Hyperspectral Image Visualization with a 3-D SOM

Johannes Jordan, Elli Angelopoulou johannes.jordan@cs.fau.de
Pattern Recognition Lab, University of Erlangen-Nuremberg
FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG

Motivation

Use-case Scenario:

- Interactive multispectral image analysis
- False-color visualization in short time
- Non-linear methods typically too slow

Contributions:

- Revisit false-coloring based on the **Self-organizing Map (SOM)** [1]
- Design a novel SOM for higher output quality
- Benchmark new method against PCA on diverse images

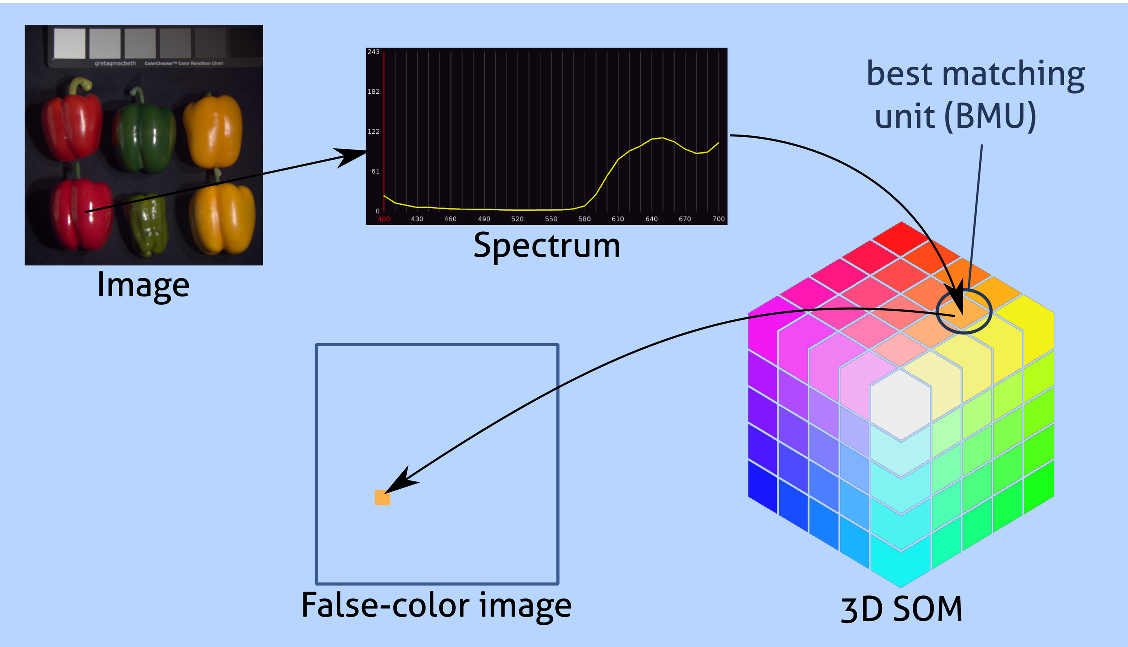
Source code is available at:

```
http://gerbil.sf.net/
```

Algorithm

Self-organizing map for false-coloring:

- 3D mesh of model vectors (neurons)
- Mapping: spectral vector $\mathbf{v} \rightarrow$ model vector $\mathbf{m}_i$
- Result after training: Topological representation of original spectral distribution
- SOM topology coordinates mapped to **R**, **G**, **B**



SOM training phase:

- For d bands, we have n model vectors $\mathbf{m}_i \in \mathbb{R}^d$, and a side length $n' = \sqrt[3]{n}$.
- The **best matching unit (BMU)** $\mathbf{m}_c$ has the index:

$$c^{(\mathbf{v})} = \operatorname*{argmin}_i L_2(\mathbf{v}, \mathbf{m}_i), \quad (\mathbf{v}\text{: input vector})$$

- The *location* of $\mathbf{m}_i$ is $\mathbf{r}^{(i)} \in \mathbb{Z}^3$, $r_j^{(i)} \in [1, n']$.
- At iteration t, the neighborhood function

$$h_{c,i}(t) = \alpha(t) \cdot \exp\left(-\frac{\left\|\mathbf{r}^{(c)} - \mathbf{r}^{(i)}\right\|^2}{2\sigma^2(t)}\right)$$

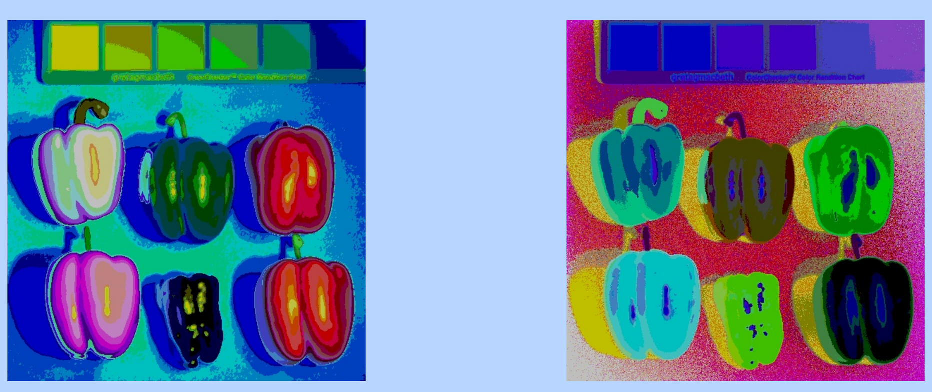
defines the influence of $\mathbf{v}(t)$ on each $\mathbf{m}_i$.

False-color generation:

- The false-color values of a pixel $\mathbf{v}$ are obtained as

$$\mathrm{r}_{\mathbf{v}} = \frac{r_1^{(c^{(\mathbf{v})})}}{n'}, \quad \mathrm{g}_{\mathbf{v}} = \frac{r_2^{(c^{(\mathbf{v})})}}{n'}, \quad \mathrm{b}_{\mathbf{v}} = \frac{r_3^{(c^{(\mathbf{v})})}}{n'}.$$

- **Problem:** Quantization effects, low quality output
- Examples with $n' = 4$ (as suggested in [2]):



New Method

Provide higher quality output:

- Use larger SOM size: 10^3 neurons (previous work: 64 to 256 neurons)
- Train with 100,000 samples
- Change false-color generation: several BMUs instead of single BMU

BMU lookup and combination:

- We first obtain a vector of C BMU indices

$$\mathbf{c}^{(\mathbf{v})} = \operatorname*{argmin}_{\mathbf{i}} \sum_j^C d(\mathbf{v}, \mathbf{m}_{\mathbf{i}_j}).$$

- Then, for each pixel $\mathbf{v}$, we calculate location $\mathbf{r}'$ as

$$\mathbf{r}' = \sum_j^C w_j \cdot \mathbf{r}^{(c_j^{(\mathbf{v})})}$$

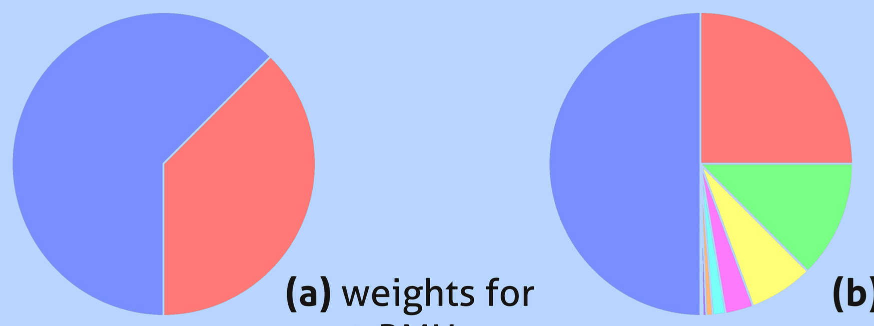
given

$$\begin{aligned} \forall w_j, j < C: \quad & w_j = 2w_{j+1} \\ & \textstyle\sum_{j=1}^C w_j = 1 \\ \forall \mathbf{m}_{\mathbf{c}_j}, j < C: \quad & d(\mathbf{v}, \mathbf{m}_{\mathbf{c}_j}) < d(\mathbf{v}, \mathbf{m}_{\mathbf{c}_{j+1}}). \end{aligned}$$

- We finally obtain

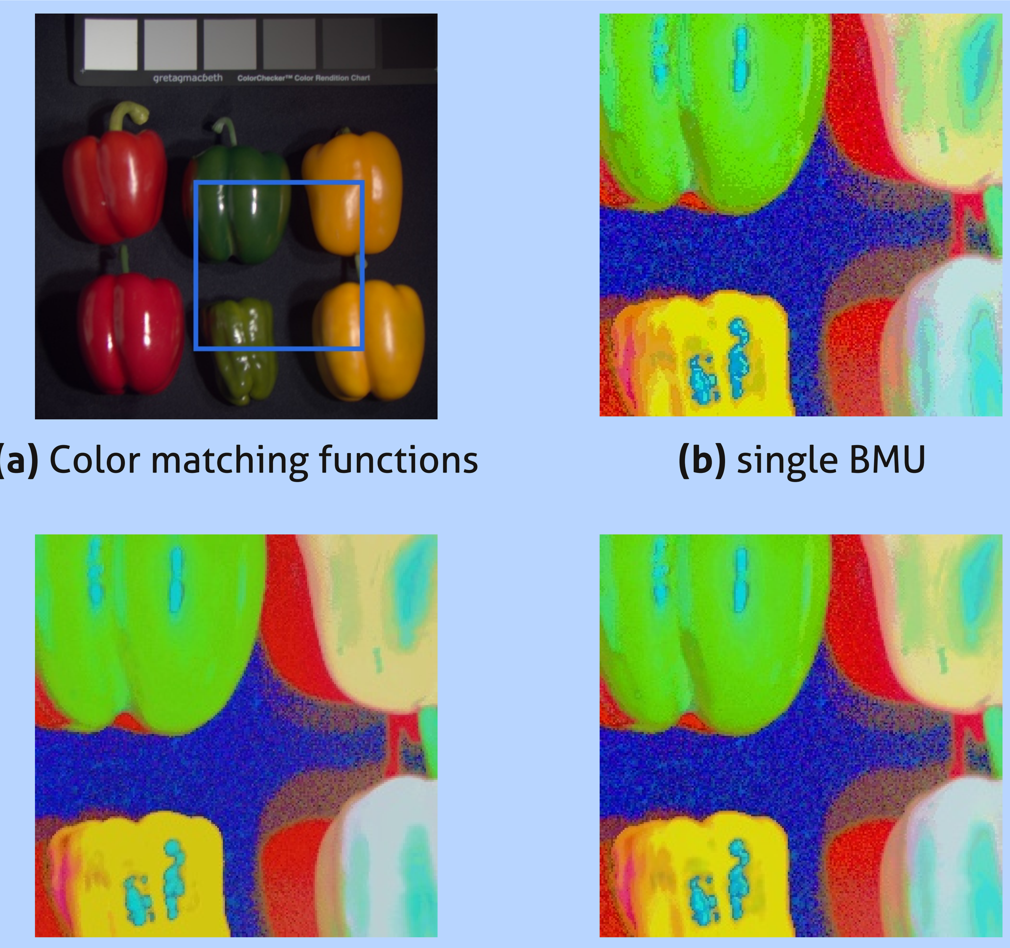
$$\mathrm{r}_{x,y} = \frac{r'_1}{n'}, \quad \mathrm{g}_{x,y} = \frac{r'_2}{n'}, \quad \mathrm{b}_{x,y} = \frac{r'_3}{n'}.$$

Novel rank-based weighting scheme:



(a) weights for 2 BMUs **(b)** weights for ∞ BMUs

- always high influence of primary BMU
- exponential decay of rank weights
- example comparison with $C = 10$ against $w_j = \frac{1}{C}, \forall j$:



(a) Color matching functions **(b)** single BMU
(c) averaged BMUs **(d) proposed method**

Timing Results

- measured on Intel Core i7-2600 CPU
- training takes almost all time
- computational complexity independent of image size, parameter C

#neurons n	6^3	8^3	10^3
remote sensing images	4.8 s	10.1 s	17.8 s
CAVE images	2.9 s	6.0 s	10.1 s

Evaluation

Dataset:

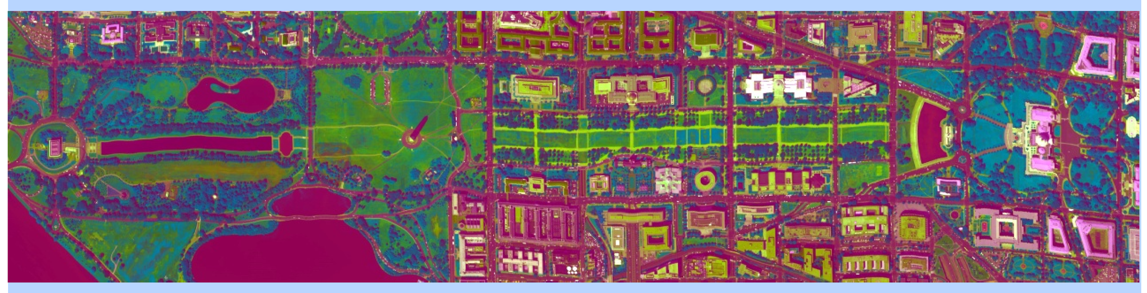
- CAVE Multispectral Image Database [3] 512×512 pixels, 31 bands
- AVIRIS Indian Pines, 145^2 pixels, 220 bands
- HYDICE D.C. Mall, 1280×307 pixels, 191 bands

Experimental setup:

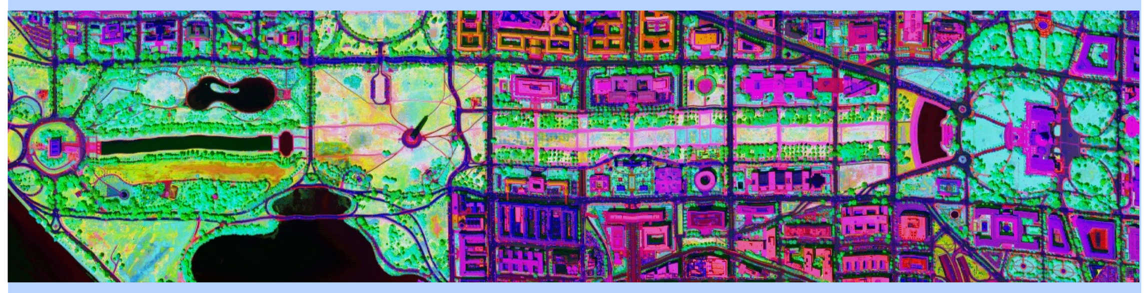
- SOM settings: $n = 10^3$, 100 000 iterations, $C = 5$
- Per-channel entropy: $H = -\sum_{i=0}^{255} p_i \ln p_i$, where p_i is the probability of observing intensity i.

Algorithmic Results

Washington D.C. Mall: 400 nm - 2475 nm

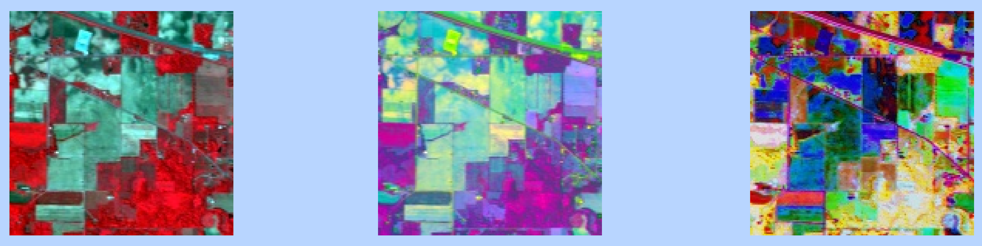


(a) PCA false-color visualization, $H_R = 0.54$, $H_G = 0.75$, $H_B = 0.76$

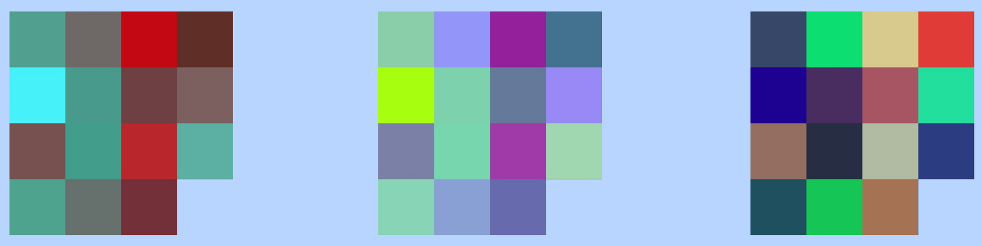


(b) SOM false-color visualization, $H_R = 0.96$, $H_G = 0.92$, $H_B = 0.93$

Indian Pines: 400 nm - 2500 nm

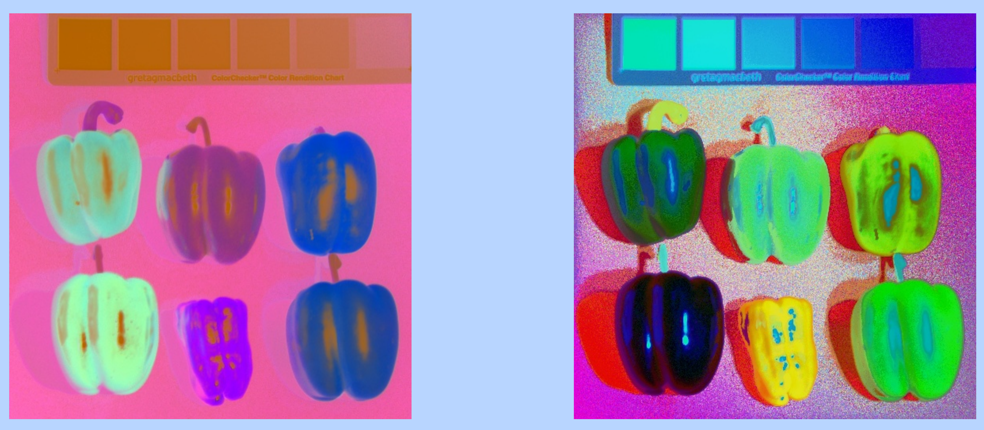


(a) False-color visualizations: band composite, PCA, SOM



(b) average color assigned to ground-truth pixels of each class

Fake and Real Peppers: 400 nm - 700 nm



(a) PCA false-color visualization, $H_R = 0.80$, $H_G = 0.77$, $H_B = 0.79$ **(b)** SOM false-color visualization, $H_R = 0.94$, $H_G = 0.94$, $H_B = 0.91$

Conclusions

We employ the 3D SOM to generate false-color images. Our custom BMU lookup results in:

- a high quality image,
- with more detailed information,
- at negligible increase in calculation.

Our method provides:

- a high-quality, non-linear mapping under tight time constraints.

References

[1] T. Kohonen, Self-organizing maps, *vol. 30 of Springer series in information sciences*, Springer, 3rd edition, 2001.

[2] J. Gorricha and V. Lobo, *Improvements on the visualization of clusters in geo-referenced data using self-organizing maps*, Computers & Geosciences, vol. 43, pp. 177 – 186, 2012

[3] F. Yasuma, T. Mitsunaga, D. Iso, S. K. Nayar. Generalized Assorted Pixel Camera: Post-Capture Control of Resolution, Dynamic Range and Spectrum. *IEEE Transactions on Image Processing*, vol. 99, Mar. 2010.