Northeastern University
College *of* Engineering

Optical Science Northeastern University Laboratory

Biomedical Imaging
Hyperspectral Imaging

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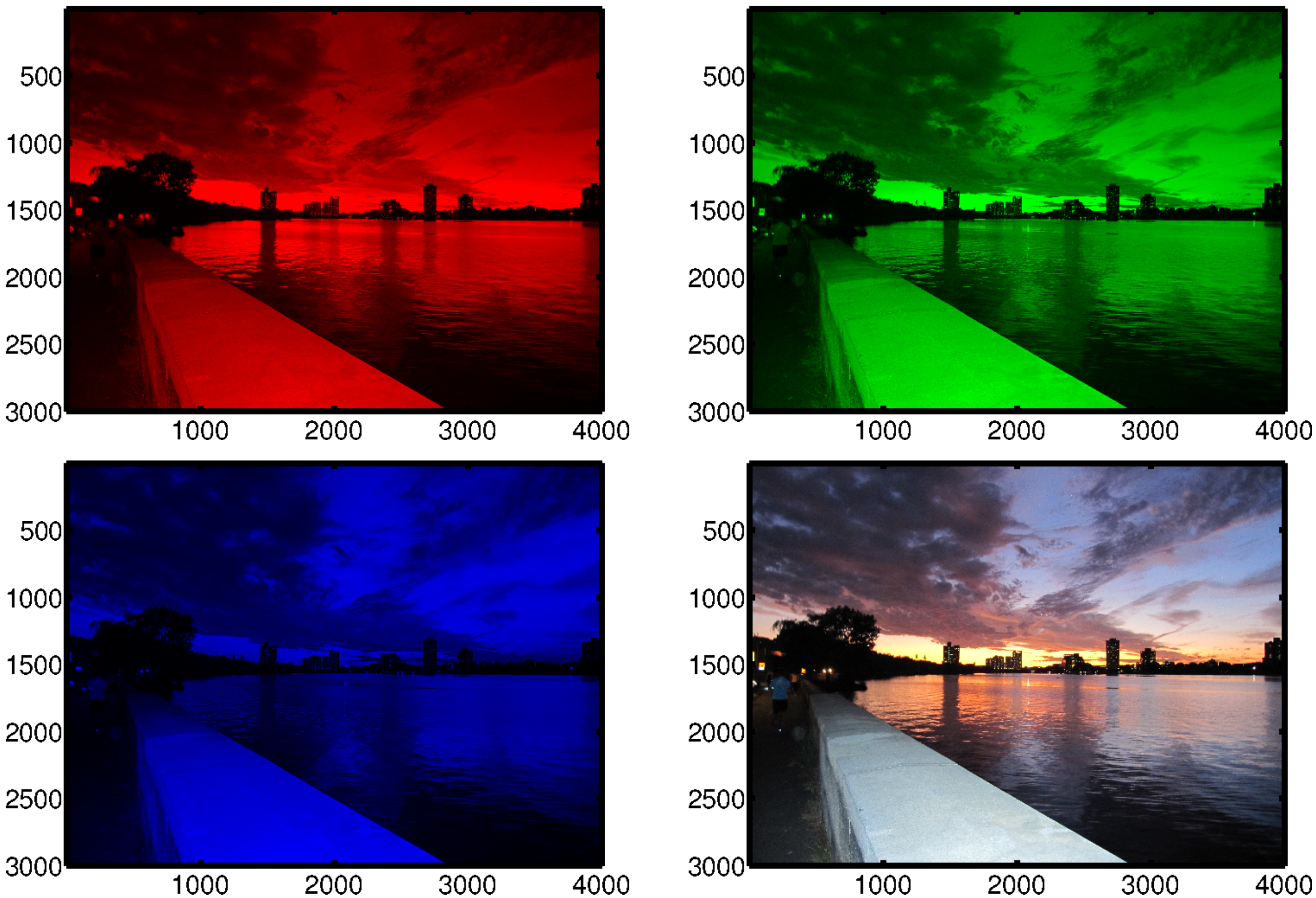
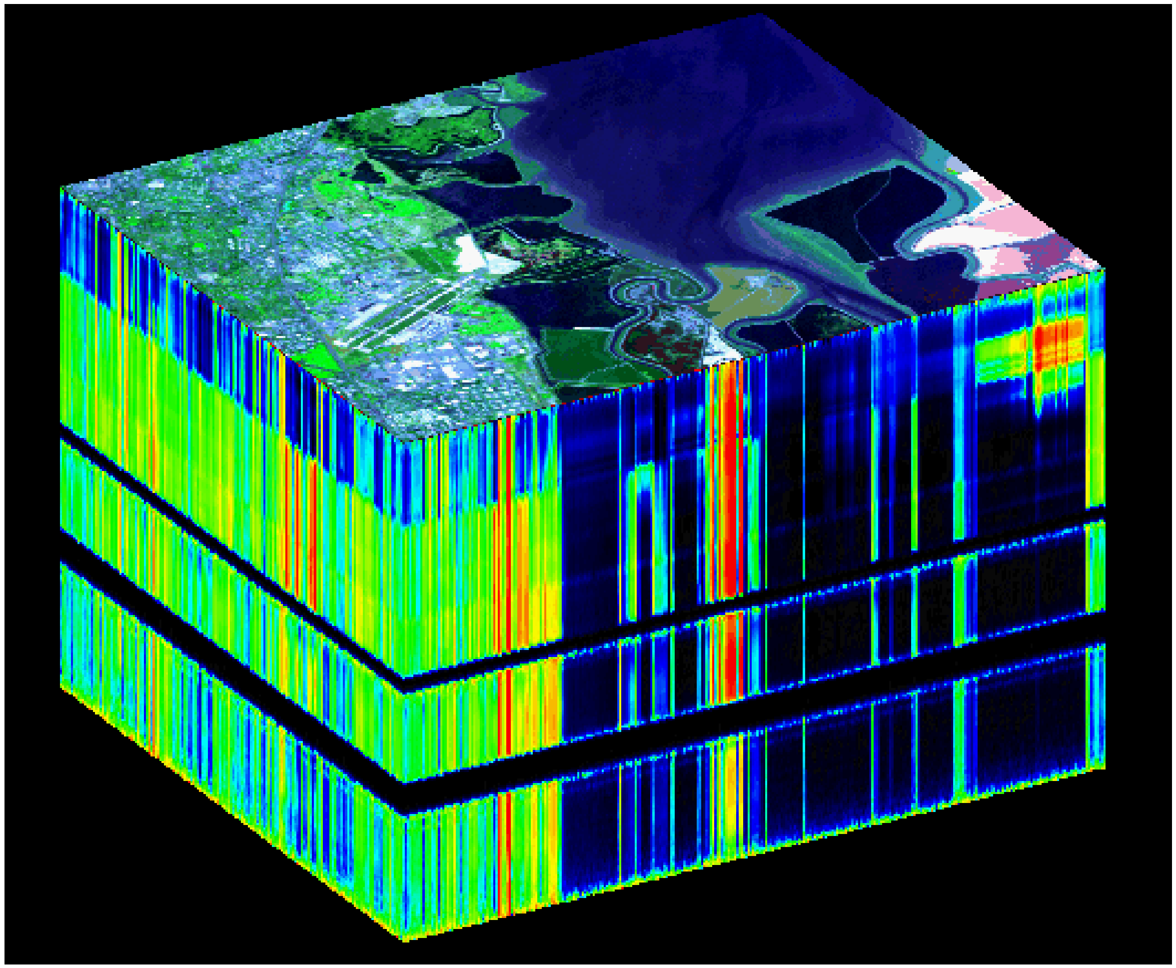
Why Spectral?

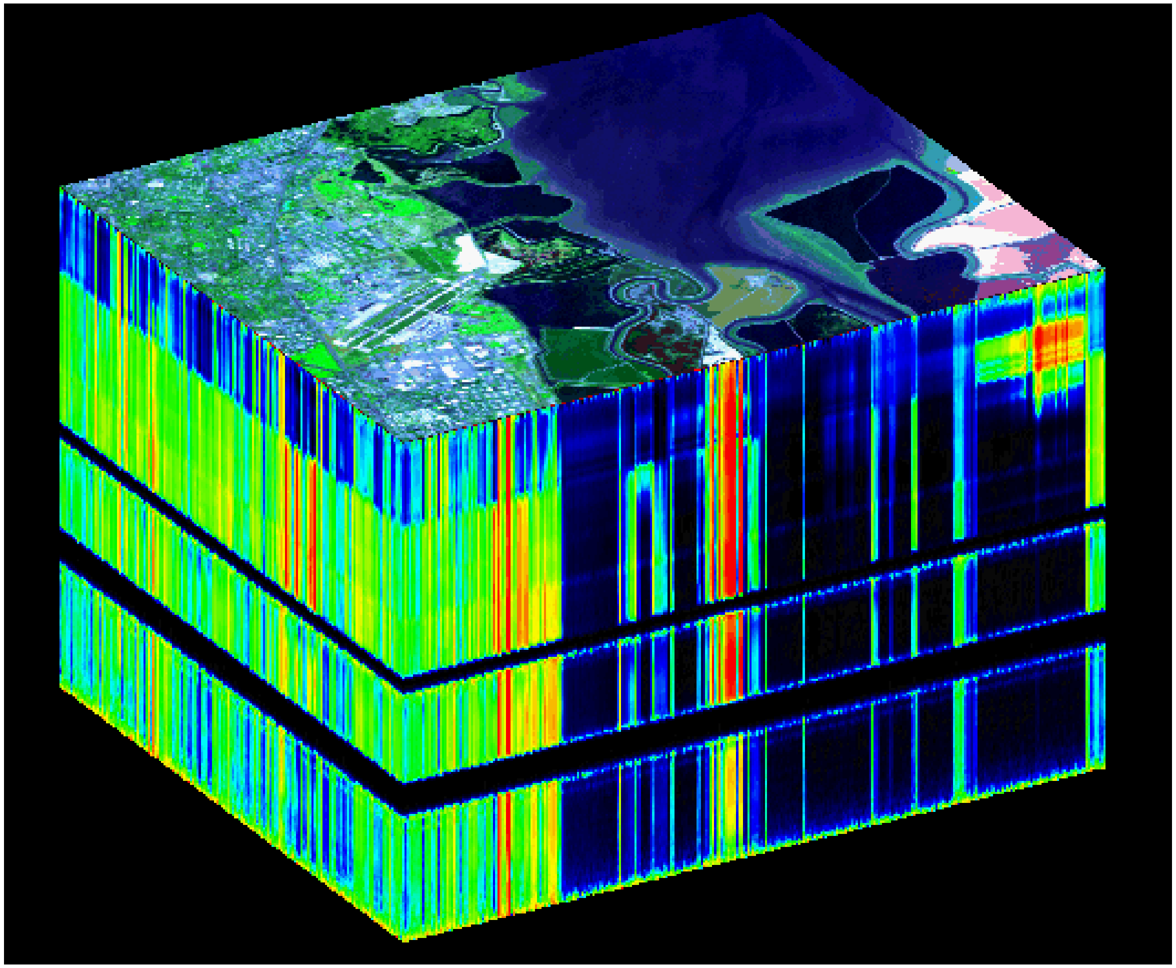


Why Hyperspectral



Right ≈ North, Down = [400 to 2400 nm] (not Linear)
South Bay of California; 101 curves down on the left.

Why Hyperspectral



Right ≈ North, Down = [400 to 2400 nm] (not Linear)

Where are the Shrimp?

Hardware

- Tunable Filter (Lyot Filter, Pronounced "Leo")
  - x, y on camera
  - λ with time
- Grating spectrometer with Pinhole
  - λ on Camera
  - x, y with time (whiskbroom: Slow)
    - Slit, Grating and 2D Camera
      - x, λ on camera
      - y with time (pushbroom)

Applications

- Military (Where's the Tank in the Trees?)
- Law Enforcement (Which crop is illegal?)
- Environmental (*e.g.* Deep Horizon
- Biomedical
  - Fluorescence Spectroscopy (Multiple, Overlapping Fluorophores)
  - Hemoglobin Spectroscopy

Forward Models

- Monte–Carlo
- Diffusion
- FDTD
- Linear Spectral Prediction

$$Y_\lambda = \sum_{n=1}^{N} M_{\lambda,n} X_n$$

- Backscatter

$$Y = \mu_a \qquad M = \kappa_n(\lambda)$$

- Fluorescence

$$Y = E_\lambda \qquad M = E_{\lambda,n}$$

- Intuitive Backscatter

$$\frac{1}{W} = \frac{\mu_s + \mu_a}{\mu_s}$$

$$\frac{1}{W} = 1 + \frac{\mu_a}{\mu_s}$$

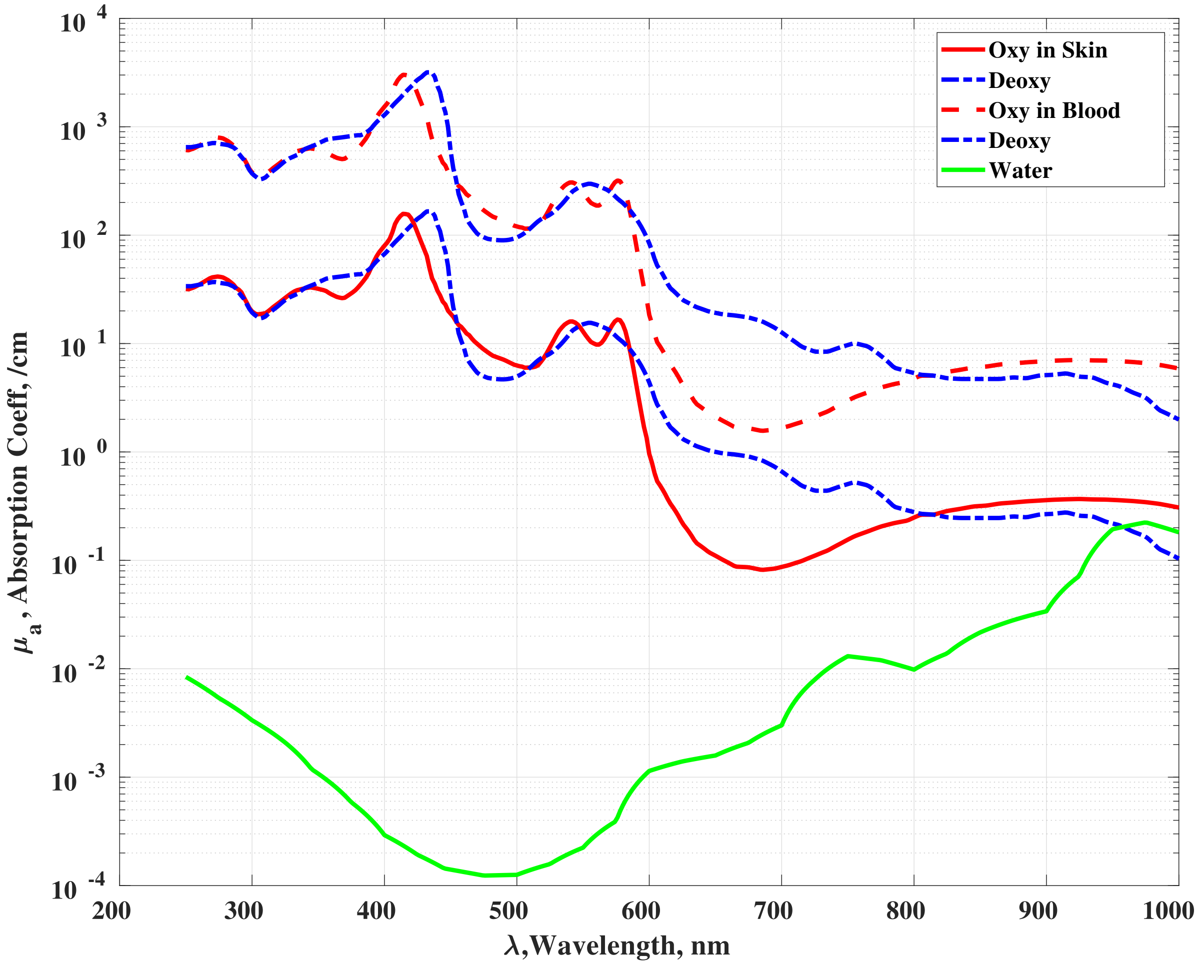
- or $\mu_a \ell_{eff} = \ln(1/T)$
- Linear Superposition

$$\mu_a(\lambda) = \sum_{n=1}^{N} \kappa_n(\lambda) X_n$$

- Fluorescence
  Source Powers Add

$$E_\lambda(\lambda) = \sum_{n=1}^{N} E_{\lambda,n}(\lambda) X_n$$

Some Common Absorbers



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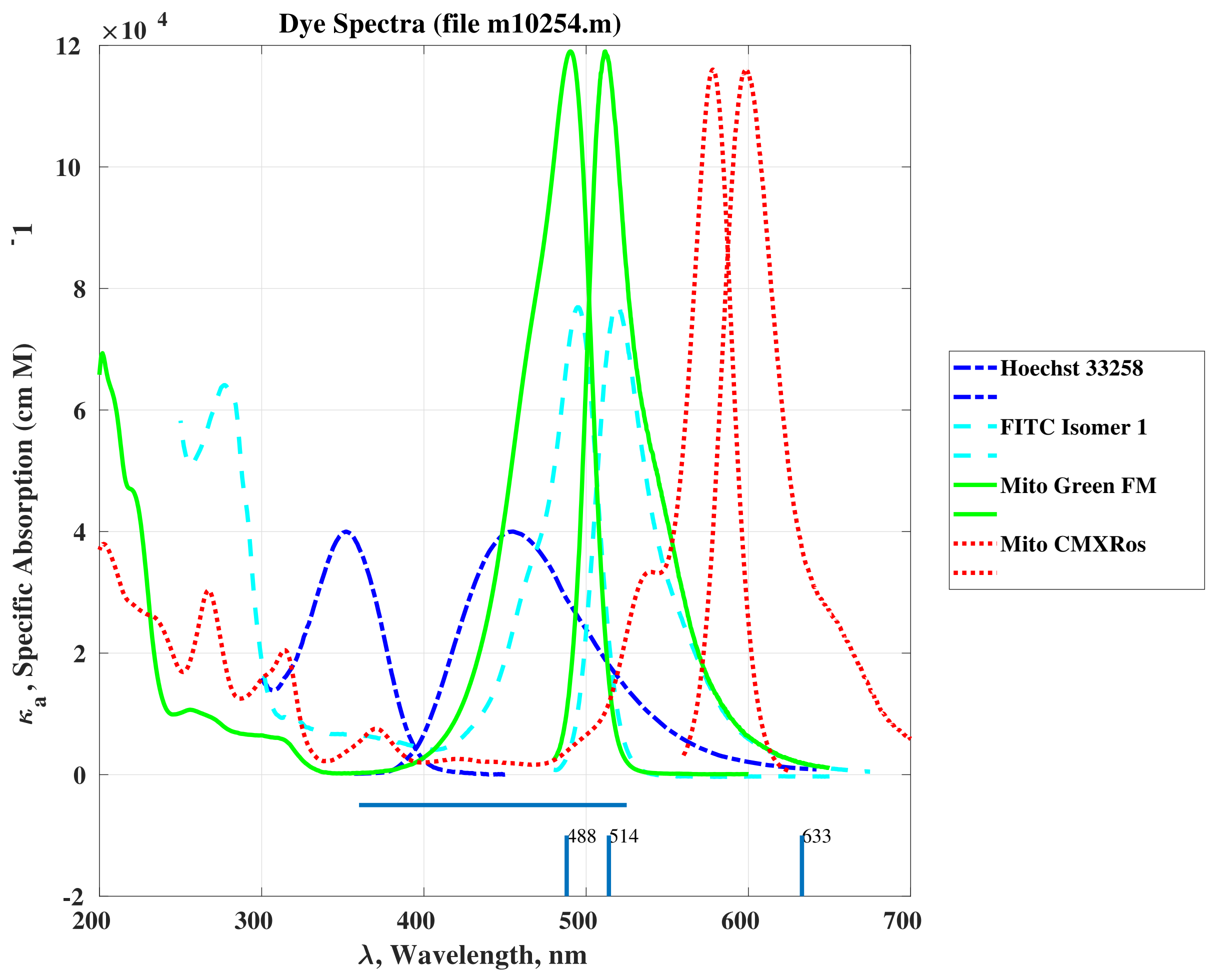
Some Common Fluorophores



Matrix Methods

- Forward Problem

$$\mathbf{Y} = \mathcal{M}\mathbf{X}$$

- Typical Example

$$\begin{pmatrix} Y(\lambda_1) \\ Y(\lambda_2) \\ Y(\lambda_3) \\ Y(\lambda_4) \\ \vdots \\ Y(\lambda_{200}) \end{pmatrix} = \begin{pmatrix} M_{1,1} & M_{1,2} & M_{1,3} \\ M_{2,1} & M_{2,2} & M_{2,3} \\ M_{3,1} & M_{3,2} & M_{3,3} \\ M_{4,1} & M_{4,2} & M_{4,3} \\ \vdots & \vdots & \vdots \\ M_{200,1} & M_{200,2} & M_{200,3} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}$$

- Inverse Problem

$$\mathbf{X} = \mathcal{M}^{-1}\mathbf{Y} \qquad \text{Oh No!!!}$$

Variance, Covariance

- Variance:
  Mean of Squared Difference from Mean

- Covariance:
  Mean of Squared Difference

- Each Pixel (k) is a Column

$$\mathcal{Y} = \begin{pmatrix} Y_1(\lambda_1) & Y_2(\lambda_1) & \dots \\ Y_1(\lambda_2) & Y_2(\lambda_1) & \dots \\ Y_1(\lambda_3) & Y_2(\lambda_1) & \dots \\ \vdots & \ddots & \\ Y_1(\lambda_{200}) & Y_2(\lambda_{200}) & \dots \end{pmatrix} \qquad COV(\mathcal{Y}) = \mathcal{Y}\mathcal{Y}^\dagger$$

- We can visualize this in 3D space

Variance, Covariance, Principal Components

- Covariance

$$COV(\mathcal{Y}) = \mathcal{Y}\mathcal{Y}^{\dagger}$$

- Find Eigenvalues and Eigenvectors
- Arrange in Eigenvalue Order Decending
- Remember $\mathbf{Y} = \mathcal{M}\mathbf{X}$ for a pixel or $\mathcal{Y} = \mathcal{M}\mathcal{X}$ for an image
- It's Possible from this to Guess
  - $\mathcal{M}$, the basis comonent spectra in columns
  - $\mathcal{X}$, the strength of each component in each pixel

Non–Negative Least Squares

Real–Time NLSS
Someone who Needs
no Introduction

Application to Skin Imaging
Jaime Prieto & Matias Rivera
(UAndes)
Everett O'Malley (NU, UCSB)