HyperColorization: Propagating Spatially Sparse Noisy Spectral Clues over Hyperspectral Images

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Motivation

Hyperspectral cameras face challenging spatial-spectral resolution trade-offs and are more affected by shot noise than RGB photos taken over the same exposure time.

Capturing a grayscale image is significantly cheaper than capturing a hyperspectral image.

Inspired by RGB colorization from spatially sparse hints, we explore trade-offs in grayscale-guided hyperspectral colorization.

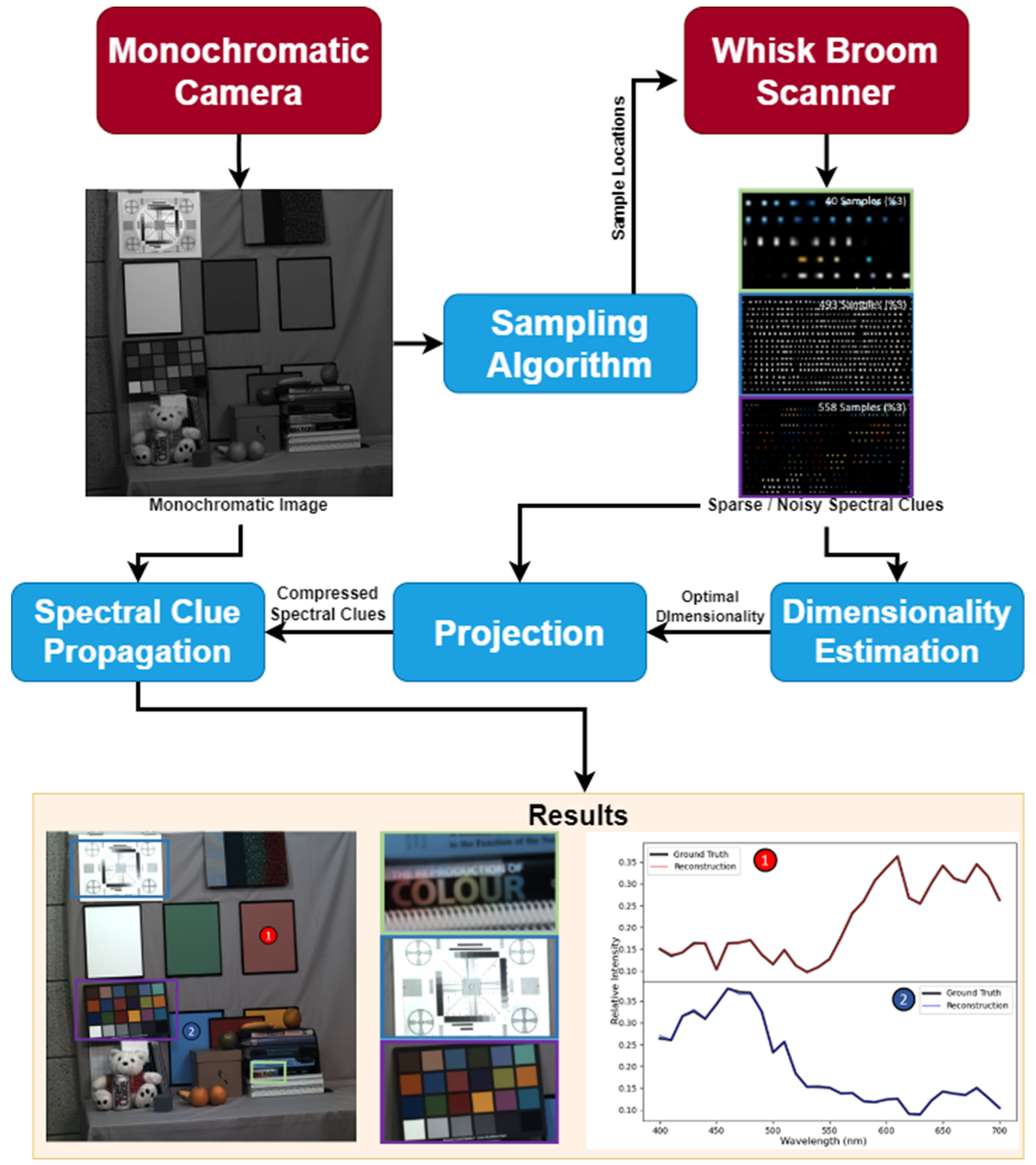
Inspiration

Following Levin et al. 2004, we propagate spectral information over pixels with similar intensity in the grayscale image:

$$J(H(\lambda)) = \sum_{r}\left(\kappa \cdot H(\mathbf{r},\lambda) - \frac{\sum_{\mathbf{s}\in N(\mathbf{r})} w_{\mathbf{rs}} H(\mathbf{s},\lambda)}{\sum_{\mathbf{s}\in N(\mathbf{r})} w_{\mathbf{rs}}}\right)^2$$

$$w_{\mathbf{rs}} \propto e^{-\frac{(\mathrm{G(r)}-\mathrm{G(s)})^2}{2\sigma_r^2}}$$

Proposed Method



Extending to Hyperspectral

- Colorization is well suited to hyperspectral imaging because whisk broom and push broom scanners naturally collect spatially sparse color clues.
- Moving to higher dimensional color presents unique challenges and unique opportunities.
- Our extensions:
  - Grayscale-guided sampling
  - Spectral dimensionality estimation
  - Grayscale-guided filtering
  - Color clue refinement
  - Luminance and saturation stabilization
  - Vectorized optimization for faster compute (408x408x31 in 2s on laptop)

$$H_{balanced}(\mathbf{r},\lambda) = \frac{G(\mathbf{r})}{\sum_{\lambda}|H(\mathbf{r},\lambda)|}\, H(\mathbf{r},\lambda)$$

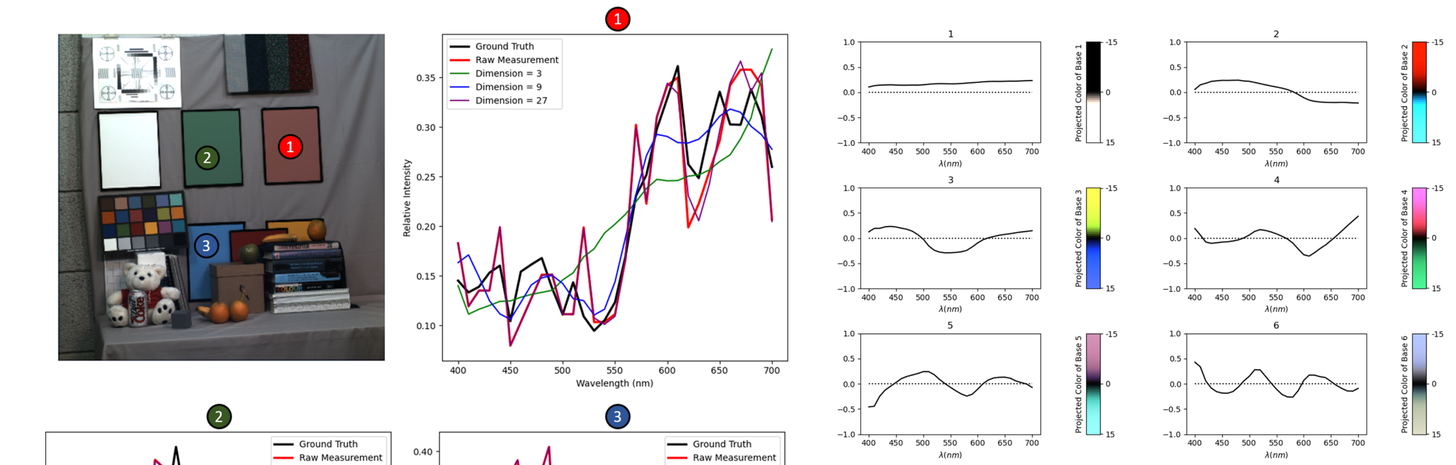
Handling Noise

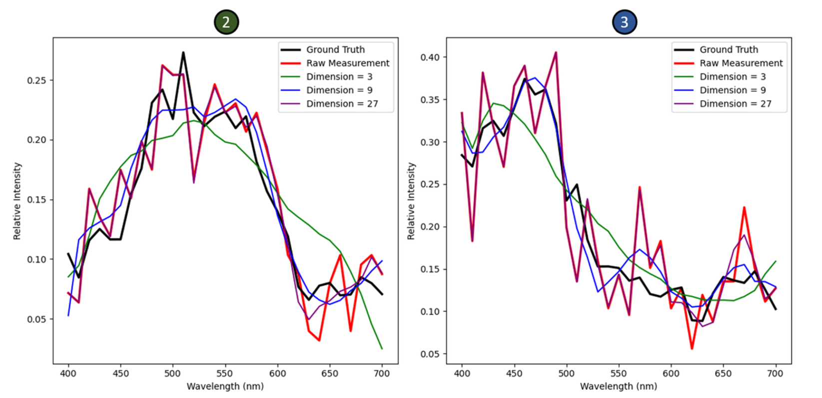
- Hyperspectral images suffer more due to shot noise; colorization risks propagating noisy samples across large regions.
- HyperColorization algorithm works in *any* spectral subspace.
- Spectral responses in an image occupy a low rank space and an orthonormal basis for this space can be learned with SVD.
- Colorizing in a low rank space can boost performance by improving robustness to shot noise, but the most accurate reconstruction dimension will vary with scene and exposure time.
- Optimal dimensionality of the colorization space can be estimated directly from the noisy sparse spectral measurements.
- Grayscale-guided filtering refines initial color clues:

$$H_f(\mathbf{r},\lambda) = \xi \cdot H(\mathbf{r},\lambda) + \frac{(1-\xi)}{n(N(\mathbf{r}))} \cdot \sum_{\mathbf{s}\in N(\mathbf{r})} H(\mathbf{s},\lambda)$$

N: neighborhoods based on grayscale segmentation
ξ : nearness to closest edge

Results of Colorization in a Learned Space

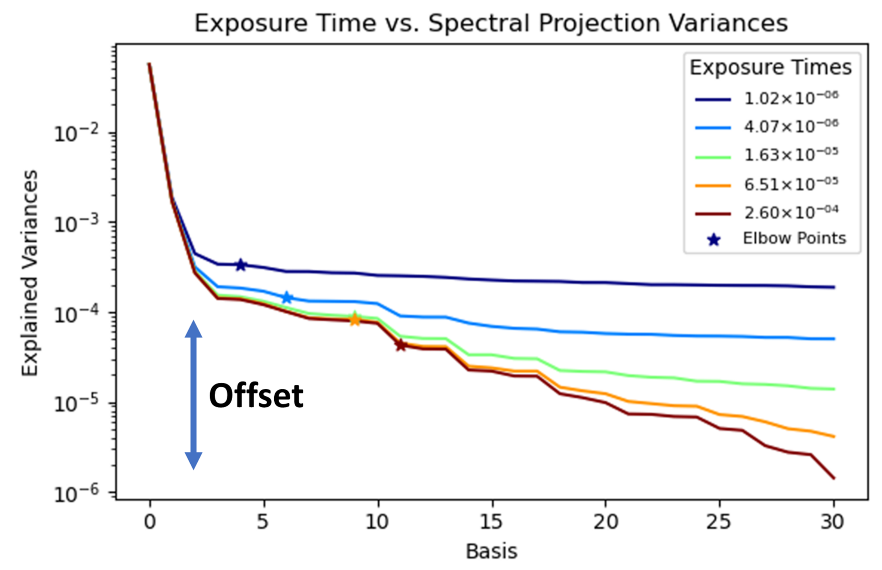




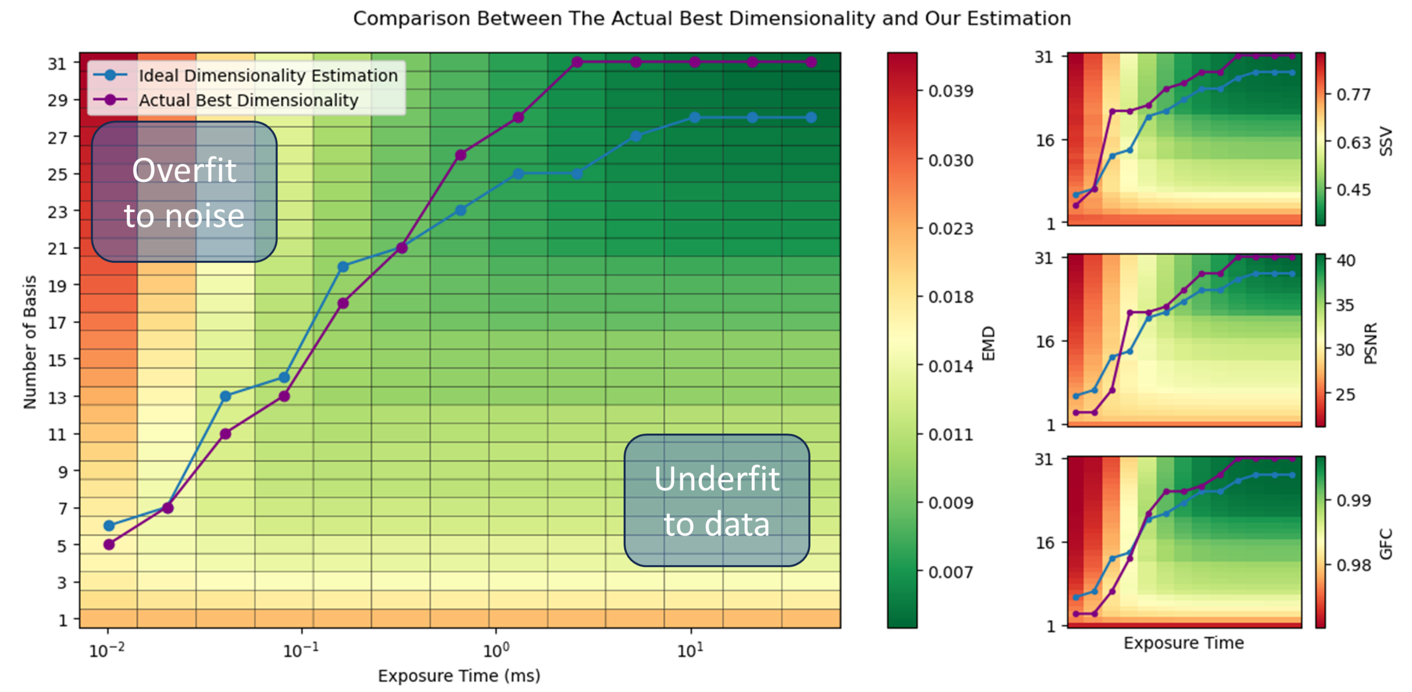
Colorization in lower dimensional color space increases speed and improves robustness to shot noise.

Ground truth (31D)
Overfitting to noise (27D)
Best performance (9D)
Underrepresentation (3D)

Selecting Dimensionality



$$\mathit{Colorization\ Dimensionality} = c_1 \cdot elbow + c_2 \cdot offset + c_3 \cdot elbow^2 + c_4 \cdot offset^2 + c_5$$



Where to Sample?

Our adaptive sampling algorithm increases the sampling frequency based on grayscale image features indicating spectral diversity.

$$frequency \propto \alpha \cdot (\text{gray level count in posterized image}) + (1-\alpha)\cdot(\text{corner count})$$

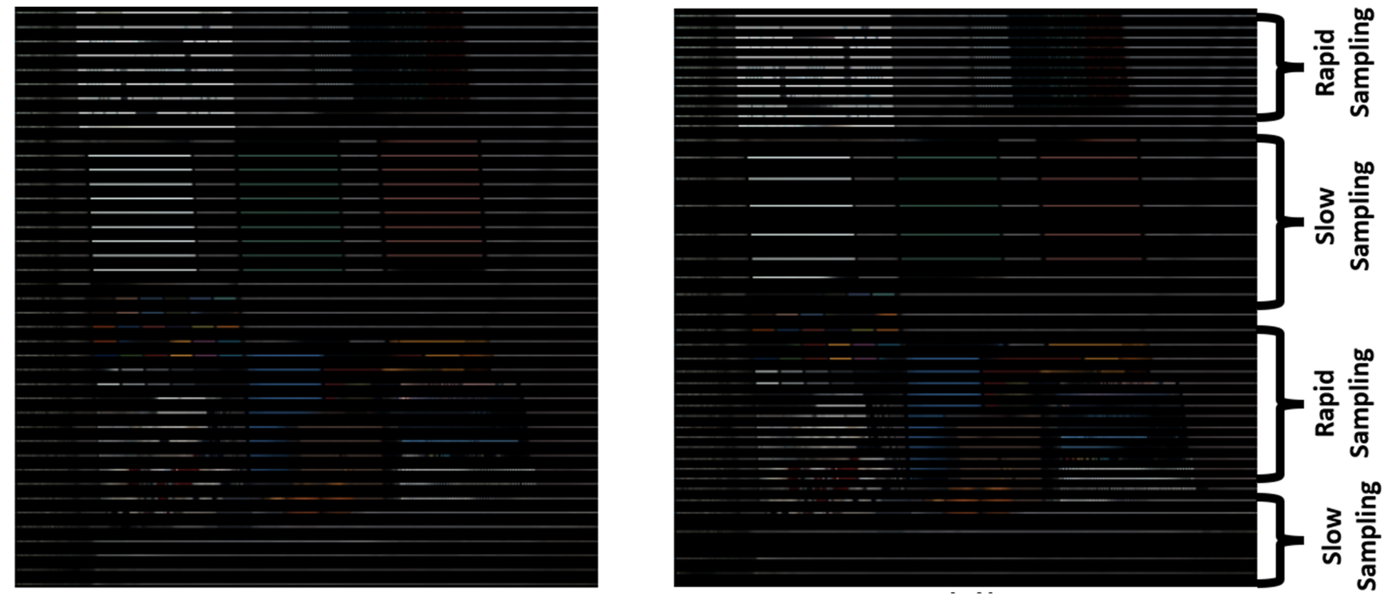


Table 2. Performance on Harvard dataset

Sampling Type	Sampling Ratio	PSNR↑	GFC↑	SSV↓	EMD↓
Uni. push broom	10%	37.938	0.342	0.992	6.865
Uni. push broom	4%	35.155	0.433	0.989	9.340
Uni. whisk broom	4%	37.895	0.358	0.992	6.789
Uni. whisk broom	1%	36.290	0.416	0.990	8.881

Uniform Sampling Pattern

Table 2. Performance on Harvard dataset

Sampling Type	Sampling Ratio	PSNR↑	GFC↑	SSV↓	EMD↓
Ours, push broom	10%	38.409	**0.992**	**0.340**	6.831
Ours, push broom	4%	35.500	0.989	0.409	9.261
Ours, whisk broom	4%	**38.457**	**0.992**	0.352	**6.607**
Ours, whisk broom	1%	36.597	0.989	0.413	7.853

Guided Sampling Pattern

Results on Chakrabarti et. al (2004)

Conclusion

- We present a framework that reconstructs hyperspectral images from a set of sparse and noisy spectral responses paired with a grayscale image.
- We demonstrate that colorization in a low rank space gives robustness to shot noise and we can predict the optimal colorization dimensionality from the noisy spectral measurements.
- We introduce an adaptive sampling algorithm to guide hyperspectral capture.

References

A. Levin, D. Lischinski, Y. Weiss, "Colorization using optimization," SIGGRAPH 2004
A. Chakrabarti T. Zickler, "Statistics of real-world hyperspectral images," CVPR 2011
D. H. Brainard, Hyperspectral Image Data, http://color.psych.upenn.edu//hyperspectral/.

Supported by Dolby