

Multispectral Image Recovery using Sparsity

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Overview

- Sparse Recovery for 1-D Spectra
- Recovery Method for 3-D Multispectral Scenes
- Examples:
 - LED Illumination with Multiple Acquisitions
 - Custom CFA with Single Acquisition

Sparse Recovery of Spectra

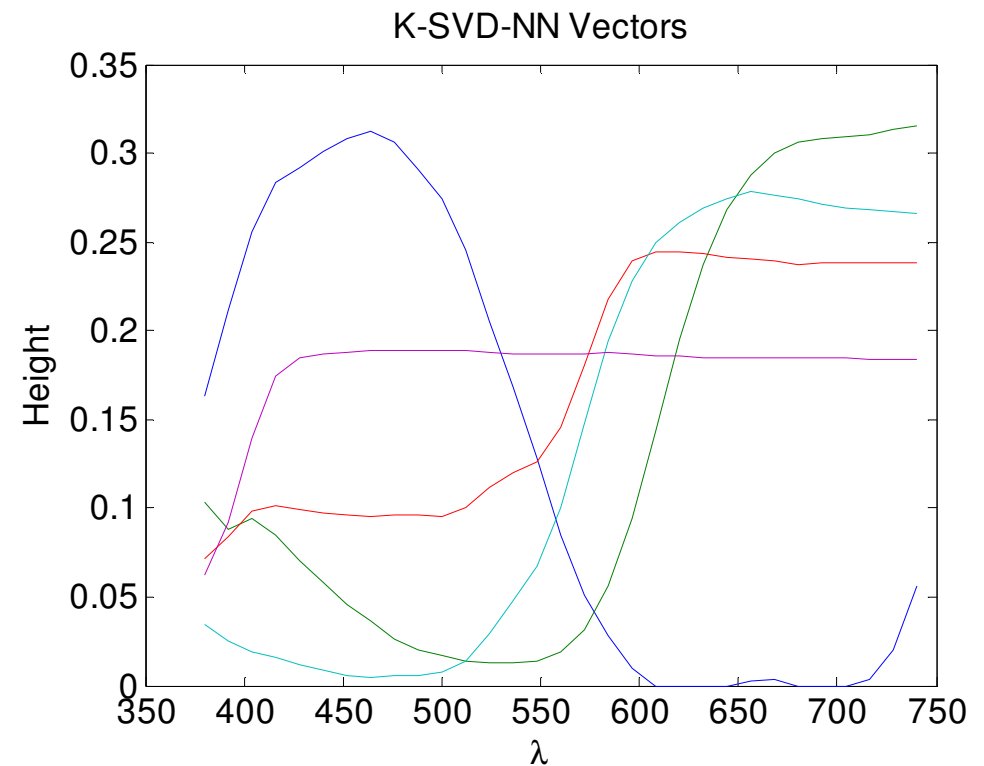
- Assume any spectral curve, $s(\lambda)$, can be well represented by a linear combination of a small number of vectors in a fixed basis, D .
- Try to estimate spectra from small number of noisy measurements:

$$y = \Phi s + \eta$$

where Φ is matrix of measurement filters
 η is measurement noise

Sparse Basis

- Learned from training data
- Used K-SVD-NN algorithm
- Results in basis vectors that resemble actual spectra



Reconstruction Method for Spectra

- Goal is to find a spectral curve that agrees with measurements and is sparse in given basis, D
- The reconstruction is $\hat{s} = D\hat{x}$ where

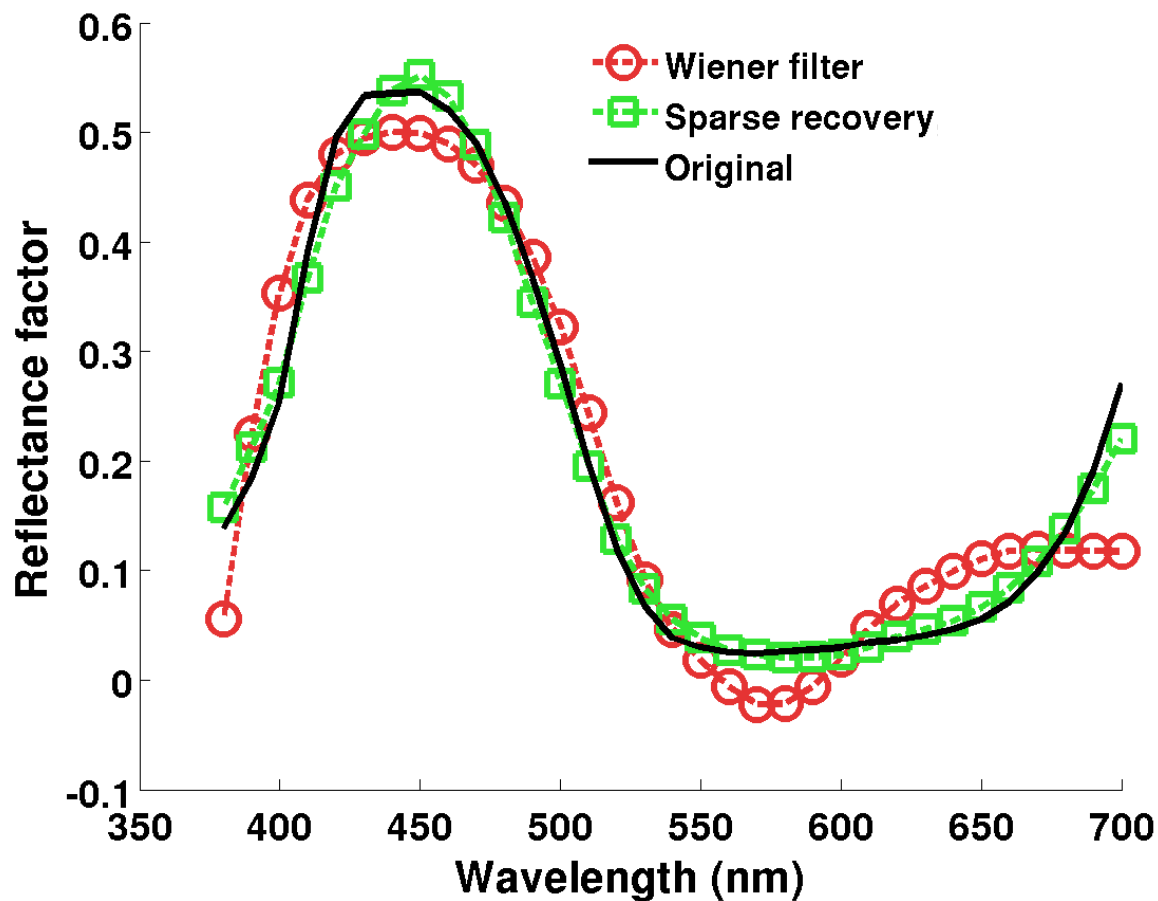
$$\hat{x} = \underset{x}{\operatorname{argmin}} \left(\frac{1}{2} \|y - \Phi D x\|_2^2 + \tau \|x\|_1 \right)$$

\hat{x} are the sparse coefficients

τ is a constant parameter

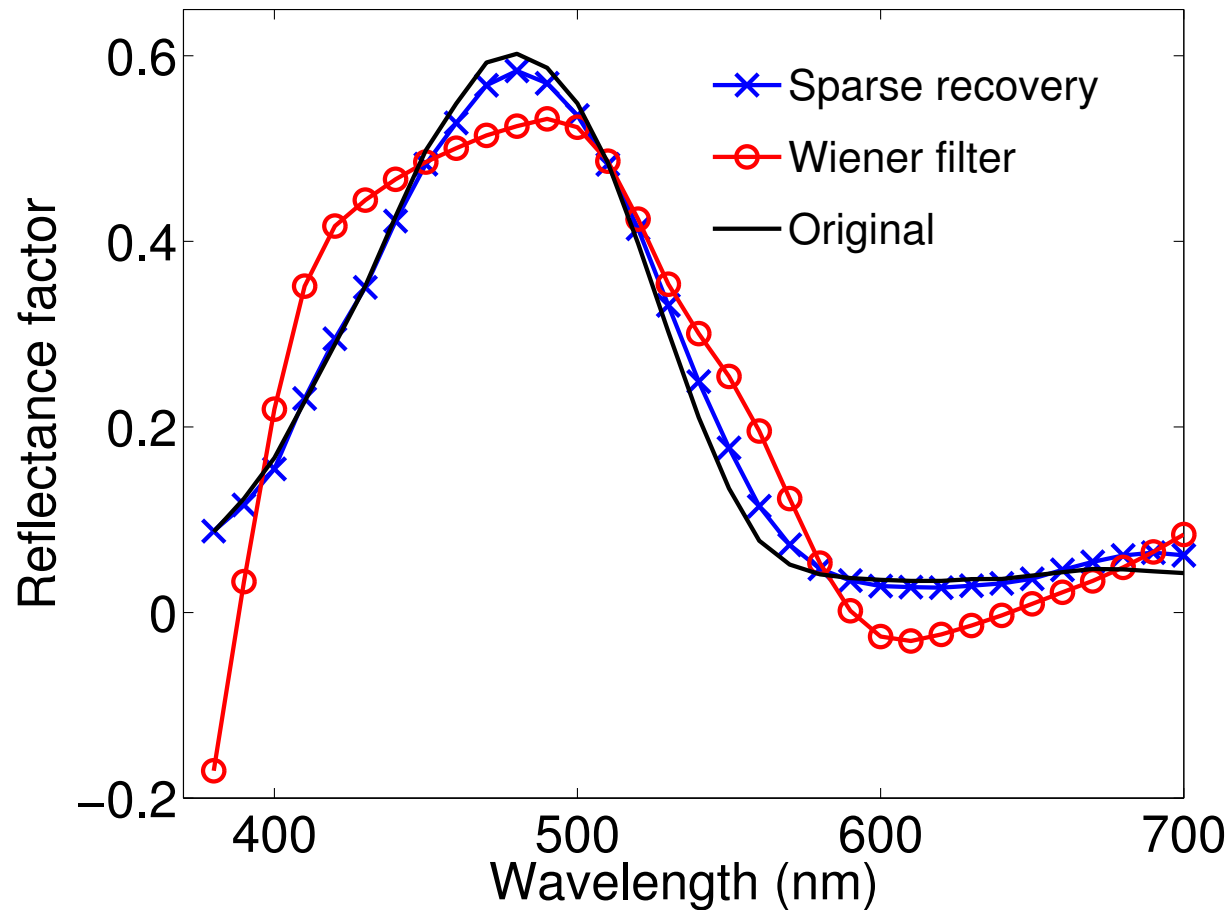
Reconstruction Example 1

- Measured using 4 equally spaced Gaussian filters with 35dB SNR



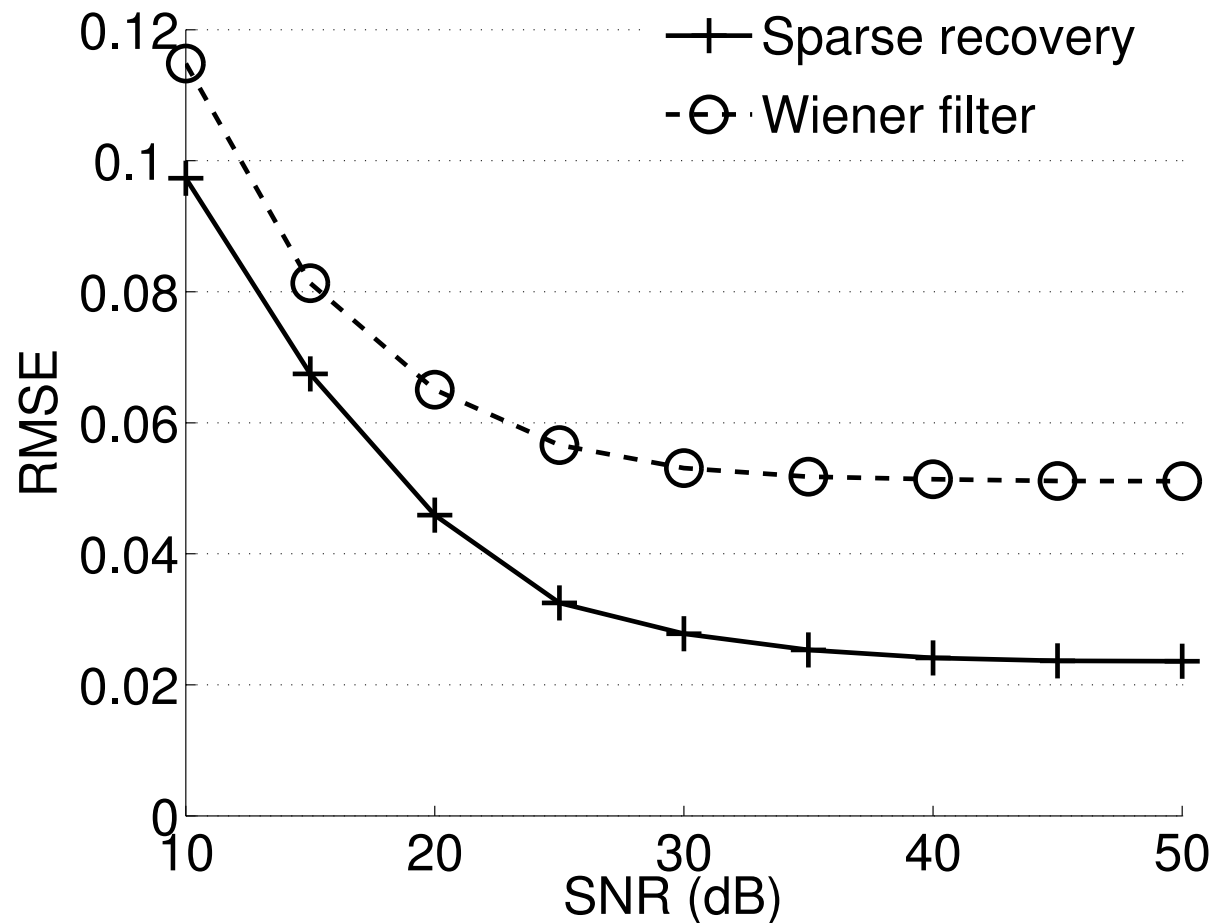
Reconstruction Example 2

- Measured using 4 equally spaced Gaussian filters with 35dB SNR



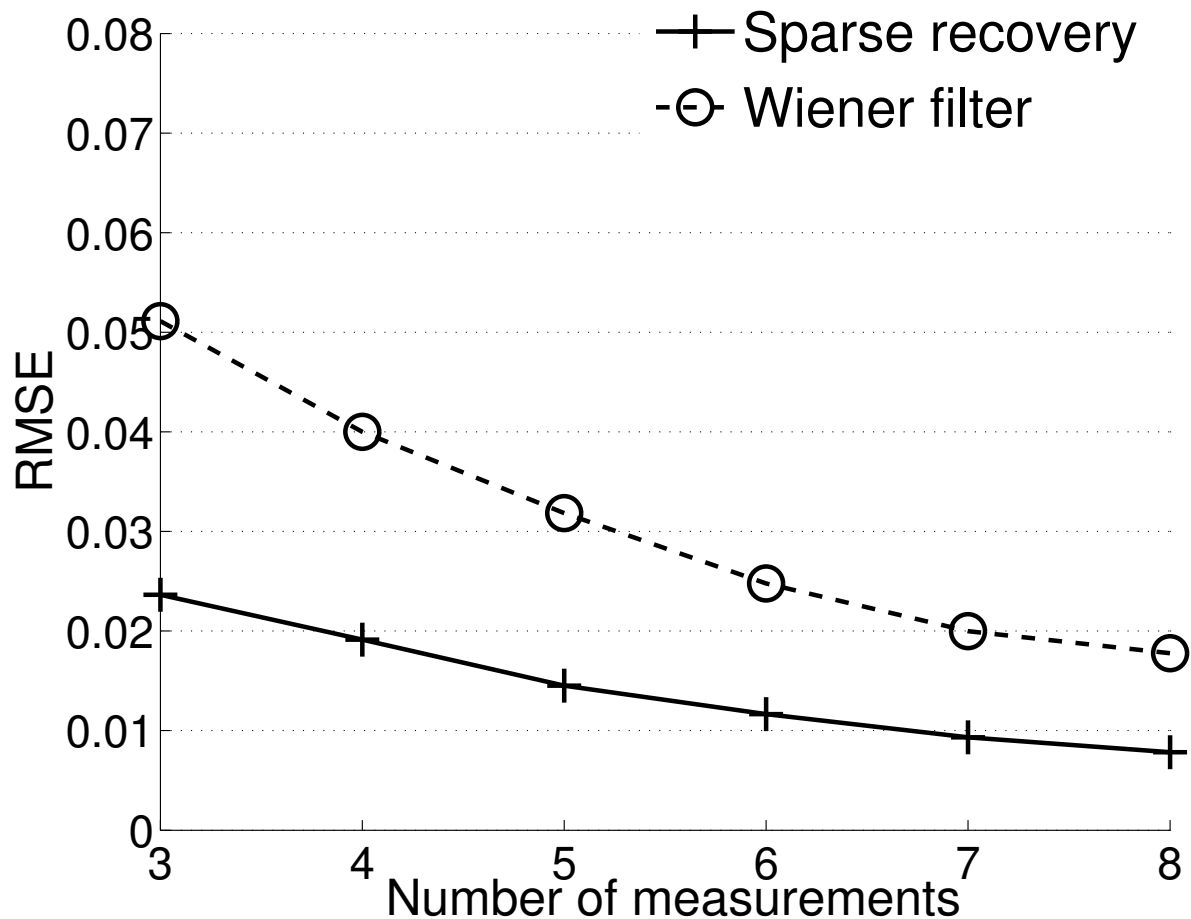
Performance for Various Noise Levels

- Measured using 3 equally spaced Gaussian filters



Performance for Various Number of Measurements

- Measured using SNR of 40dB



Multispectral Problem

- Want to obtain spectral curve at every pixel
- Typically too few measurements are available at each pixel for good reconstruction
- Often adjacent pixels have different measurements due to CFA



Reconstruction Method for Multispectral Scenes

- Same basic sparse reconstruction algorithm as 1-D spectrum method
- The reconstructed datacube is $\hat{s} = D\hat{x}$ where

$$\hat{x} = \underset{x}{\operatorname{argmin}} \left(\frac{1}{2} \|y - \Phi D x\|_2^2 + \tau \|x\|_1 \right)$$

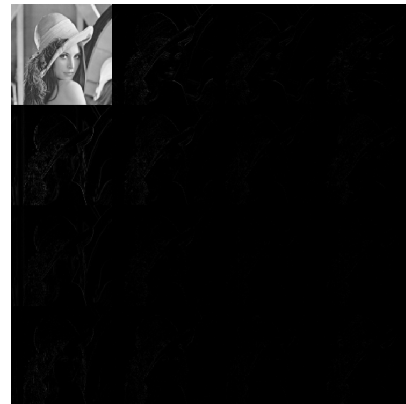
- Now we need datacubes to be sparse in basis D

Sparse Basis for Datacubes

- Basis is Cartesian product of previous dictionary in spectral dimension and Haar wavelet in the spatial dimensions
- Haar wavelet gives sparse representations for images

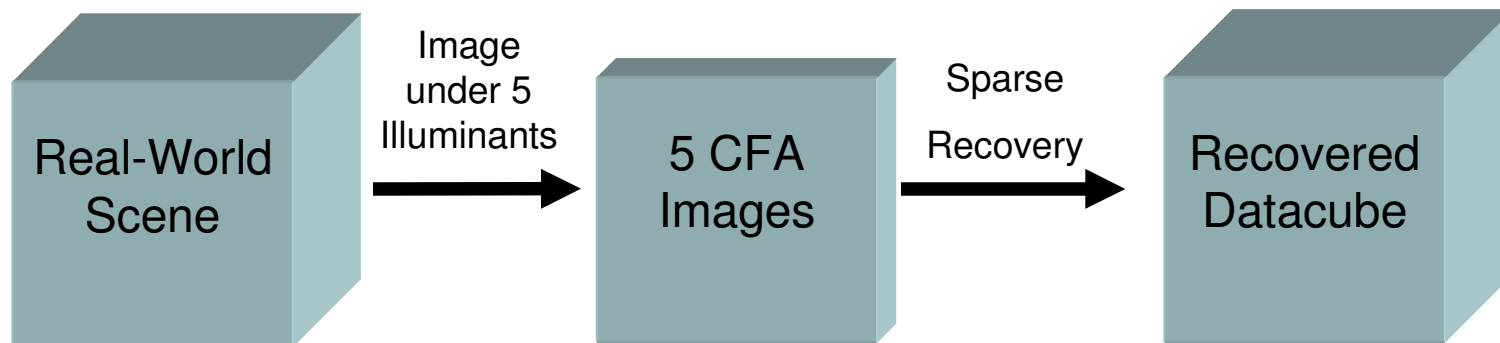


Level 2 Haar
Transform



Example 1: Image under Illuminants

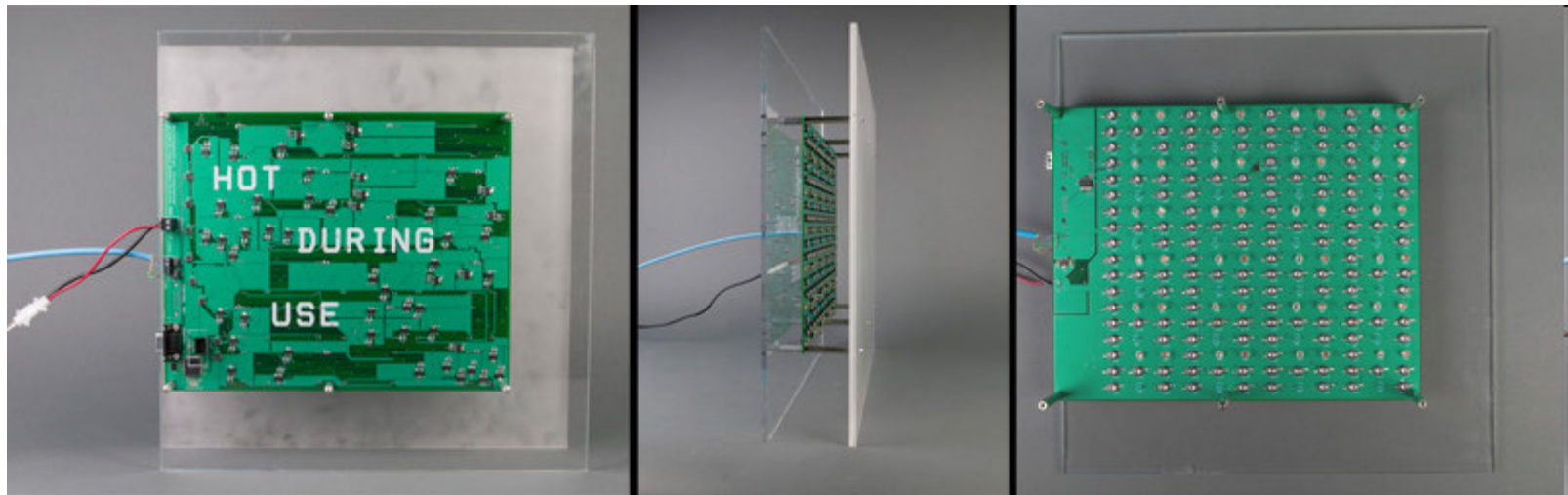
Recovery using Multiple Illuminants and Acquisitions



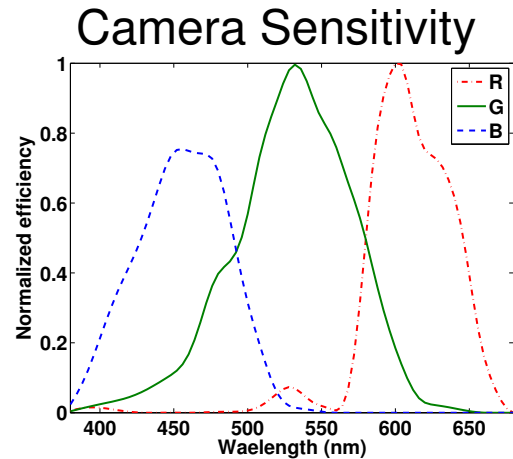
- Imaged Real-World Scenes in Lab
- Used Camera with Bayer Pattern

System Setup

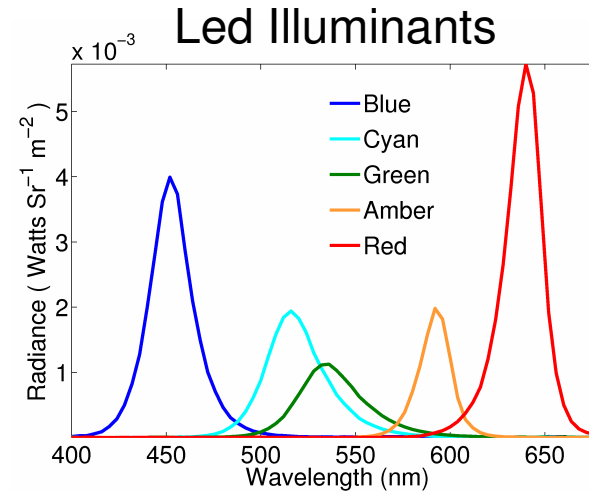
- 5 Different Color Illuminants using 25 LEDs each
- 5 Acquisitions in 1.5 seconds



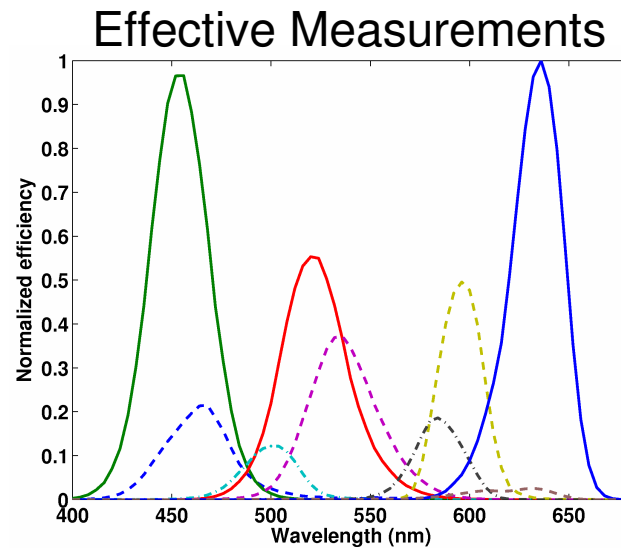
Measurement Filters



X

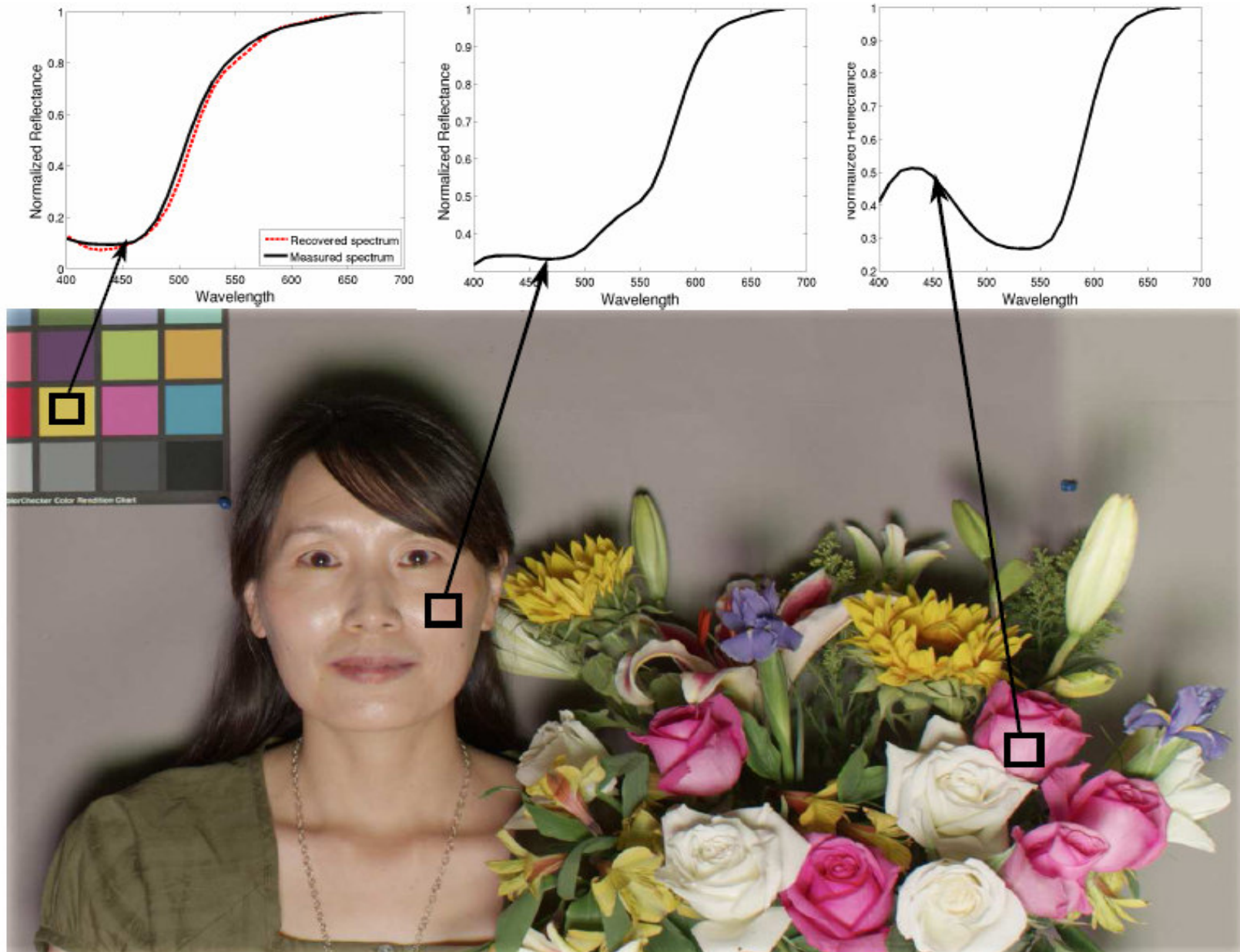


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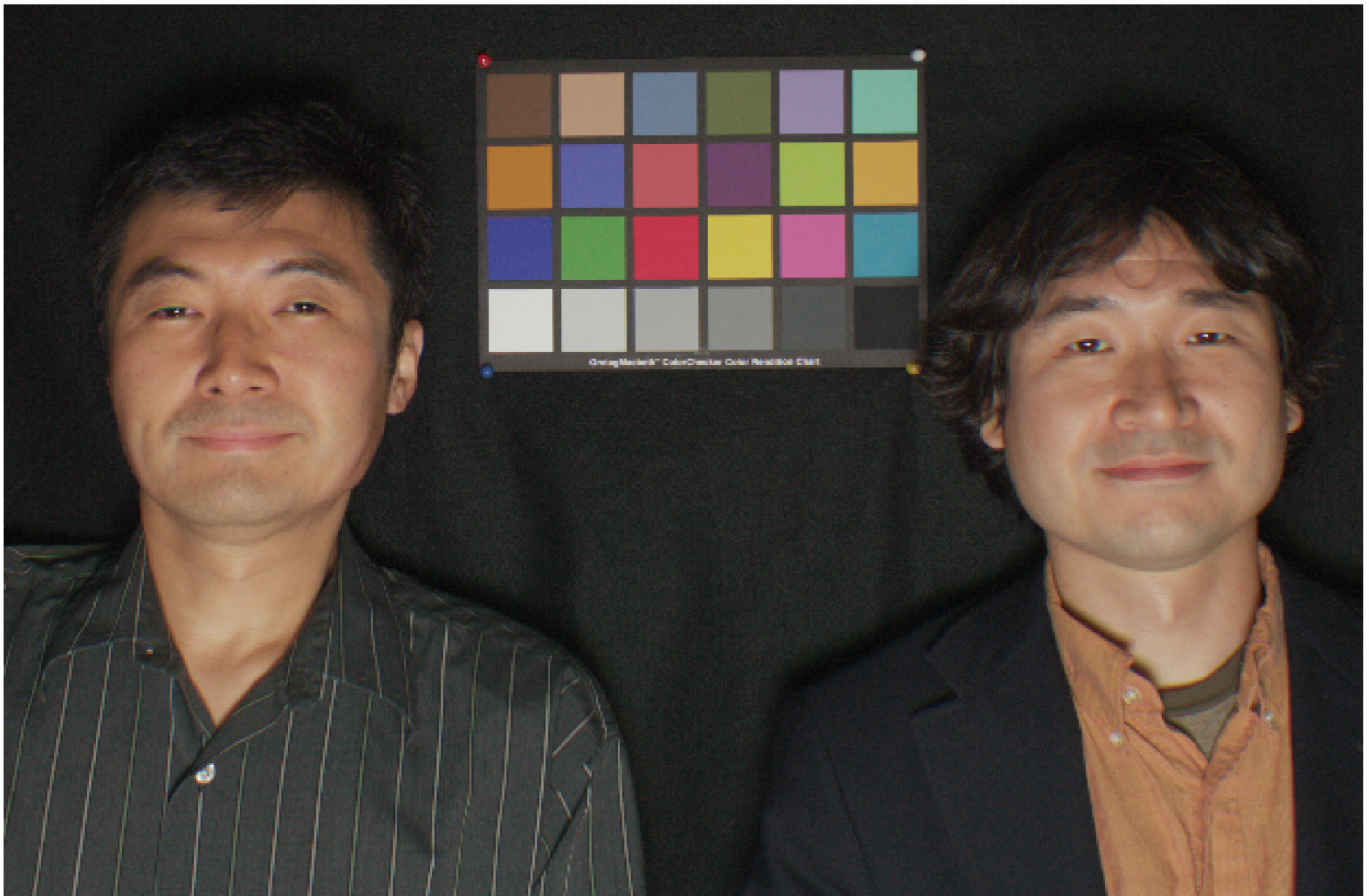


Results in 2 to 4
measurements at each
pixel

Reconstruction Result



Reconstruction Result

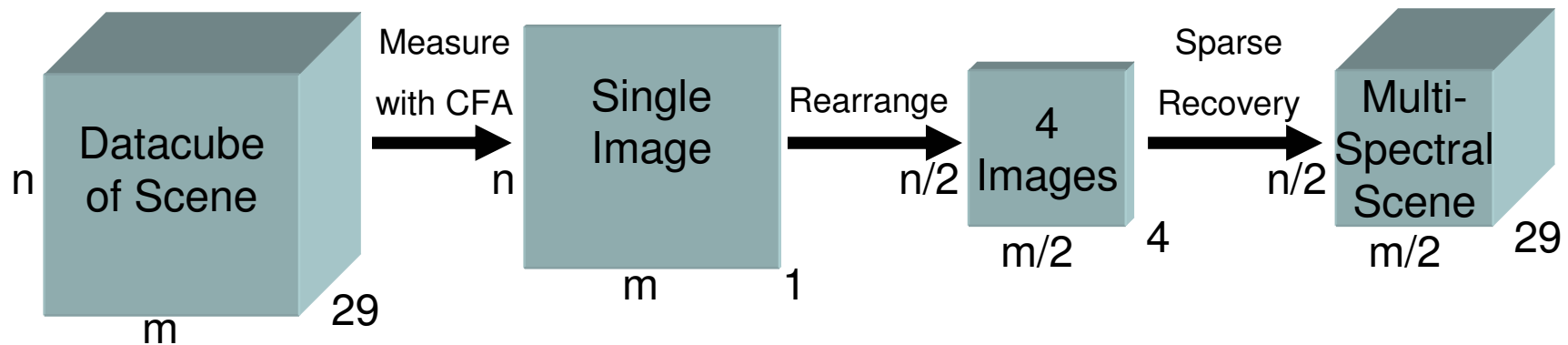


Illumination Method Limitations

- Object must be indoors at a close distance
- Object may not move for 1.5 seconds
- Special illumination device required
- But regular RGB camera can be used

Example 2: Custom CFA

Recovery using Custom CFA and Single Acquisition



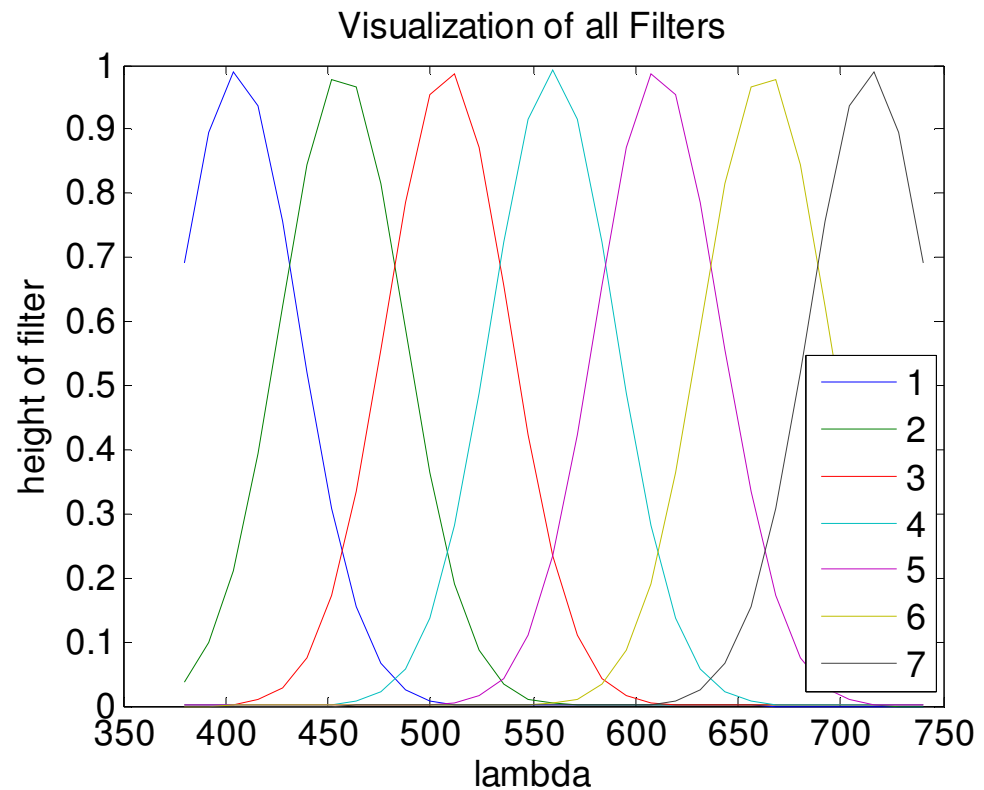
Experimental Setup:

- Datacube of scene is from published data
- Measurements are simulated from datacube

Measurement Method

- CFA is 4x4 block pattern using 7 equally spaced Gaussian filters

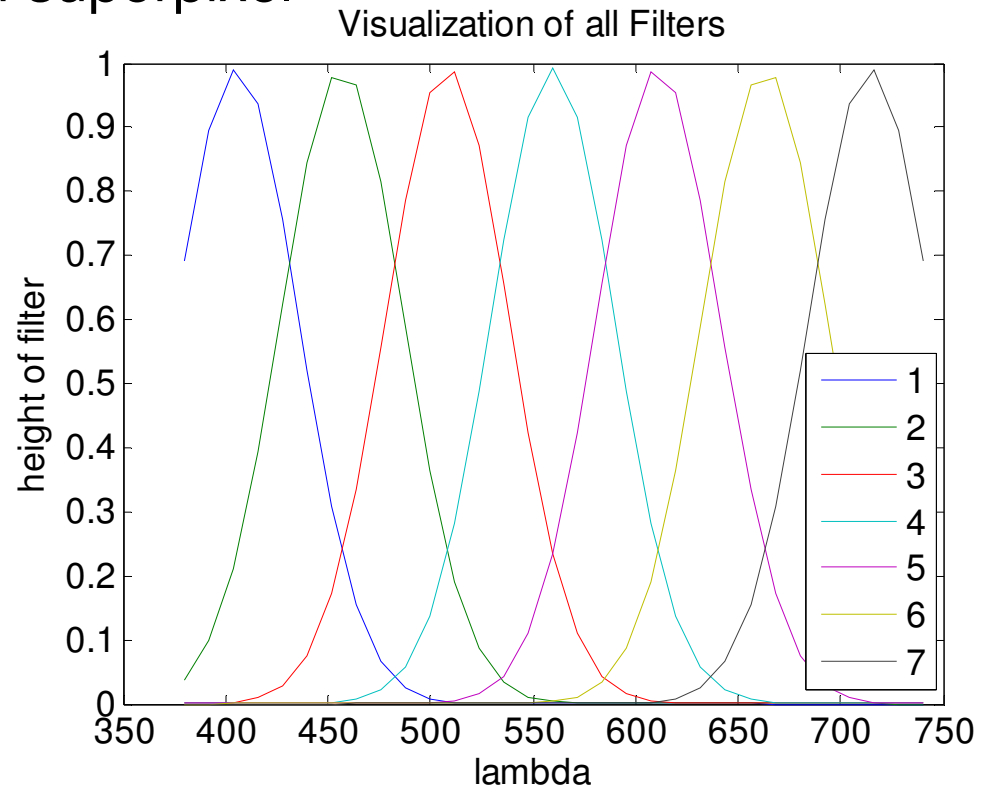
6	2	1	4	6	2	1	4
1	5	3	7	1	5	3	7
7	3	2	5	7	3	2	5
2	6	4	1	2	6	4	1
6	2	1	4	6	2	1	4
1	5	3	7	1	5	3	7
7	3	2	5	7	3	2	5
2	6	4	1	2	6	4	1



Measurement Method

- Form 2x2 superpixels so each superpixel has 4 measurements
- Recover spectra at each superpixel

6	2	1	4	6	2	1	4
1	5	3	7	1	5	3	7
7	3	2	5	7	3	2	5
2	6	4	1	2	6	4	1
6	2	1	4	6	2	1	4
1	5	3	7	1	5	3	7
7	3	2	5	7	3	2	5
2	6	4	1	2	6	4	1



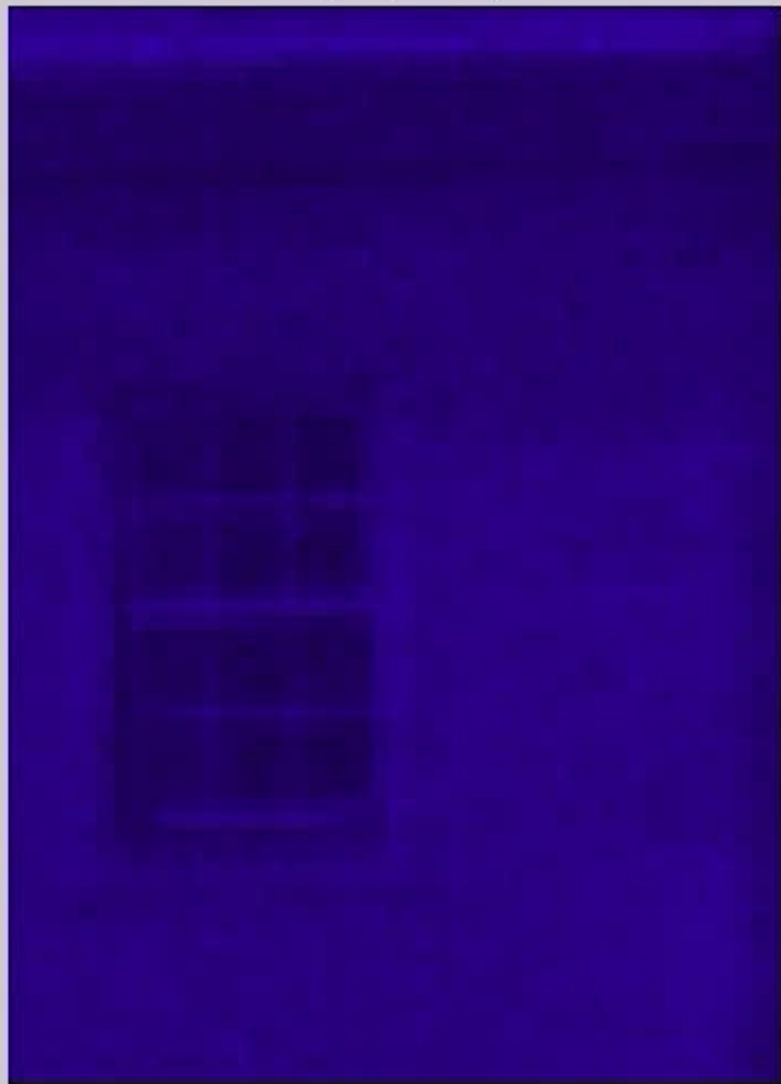
Original



Reconstruction



Original (400 nm)



Reconstruction (400 nm)



Future Work

- Develop algorithm to train better sparse bases
- Improve sparse basis for multispectral scenes
- Consider improved measurement schemes
- Simulate full camera pipeline
- Consider narrower applications for improved performance