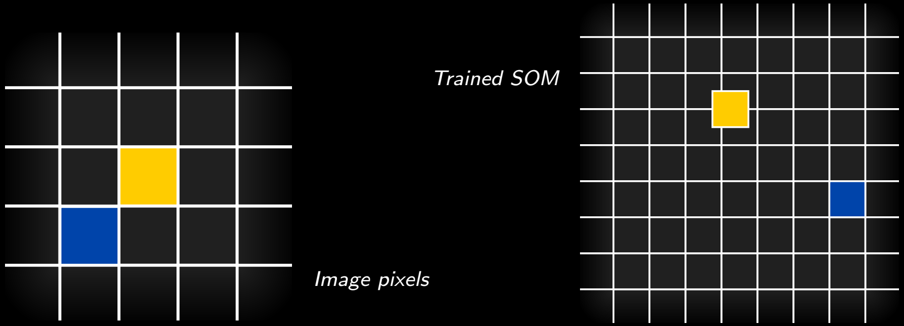

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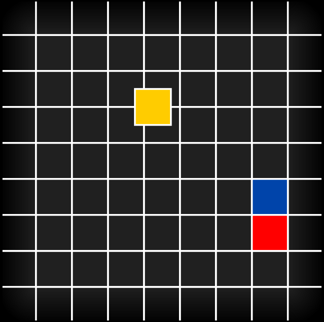

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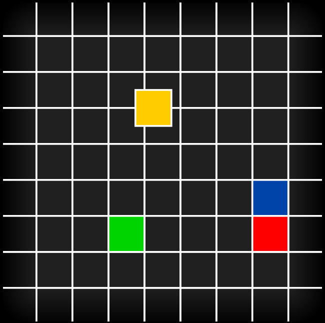

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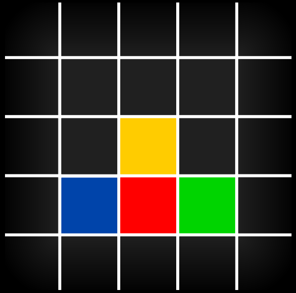


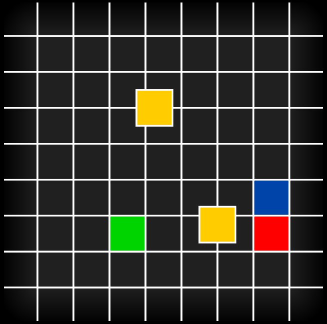

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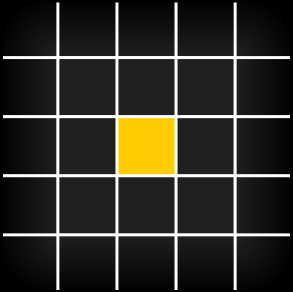


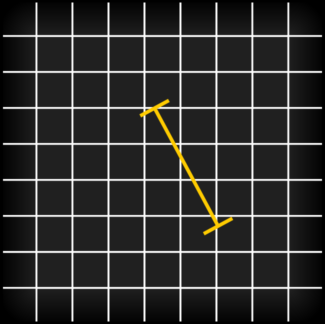

# Evaluation

Testing data:

- Images from the *CAVE Multispectral Image Database*
- Objects of different materials in a laboratory setting
- High quality, $512 \times 512$ pixels, $400\,$nm - $700\,$nm in $31$ bands

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Canny parametrization:

- Thresholds selected per image and method
- Two goals: **Maximum edge preservation** vs. **Minimum noise**

# Results *Fake and Real Food*

*Input image in sRGB*

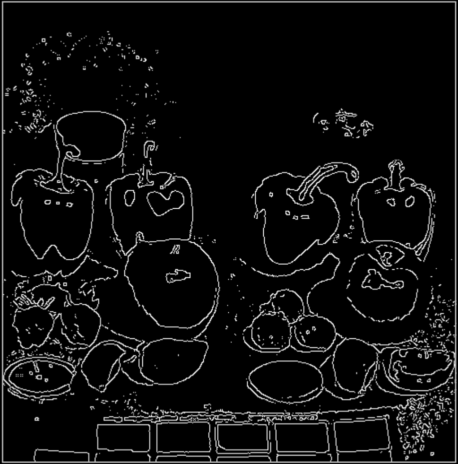
*Canny output, 1D-SOM (64 neurons)*

# Results *Fake and Real Food* (2)

*Canny output, 2D-SOM (16x16 neurons)*

*Canny output, new method (16x16 neurons)*

# Results *Fake and Real Food* (3)



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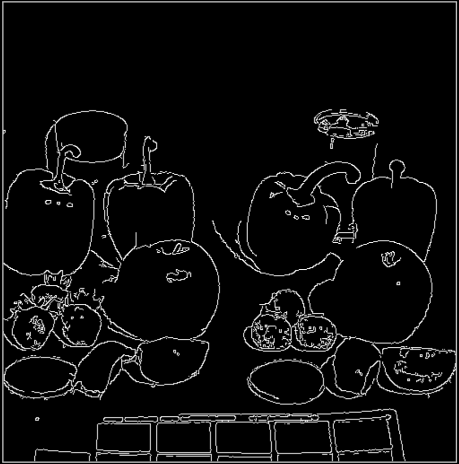

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# Results *Egyptian Statue*


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**Our method provides:**

- Better edge detection quality
- More reliable results
- Higher flexibility

# Thank you for your attention!

Source code will be released as free software as part of the *Gerbil* framework: http://gerbil.sf.net/