Mean-shift Clustering for Interactive Multispectral Image Analysis

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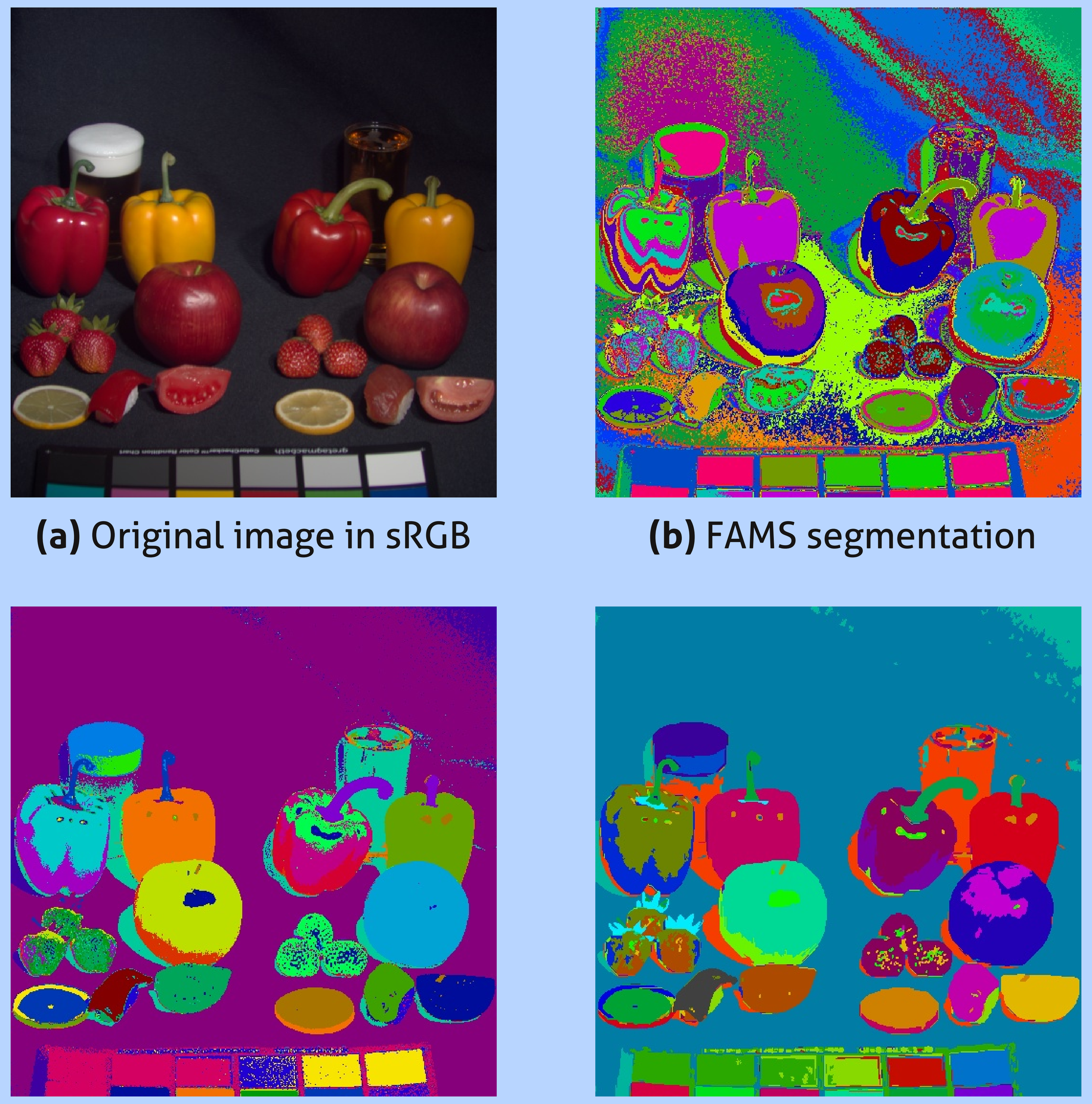
Motivation

Use-case Scenario:

- Interactive hyperspectral image analysis
- On-demand (fast!) global segmentation/labeling

Contributions:

- mean-shift [1] on the spectral gradient [2],
- adapted superpixel segmentation method [3],
- two variants of superpixel-based mean shift



(a) Original image in sRGB (b) FAMS segmentation (c) SG-FAMS segmentation (d) PSPMS segmentation

Figure 1: 31-band *fake and real food* image and segmentation results. We propose SG-FAMS and PSPMS.

Mean Shift

Fast Adaptive Mean Shift (FAMS) by Georgescu et al. [1]

- adaptive bandwidth selection for each data point
- *mean shift step:* starting from each query point kernel-based hill-climbing to next density mode
- identification and merging of common modes

Adaptation to hyperspectral data: SG-FAMS

- FAMS operates in L1, geometry effects dominant
- Solution: *Spectral Gradient* feature space [2], separates material from reflectance content

Superpixels

Algorithm by Felzenszwalb and Huttenlocher [3]

- time complexity of $O(N \log N)$, N: #pixels
- 4-connected graph, each pixel is a node
- edge weights based on pixel similarity
- graph is partitioned by iteratively merging nodes
- parameter c: merge criterion → avg. superpixel size

Adaptation to hyperspectral data:

- spectral similarity measures for edge weights
- *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 $\mathbf{p}^{(\mathbf{x})}_{1 \le l \le N} = \frac{x_l}{\sum_{k=1}^{N} x_k}$, N number of bands.

- Problem: highly non-uniform distribution of SID
  Solution: histogram equalization with 10 000 bins

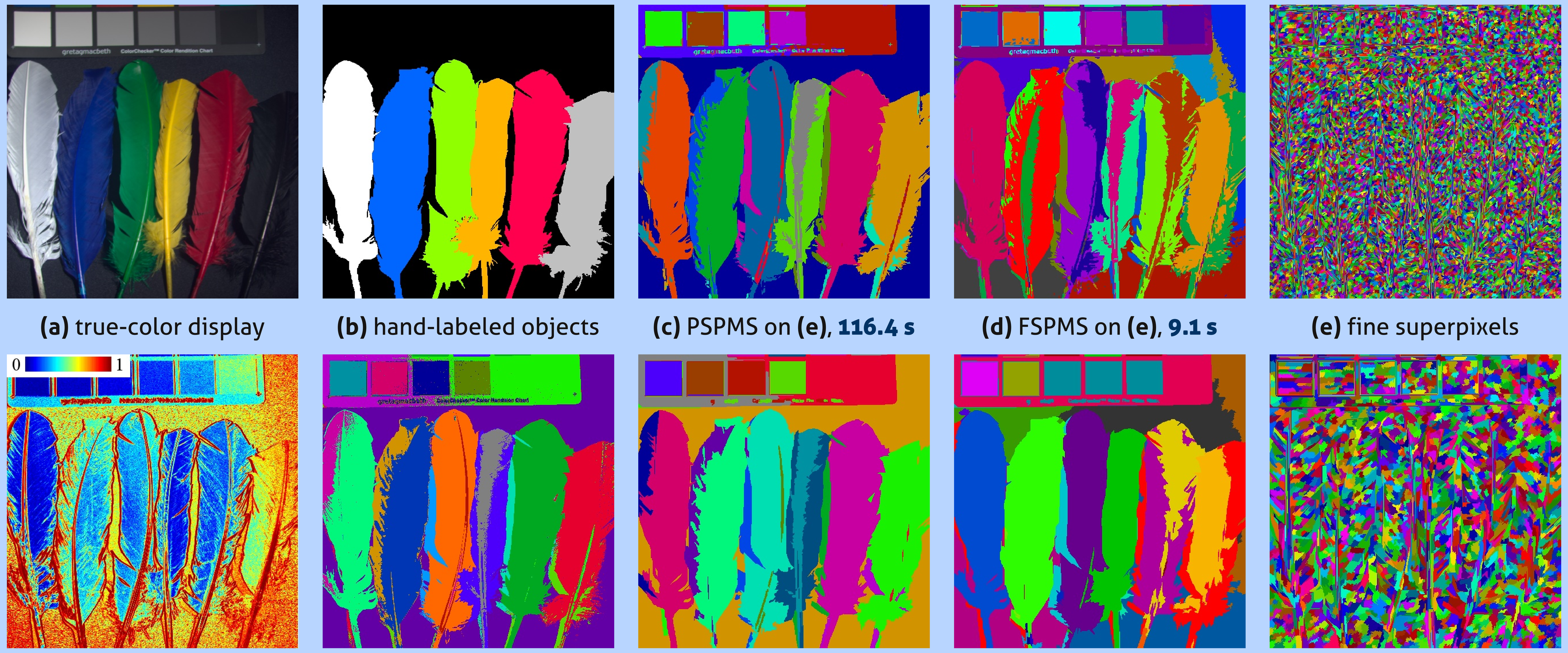
Combinations

PSPMS: original feature space, query per superpixel

- sacrifice spatial detail for execution speed
- hill-climbing starts from each superpixel centroid
- adaptive bandwidth selection still $O(N^2)$

FSPMS: superpixel centroids form feature space

- bandwidth selection on superpixels with custom rule for k-NN: $k = p \cdot \sqrt{N_F}$ (here: $N_F = N_S$: #superpixels)
- bandwidths weighted by resp. superpixel size
- complexity reduced to $O(N \log N + N_S^2)$



(a) true-color display (b) hand-labeled objects (c) PSPMS on **(e)**, **116.4 s** (d) FSPMS on **(e)**, **9.1 s** (e) fine superpixels

(f) horizontal edge weights (g) SG-FAMS, **744.9 s** (h) PSPMS on **(j)**, **82.4 s** (d) FSPMS on **(j)**, **5.7 s** (j) coarse superpixels

Figure 2: 31-band *feathers* image with corresponding histogram-equalized SID edge weights, superpixel segmentations, and mean shift segmentation results compared to hand-labeled objects. Running times are denoted next to algorithm names.

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**

Setup: algorithms SG-FAMS, PSPMS, FSPMS

- superpixels for PSPMS, FSPMS with $c = 0.05$, $c = 0.25$
- mean shift parameters fixed

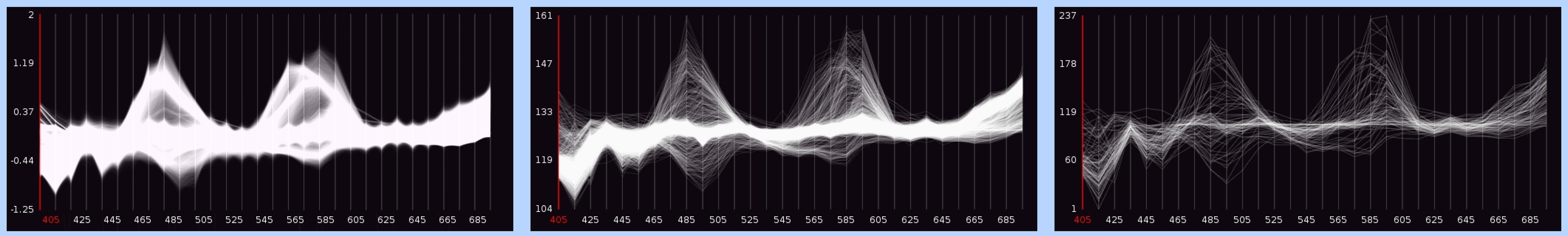
Experimental Results:

- enough detail, no adverse oversegmentation
- only objects of same material share a segment
- number of segments stable across images, methods

- PSPMS results similar to SG-FAMS, good speedup
- FSPMS emphasizes differently, **vast** speedup

Algo.	c	Superpixels	Segments	Seconds
SG-FAMS			22.3 ± 7.4	629.3 ± 262
PSPMS	**0.25**	2349 ± 230	35.0 ± 17.3	79.6 ± 32.8
	0.05	16706 ± 1178	33.0 ± 15.2	113.2 ± 39.9
FSPMS	**0.25**	2349 ± 230	23.7 ± 8.2	**5.9** ± 1.1
	0.05	16706 ± 1178	27.5 ± 6.8	9.0 ± 1.5

Table 1: Algorithmic performance on 13 test images from CAVE database. Running times measured on Intel Core i7-2600 CPU.



(a) Original image data (b) Superpixel centroids (c) Modes after pruning (clusters)

Figure 3: Spectral gradient distributions of 31-band *superballs* image and algorithmic results visualized with *Gerbil* parallel coordinates plot.

Conclusions

We introduce a family of fast unsupervised clustering algorithms for hyperspectral image data.

- mean shift on spectral gradient (SG-FAMS)
- hyperspectral adaptation of superpixels
- superpixel mean shift in two variants (PSPMS, FSPMS)
- speedup of over 100 times in our benchmark

Source-code available: `http://www.gerbilvis.org/`

References

[1] B. Georgescu, I. Shimshoni, and P. Meer, "Mean shift based clustering in high dimensions: A texture classification example," in *ICCV*, pp. 456-463, 2003.
[2] E. Angelopoulou, S. W. Lee, and R. Bajcsy, "Spectral gradient: a material descriptor invariant to geometry and incident illumination," in *ICCV*, vol. 2, pp. 861-867, 1999.
[3] P. F. Felzenszwalb and D. P. Huttenlocher, "Efficient graph-based image segmentation," *IJCV*, vol. 59, no. 2, pp. 167-181, 2004.
[4] S.A. Robila, A. Gershman, "Spectral matching accuracy in processing hyperspectral data," *Int. Symp. on Signals, Circuits and Systems*, vol. 1, pp. 163-166, IEEE, 2005.
[5] F. Yasuma, T. Mitsunaga, D. Iso, S. K. Nayar. Generalized Assorted Pixel Camera: Post-Capture Control of Resolution, Dynamic Range and Spectrum. *TIP*, vol. 99, 2010.