Supervised Multispectral Image Segmentation with Power Watersheds

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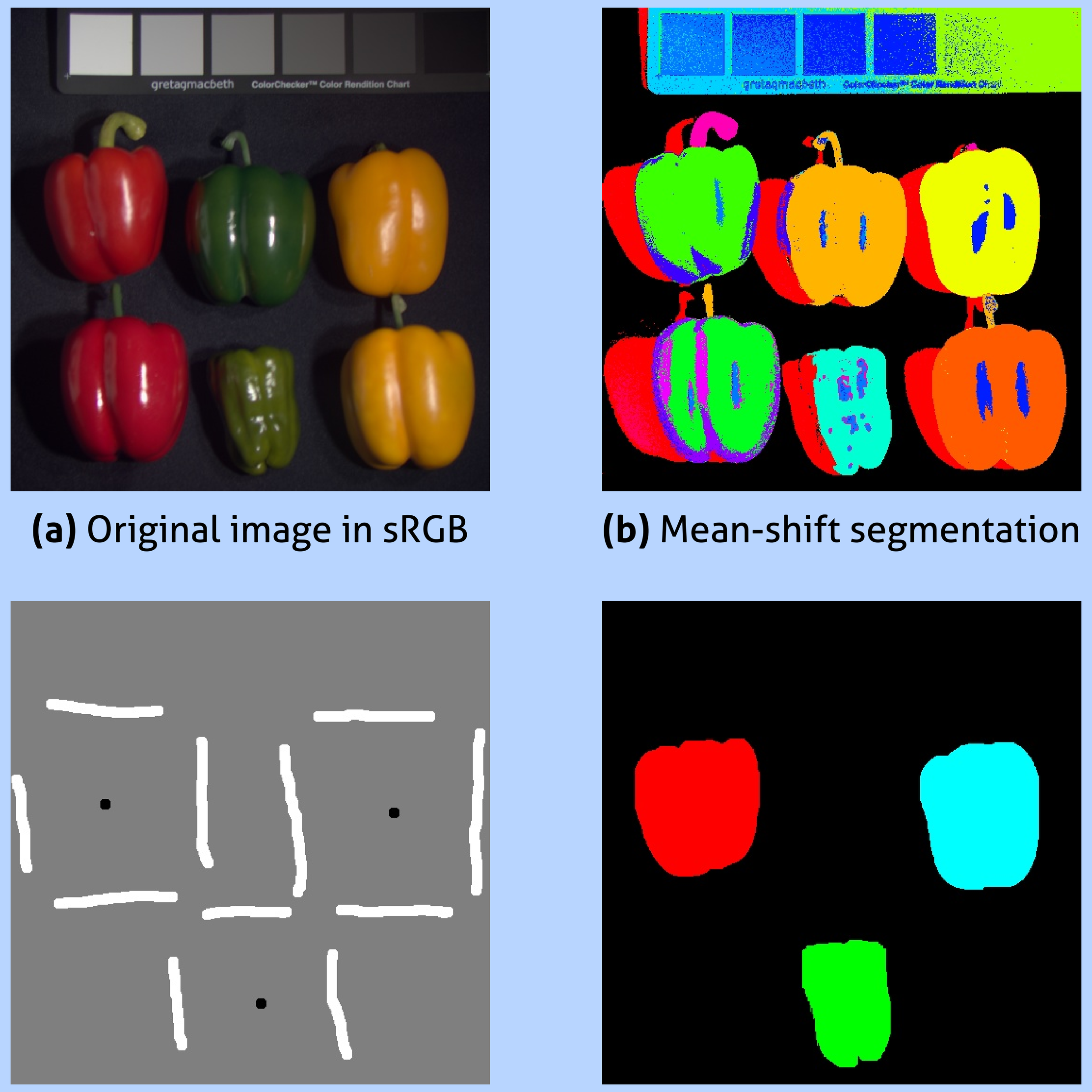
Motivation

Use-case Scenario:

- Interactive multispectral image analysis
- User provides input on segmentation goal
- Avoidance of tedious manual labeling

Contributions:

- Introduce supervised segmentation to multispectral, hyperspectral imagery,
- adapt a graph-based state-of-the-art segmentation method (Power Watersheds [1]),
- design a benchmark and report first results.



(a) Original image in sRGB **(b)** Mean-shift segmentation

(c) User-provided seed map **(d)** Graph-cut segmentation

Figure 1: Unsupervised clustering and seed-based segmentation results on an example multispectral image [5].

Algorithm

Power Watersheds by Couprie et al., 2009. [1]

- Image representation as a graph with a vertex v_i for each pixel i,
- locally 4-connected or 8-connected nodes,
- edge weights w_{ij} based on image gradient ∇I,

$$w_{ij} = \exp\left(-\beta(\nabla I)^2\right) .$$

Edge weights

- Intensity images: $\nabla I \triangleq$ normalized gradient
- RGB images: $\nabla I \triangleq$ distance in L_2 or L_∞
- Multispectral images: $\nabla I \triangleq$?

Observation: the L_p-norm is not well-suited.

We propose:

- Similarity measures from Spectral Mapping
- A novel data-driven measure

Similarity measures

Spectral Angle (SA) between spectral vectors $\mathbf{x}$, $\mathbf{y}$:

$$\mathrm{SA}(\mathbf{x},\mathbf{y}) = \cos^{-1}\left(\frac{\langle \mathbf{x},\mathbf{y}\rangle}{\|\mathbf{x}\|_2 \cdot \|\mathbf{y}\|_2}\right) .$$

Spectral Information Divergence (SID):

$$\mathrm{SID}(\mathbf{x},\mathbf{y}) = \sum_{l=1}^{N} \mathbf{p}_l^{(\mathbf{x})} \log \frac{\mathbf{p}_l^{(\mathbf{x})}}{\mathbf{p}_l^{(\mathbf{y})}} + \sum_{l=1}^{N} \mathbf{p}_l^{(\mathbf{y})} \log \frac{\mathbf{p}_l^{(\mathbf{y})}}{\mathbf{p}_l^{(\mathbf{x})}} ,$$

with $\mathbf{p}_{1 \le l \le N}^{(\mathbf{x})} = \frac{x_l}{\sum_{k=1}^{N} x_k}$, N number of bands.

SIDSAM: [3]

$$\mathrm{SIDSAM}_1(\mathbf{x},\mathbf{y}) = \mathrm{SID}(\mathbf{x},\mathbf{y}) \cdot \sin\left(\mathrm{SA}(\mathbf{x},\mathbf{y})\right) ,$$
$$\mathrm{SIDSAM}_2(\mathbf{x},\mathbf{y}) = \mathrm{SID}(\mathbf{x},\mathbf{y}) \cdot \tan\left(\mathrm{SA}(\mathbf{x},\mathbf{y})\right) .$$

Normalized Euclidean Distance (NED): [2]

$$\mathrm{NED}(\mathbf{x},\mathbf{y}) = \sqrt{\sum_{l=1}^{N}\left(\frac{x_l}{\bar{x}} - \frac{y_l}{\bar{y}}\right)^2} .$$

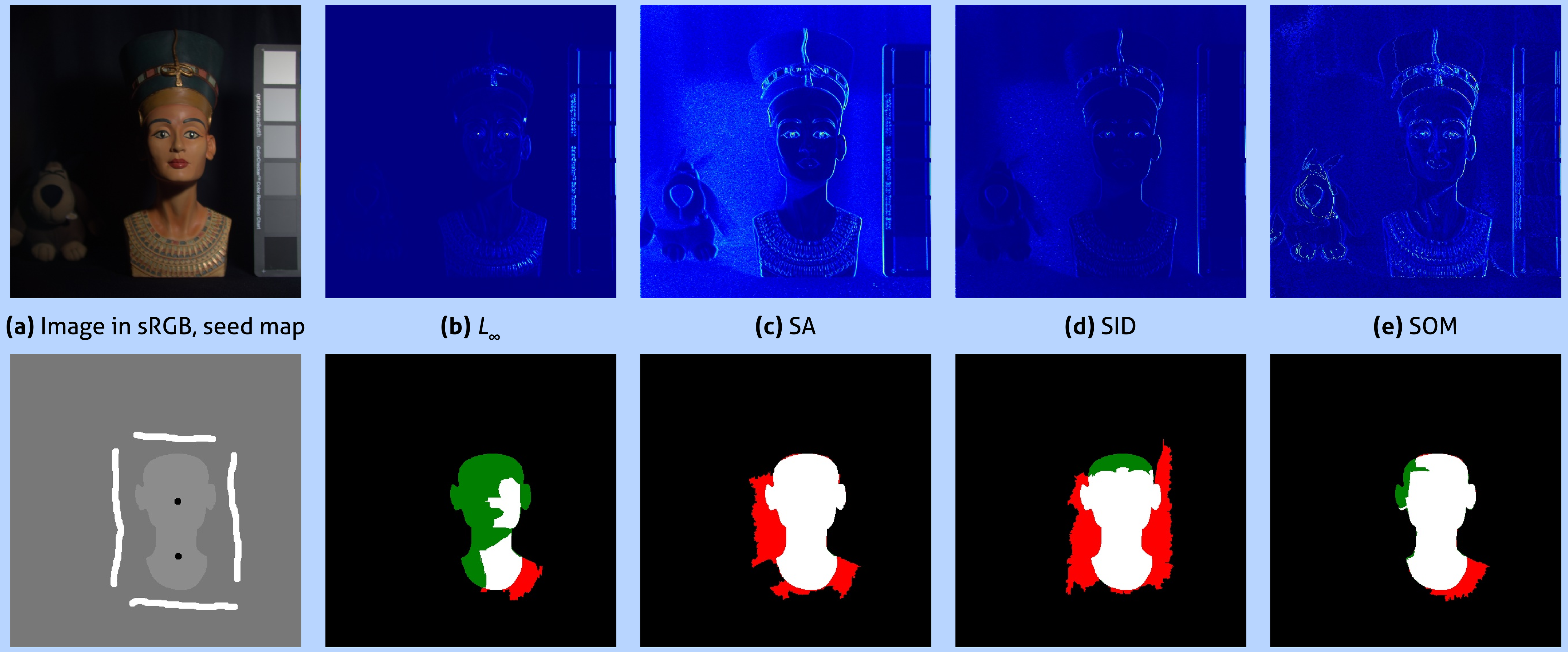
Data-driven measure

Self-organizing map (SOM)

- 1D array or 2D grid of model vectors (neurons), mapping: spectral vector $\mathbf{x} \rightarrow$ model vector $\mathbf{m}_i$.
- The SOM is trained with random image pixels.
- We obtain a topological representation of the original spectral distribution.

Similarity calculation: [4]

$$\mathrm{SOM}(\mathbf{x},\mathbf{y}) = \left\| L(\operatorname*{argmin}_i \|\mathbf{x},\mathbf{m}_i\|_2) - L(\operatorname*{argmin}_j \|\mathbf{y},\mathbf{m}_j\|_2) \right\|_2 .$$



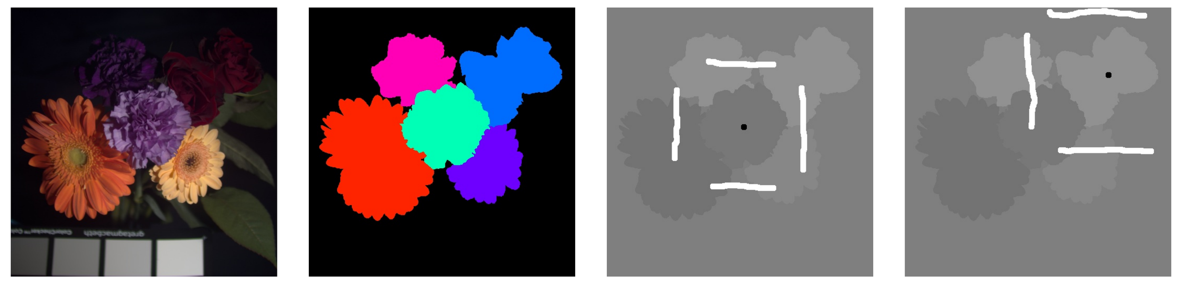
(a) Image in sRGB, seed map **(b)** L_∞ **(c)** SA **(d)** SID **(e)** SOM

Figure 2: Gradients according to different similarity measures in x-direction (top) and their segmentation results (bottom) on *statue* image [5].

Benchmark

Dataset: CAVE Multispectral Image Database [5]

- Objects of different materials in a lab setting
- 512×512 pixels, 400 nm - 700 nm in **31 bands**
- Hand-labeling of **32 objects** in 9 suitable images
- Seed inputs mimic typical usage scenario



Setup: 4 algorithms, 7 edge weight configurations

Measure	Algo.	Precision	Recall	F_1-score	Time (s)
NED	pwg	0.908	0.971	**0.929** $\pm$ 0.073	6.0
SA	pw	0.896	0.978	**0.928** $\pm$ 0.067	6.8
SA	msf	0.892	0.978	**0.926** $\pm$ 0.065	0.7
SA	pwg	0.891	0.979	**0.923** $\pm$ 0.071	6.8
NED	pw	0.911	0.962	**0.919** $\pm$ 0.089	1.0
NED	msf	0.907	0.962	**0.917** $\pm$ 0.091	1.0
SOM	pwg	0.897	0.925	**0.898** $\pm$ 0.074	18.6
SOM	pw	0.897	0.925	**0.898** $\pm$ 0.074	18.6
SOM	msf	0.894	0.903	**0.886** $\pm$ 0.057	9.6
SID	msf	0.846	0.973	**0.867** $\pm$ 0.249	2.8
SIDSAM	msf	0.819	0.972	**0.849** $\pm$ 0.245	3.4
SID	pwg	0.888	0.872	**0.837** $\pm$ 0.210	8.5
SID	pw	0.889	0.872	**0.837** $\pm$ 0.210	8.6
SIDSAM	pw	0.944	0.764	**0.793** $\pm$ 0.259	10.9
SIDSAM	pwg	0.947	0.763	**0.791** $\pm$ 0.266	10.7
L_∞	pw	0.937	0.588	**0.659** $\pm$ 0.214	8.9
L_∞	pwg	0.923	0.587	**0.655** $\pm$ 0.217	8.9
L_∞	msf	0.927	0.538	**0.598** $\pm$ 0.291	0.9

Table 1: Average performance of measure/algorithm combinations.

Conclusions

We introduce supervised segmentation to multispectral images for interactive analysis.

- Power watersheds perform well, but not L_∞.
- Good performance is obtained by similarity measures from spectral matching.
- Data-driven similarity is leading in some cases.

Benchmark dataset and source-code available:

`http://www5.cs.fau.de/research/data/msseg`

References

[1] C. Couprie, L. Grady, L. Najman, H. Talbot. Power watershed: A unifying graph-based optimization framework. *TPAMI*, vol. 33, no. 7, pp. 1384–1399, 2011.

[2] S.A. Robila, A. Gershman. Spectral matching accuracy in processing hyperspectral data. *Int. Symp. on Signals, Circuits and Systems*. IEEE, 2005, vol. 1, pp. 163–166.

[3] Y. Du, C.I. Chang, H. Ren, C.C. Chang, J.O. Jensen, F.M. D'Amico. New hyperspectral discrimination measure for spectral characterization. *Optical Engineering*, vol. 43, no. 8, pp. 1777–1786, Aug. 2004.

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