Spectral Unmixing and Segmentation of Biomedical Hyperspectral Images

Fields Undergraduate Summer Research Program Project 9

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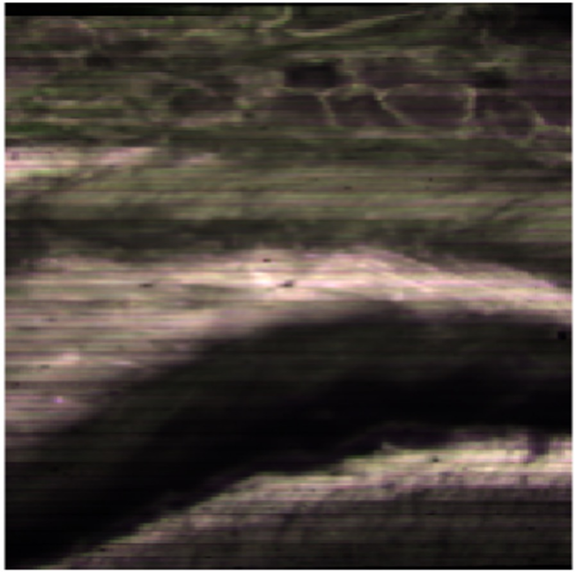
Supervised by Dr. Na Yu & Dr. You Liang

FIELDS

Outline

- → Project Introduction
- → Hyperspectral Unmixing
- → Hyperspectral Segmentation
- → Dimension Reduction

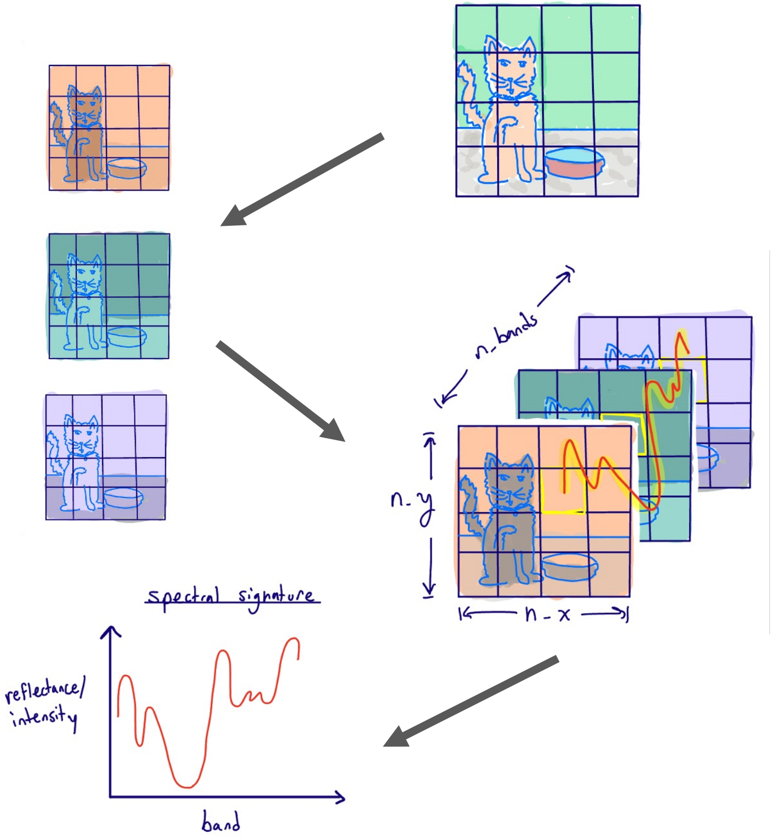


Project Introduction

- What is Hyperspectral Imaging?
- Hypercube and Spectral Signatures
- Applications to Biomedicine
- Reference Dataset Information

What is Hyperspectral Imaging?

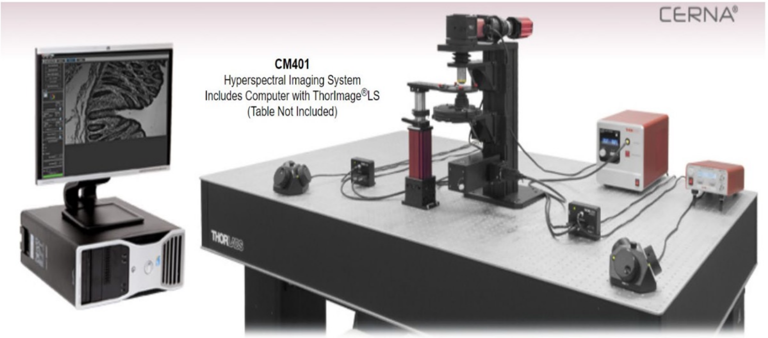
- Imaging camera measures light reflectance off of objects
- The camera separates the image by wavelength
- Different **endmembers**, or materials, in the the image reflect different amounts of light at each wavelength
- Endmembers will have different **spectral signatures** which can be used to classify elements in the image
- Commonly applied to geospatial remote sensing - ex. vegetation covers



FIELDS

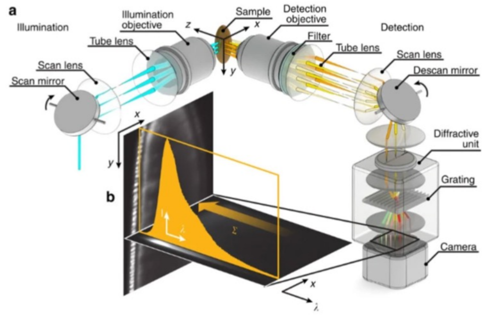
Biomedical Hyperspectral Imaging

- Applying traditional geospatial HSI techniques to **biomedical** data
- Create **open source** python package that performs dimensionality reduction, unmixing, and segmentation
- Applying HSI techniques to eye slice samples
- A special microscope called a **spectrometer** is used to collect hyperspectral data from the samples



https://www.thorlabs.com/newgrouppage9.cfm?objectgroup_id=11095

Figure 1: Hyperspectral SPIM setup and image formation.

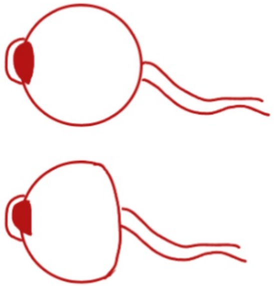


https://www.nature.com/articles/ncomms8990

HSI = Hyperspectral imaging

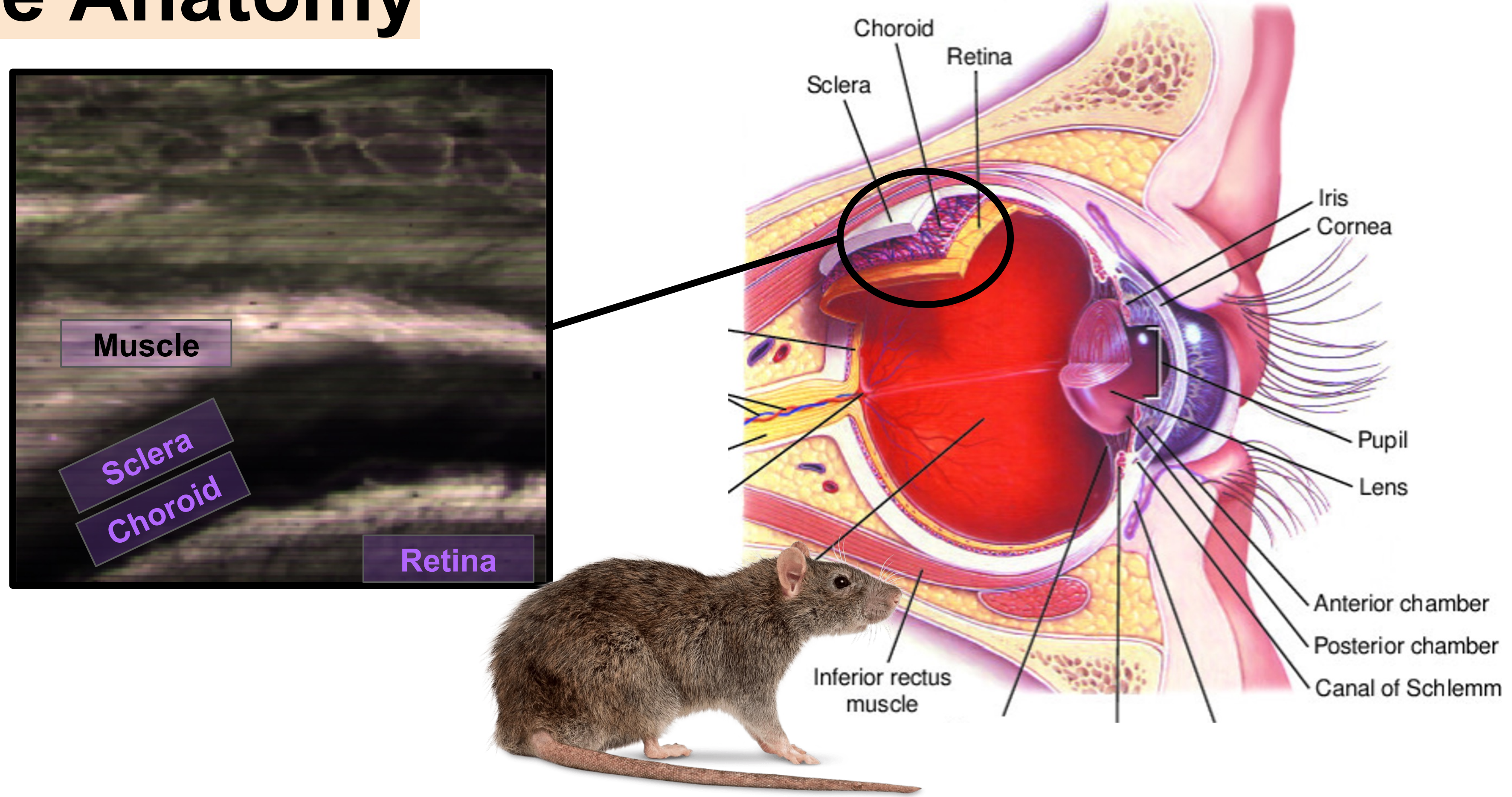
Applications of Biomedical HSI

- Dr. Yeni Yucel at Eye Pathology Lab
- Effect of going into space on the eyes
- SANS: Spaceflight-Associated Neuro-Ocular Syndrome
- In space, fluids in the body pool in the head
- Result in flattening of the back of the eye and retinal nerve fiber thickening



https://eyewiki.aao.org/Spaceflight-Associated_Neuro-Ocular_Syndrome_(SANS)

Eye Anatomy


Muscle
Sclera
Choroid
Retina
Choroid
Retina
Sclera
Iris
Cornea
Pupil
Lens
Anterior chamber
Posterior chamber
Canal of Schlemm
Inferior rectus
muscle

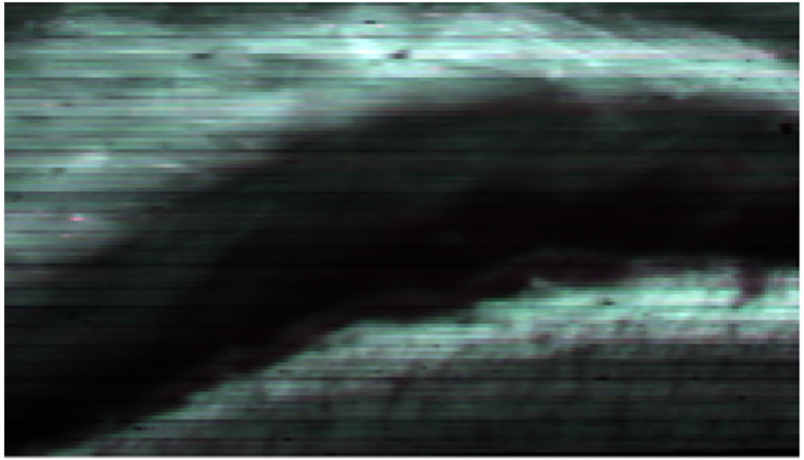
Reference Dataset

For the sake of this summer project, we focused on the lower half of the image containing the **Muscle**, **Sclera**, **Choroid**, and **Retina**

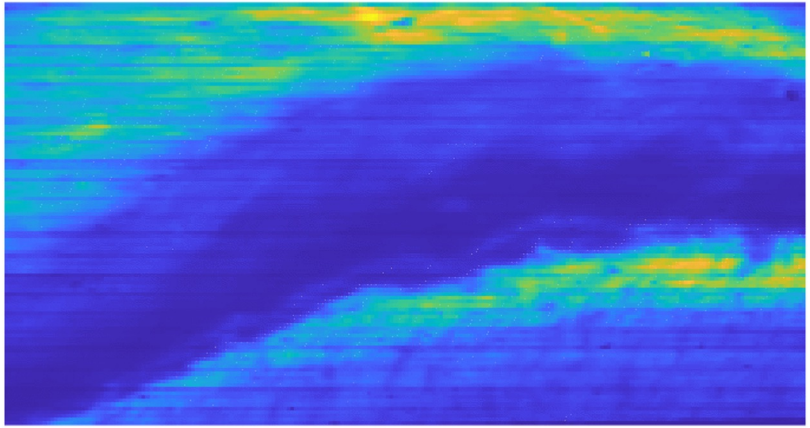
Spectral Range: 528 to 836 nm (NUV to NIR)
Band Information: 78 bands at width of 4.0 nm
Dataset Information:

$$n_x = 210 \quad n_y = 120 \quad n_{\text{bands}} = 78 \quad n_{\text{end}} = 4$$

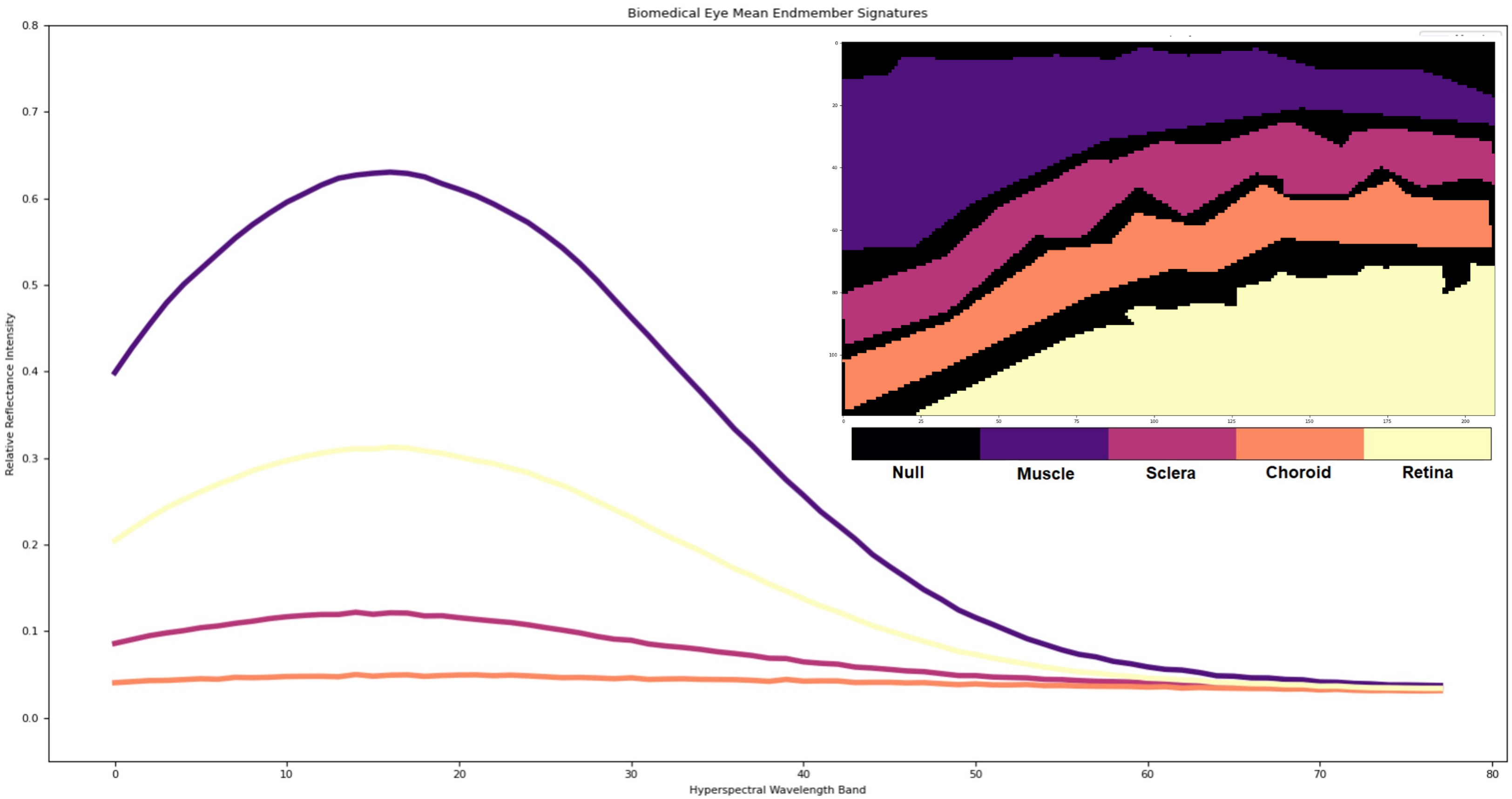
Endmembers:



Eye Image Band 1



Reference Dataset



What We've Accomplished

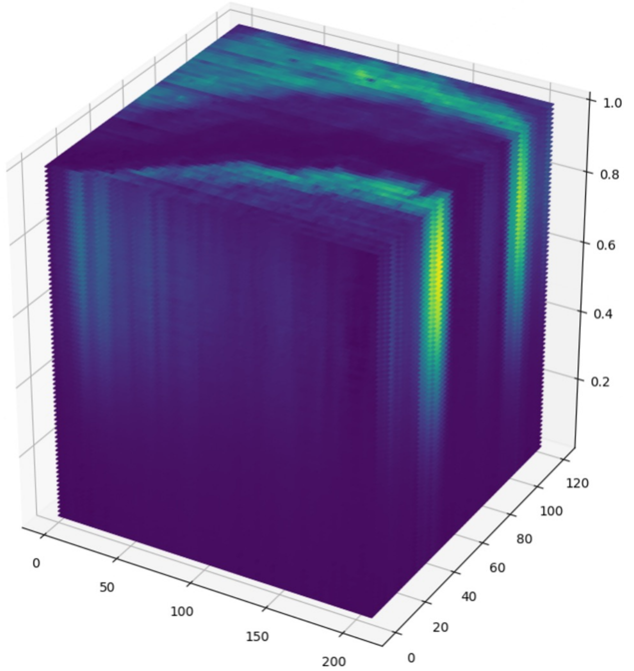
We've created a **open-source** Python package for Biomedical Hyperspectral Imaging called **BHSIpy:**

Linear Unmixing Methods:
- Supervised Methods: CVXOPT, Gradient Descent, Active Set
  - Unsupervised Methods: UFCLSU

Segmentation Methods:
- Supervised: 3D-HyperUNet
- Semi-Supervised: SAM, SIDSAM, JMSAM, NS3, K Means

Dimension Reduction:
- Linear Band Selection and Principal Component Analysis

Visualization Methods:
- 3D Plotting Method for Hyperspectral Cubes
- General Layer Plots for Unmixing and Segmentation



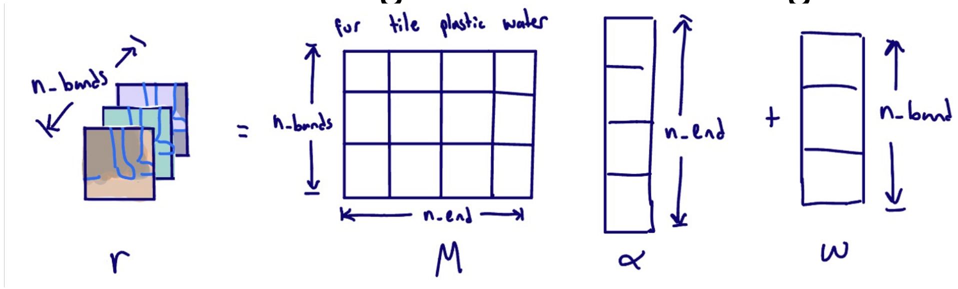
Hyperspectral Unmixing

- What is Unmixing?
- Unmixing Methods
- Results

Linear Hyperspectral Unmixing

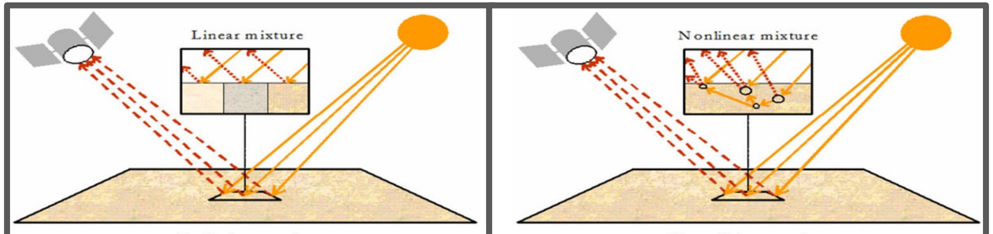
** D. Heinz and C.-I Chang, “Fully constrained least squares linear spectral mixture analysis method for material quantification in hyperspectral imagery,” IEEE Transactions on Geoscience and Remote Sensing, vol. 39, no. 3, pp. 529-545, 2001.

Pixels are assumed to be **linear combinations** of the endmember signatures in the image:



Formally:

$$r = \begin{bmatrix} | & | & & | \\ m_1 & m_2 & \cdots & m_{n_e} \\ | & | & & | \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_{n_e} \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_{n_b} \end{bmatrix} = \sum_{i=1}^{n_e} m_i \alpha_i + w = M\alpha + w$$



(a) Single scattering (b) Multiple scattering

Linear Unmixing aims to solve the following **optimization** problem:

$$\min_{\alpha} \|M\alpha - r\|_2^2$$

Unconstrained: $\alpha = (M^T M)^{-1} M^T r$

Non-negative Constraint: $\alpha_i \geq 0$

Solved using **convex optimization** packages or **active-set methods** or **gradient descent**

Fully Constrained: $\alpha_i \geq 0 \quad \sum a_i = 1$

Reformat in Non Negative Constrained Least Squares Problem**:

$$M^* = \begin{bmatrix} \delta M \\ 1^T \end{bmatrix} \qquad r^* = \begin{bmatrix} \delta r \\ 1 \end{bmatrix}$$

$$\min_{\alpha} \|M^*\alpha - r^*\|_2^2 \quad \alpha_i \geq 0$$

Linear Unmixing Methods

Iterative Active Set Methods

At the beginning of the project, we had used CVXOPT, however, we found that it was slow and computationally heavy.

We switch over to a faster **active-set** method*:

MATLAB: *lsqnonneg*

Python: *nnls*

From what we had seen, nobody really bothered to code the function in Python until we did.

[*] Lawson, C. L. and R. J. Hanson. *Solving Least-Squares Problems*. Upper Saddle River, NJ: Prentice Hall. 1974. Chapter 23, p. 161.

Gradient Descent Methods

- Applying Gradient Descent to Solve FCLSU Problems*

$$\boldsymbol{\alpha}^* = \arg\min_{\boldsymbol{\alpha}} J(\boldsymbol{\alpha})$$

$$\text{subject to} \quad \alpha_i \geq 0, \quad i = 1, \ldots, R$$

$$\sum_{i=1}^{R} \alpha_i = 1.$$

$$\alpha_j = \frac{w_j}{\sum_{\ell=1}^{R} w_\ell}$$

$$0 < \mu_i(k) \leq \frac{1}{[\nabla J(\boldsymbol{\alpha})]_i}$$

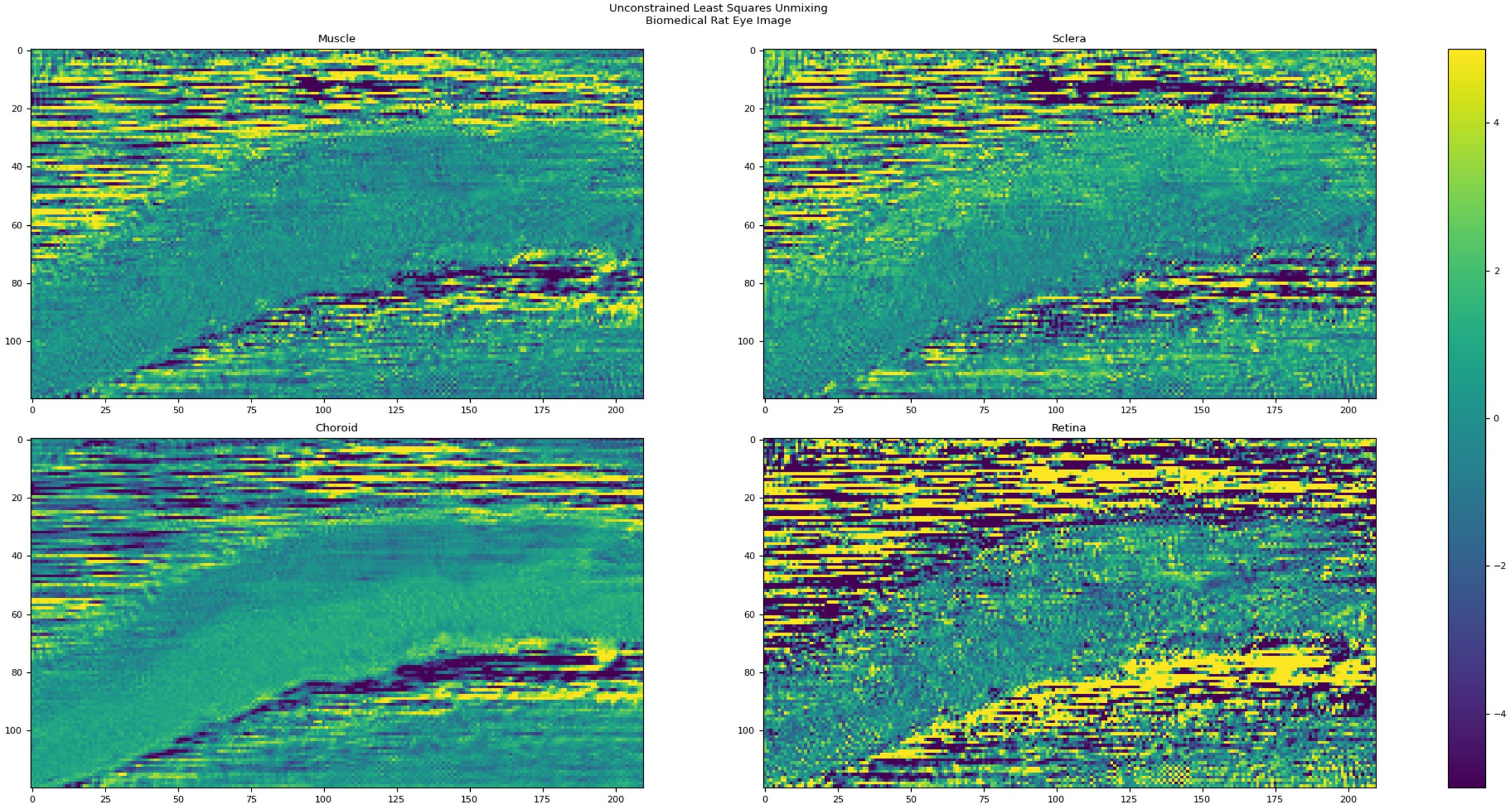
$$\boldsymbol{\alpha}(k+1) = \boldsymbol{\alpha}(k) + \ldots$$
$$+ \mu \operatorname{diag}\{\boldsymbol{\alpha}(k)\} \left[\nabla_{\boldsymbol{\alpha}} J(\boldsymbol{\alpha}) - \mathbf{1} \nabla_{\boldsymbol{\alpha}} J(\boldsymbol{\alpha})^\top \boldsymbol{\alpha}(k)\right]$$

[*] Jie Chen, Cédric Richard, Henri Lantéri, Céline Theys, Paul Honeine. A Gradient Based Method for Fully Constrained Least-Squares Unmixing of Hyperspectral Images. Proc. IEEE workshop on Statistical Signal Processing (SSP), 2011, Nice, France, pp.301-304.

FIELDS

Unmixing Results

$$\alpha = (M^T M)^{-1} M^T r$$

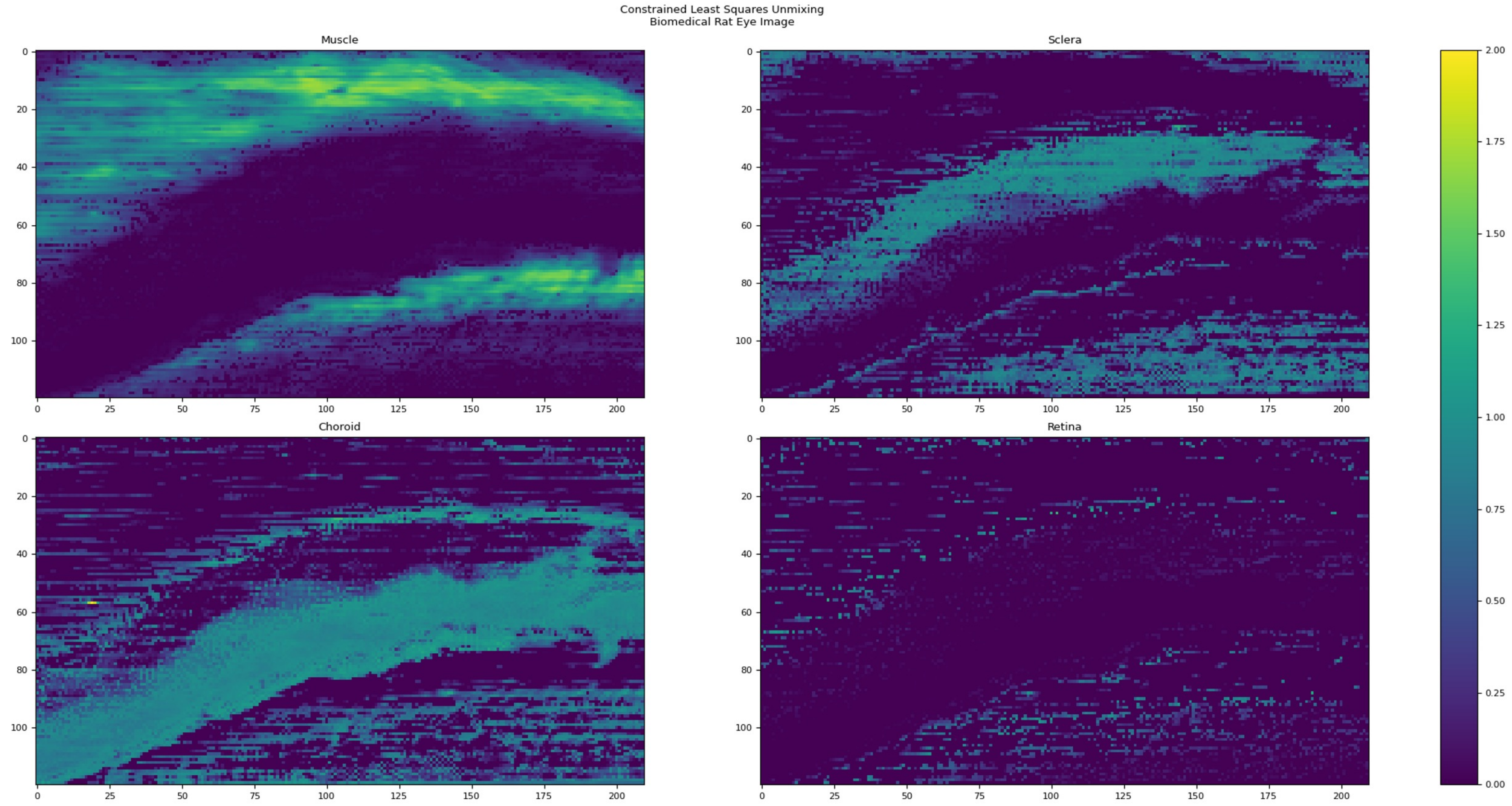


Pixelwise Average LSE: 0.0011

Running Time: 0.074 s

Unmixing Results

$$\alpha_i \geq 0$$

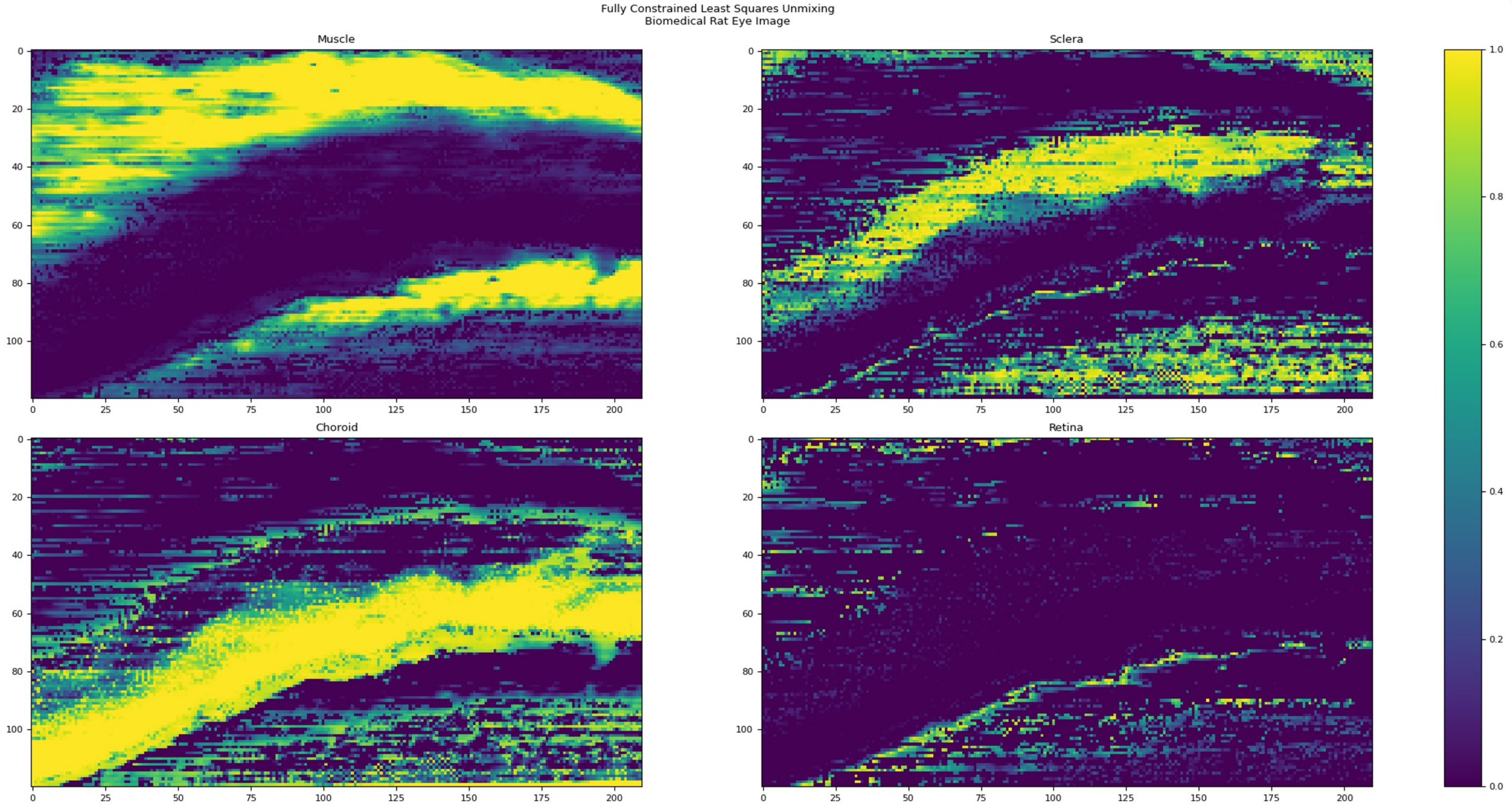


Pixelwise Average LSE: 0.0062

Running Time: 16.583 s

Unmixing Results

$$\alpha_i \geq 0 \quad \sum a_i = 1$$



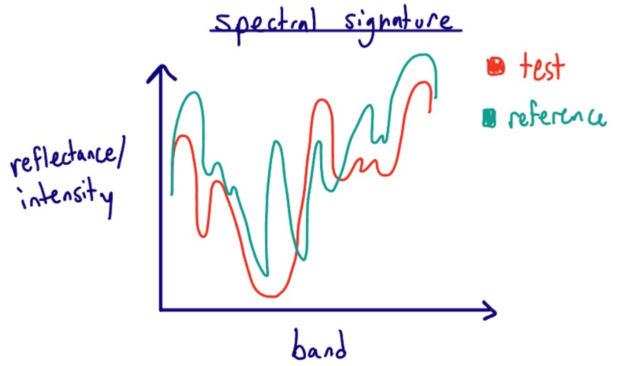
Pixelwise Average LSE: 0.1532

Running Time: 17.808 s

Hyperspectral Segmentation

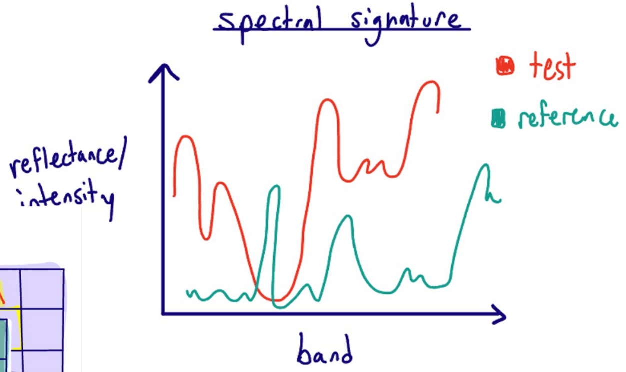
- What is Segmentation?
- Segmentation Measures Overview
- Results

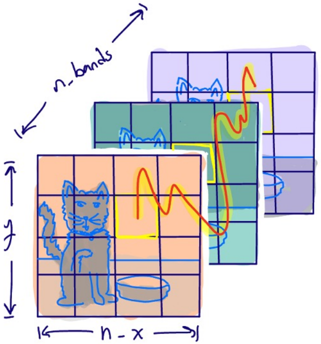
What is Segmentation?



A method to determine endmembers in an image

- Assume each pixel is ***pure***
- Compare a pixel from the image, the ***test pixel***, with the ***reference spectrum*** of an endmember
- Use various measure to determine similarity of the test ***spectral signature*** and reference ***spectral signature***





Segmentation Measures

We represent both the test and reference signatures as n-dimensional vectors:

$$s = (s_1, s_2, \ldots, s_{n_{\text{bands}}})$$
$$t = (t_1, t_2, \ldots, t_{n_{\text{bands}}})$$

Techniques for measuring similarity:

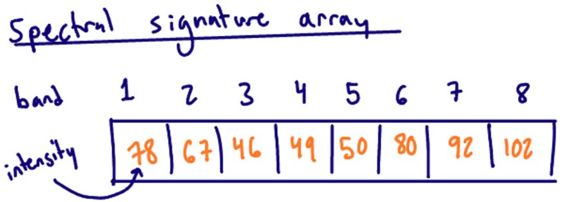
1. $$\|s - t\| = [\sum_{i=1}^{N} [s_i - t_i]^2]^{\frac{1}{2}}$$

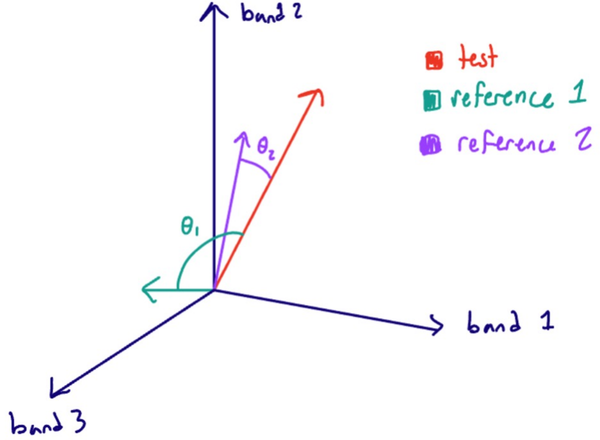
2. $$\theta_{t,s} = \arccos\left(\frac{t \cdot s}{\|t\|\|s\|}\right)$$

3. $$SID(\mathbf{r}, \mathbf{r}') = \sum_{n=1}^{L} p_j \log\left(\frac{p_j}{q_j}\right) + \sum_{n=1}^{L} q_j \log\left(\frac{q_j}{p_j}\right)$$

Measures:
- SAM
- SID

Mixed Measures:
- SID-SAM
- JMSAM
- NS3



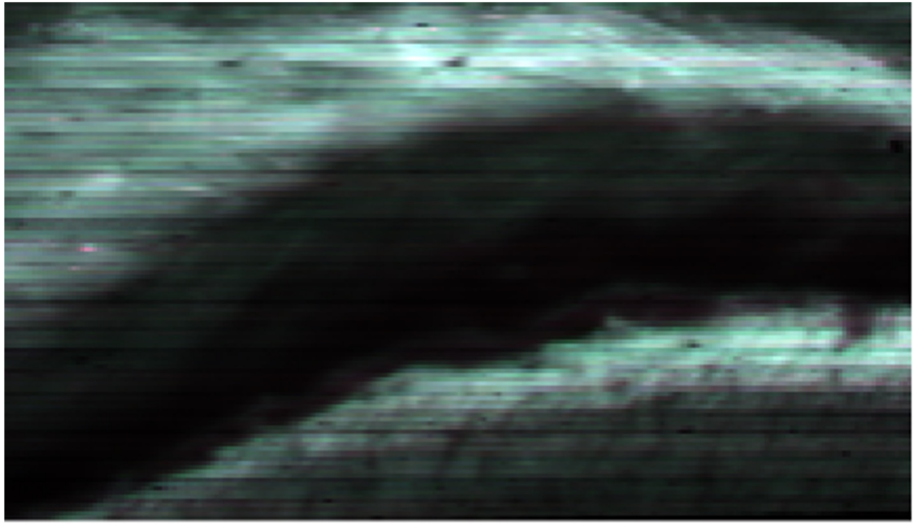


Chein-I Chang. "An Information-Theoretic Approach to Spectral Variability, Similarity, and Discrimination for Hyperspectral Image Analysis." IEEE Transactions on Information Theory 46 (2000): 1927.

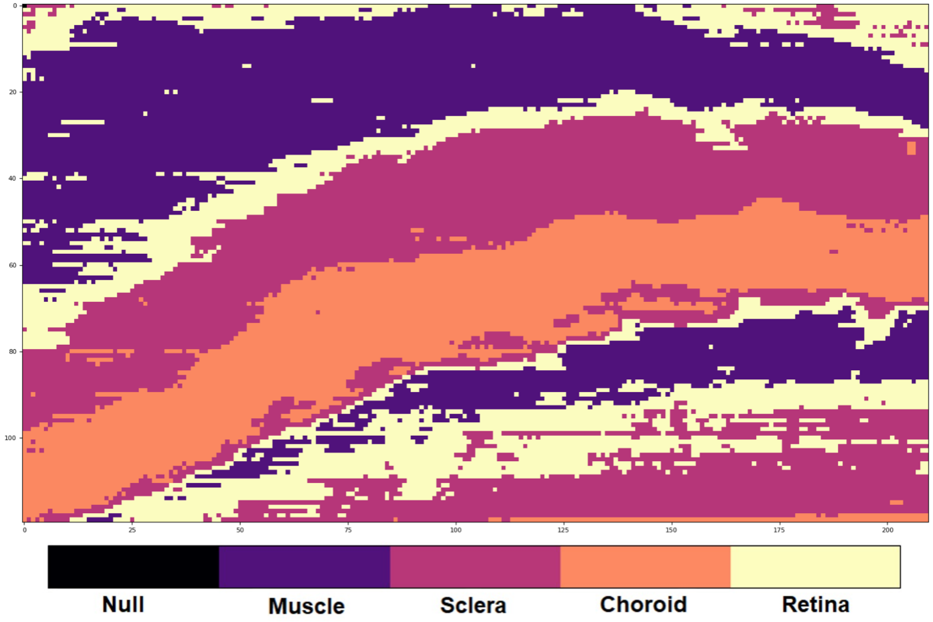
Spectral Angle Mapper Segmentation

Angle

Original Image



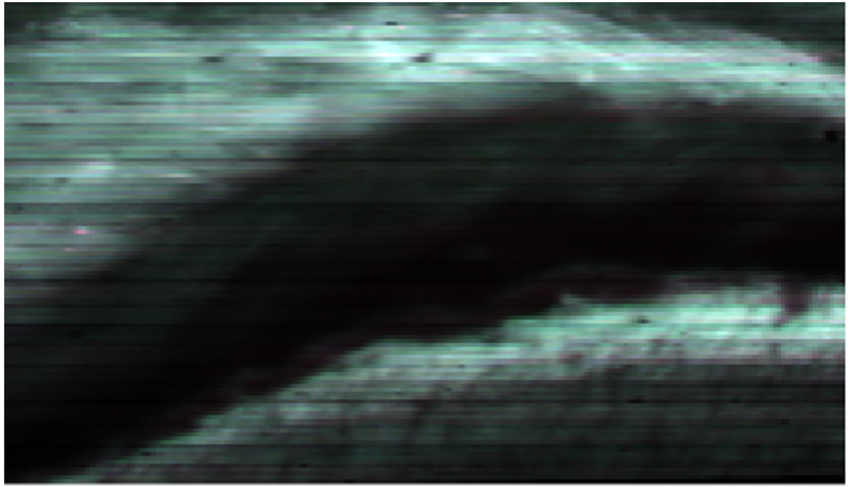
Segmented Image



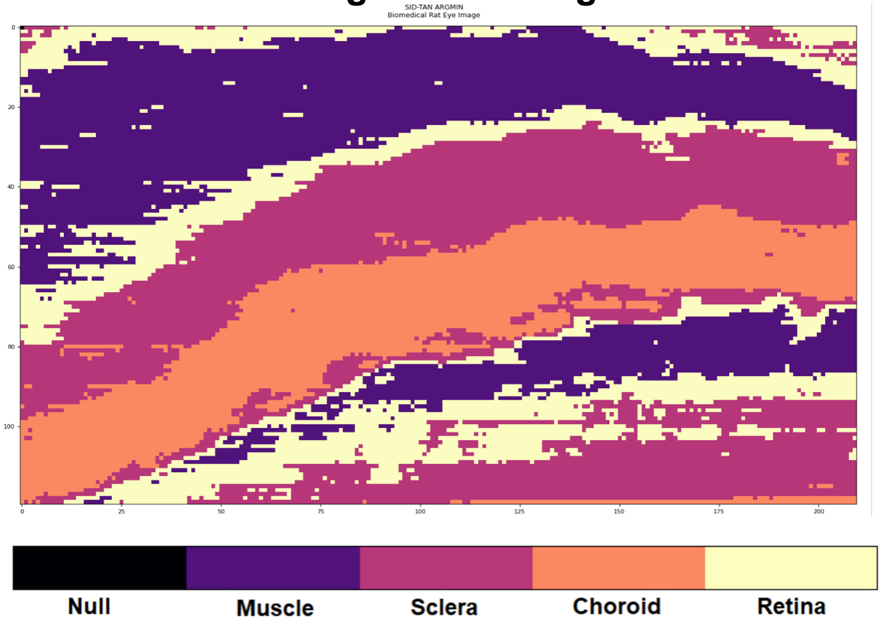
SIDSAM TAN Segmentation

Angle, Probabilistic

Original Image



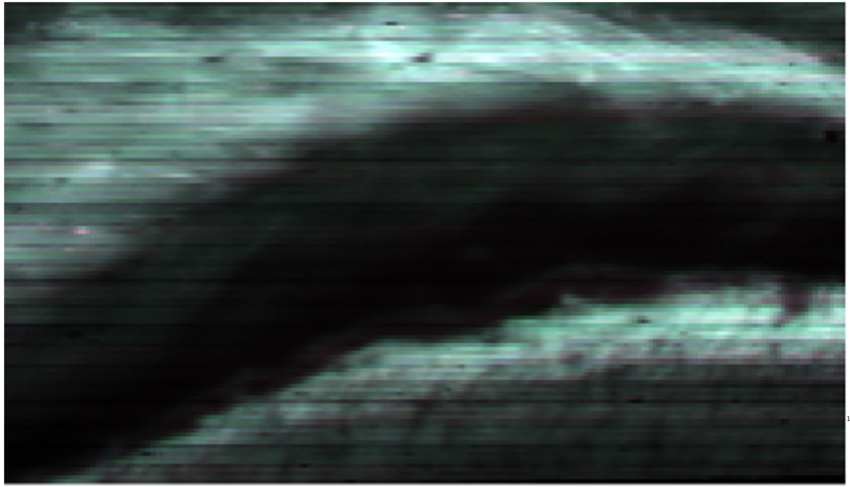
Segmented Image



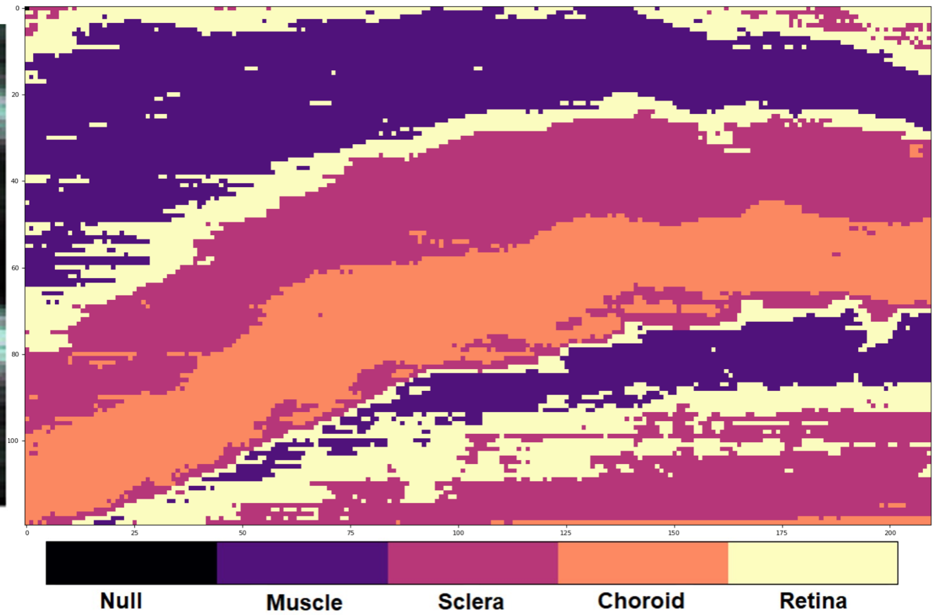
JMSAM TAN Segmentation

Angle, Distance

Original Image



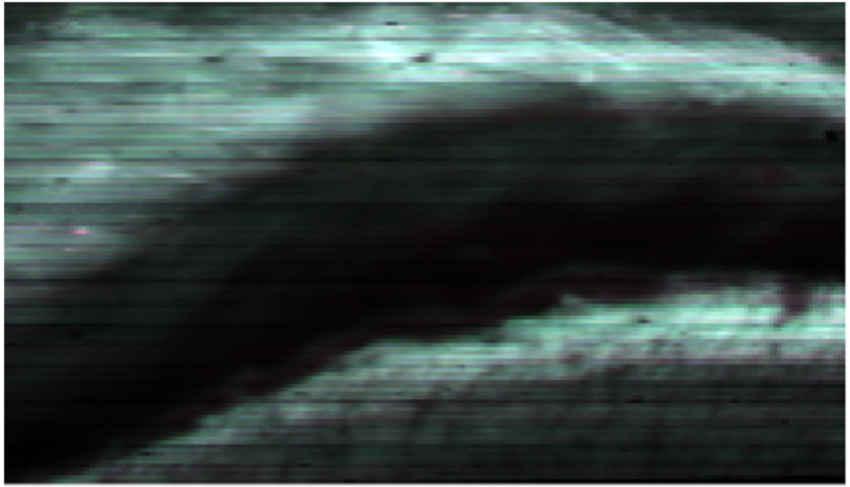
Segmented Image



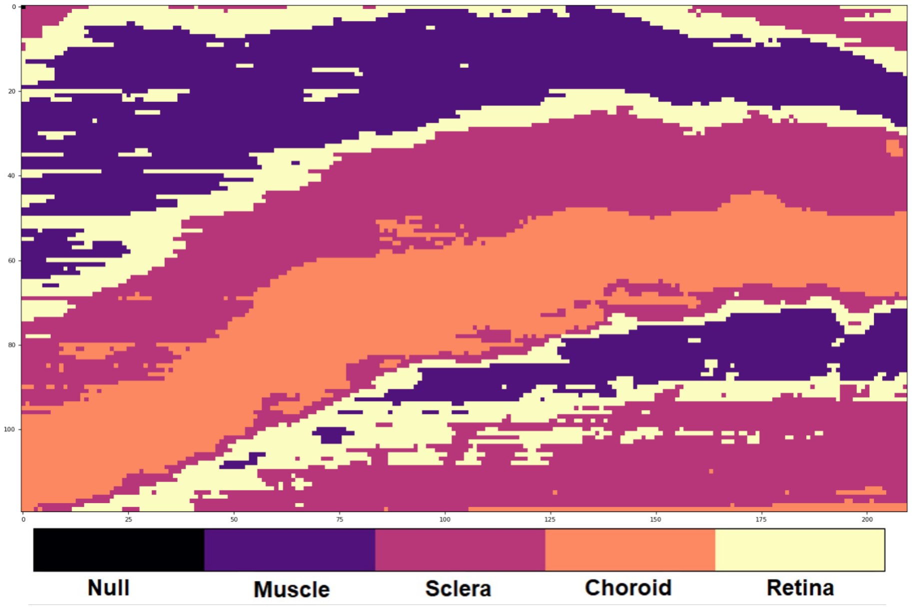
NS3 Segmentation

Angle, Distance

Original Image



Segmented Image



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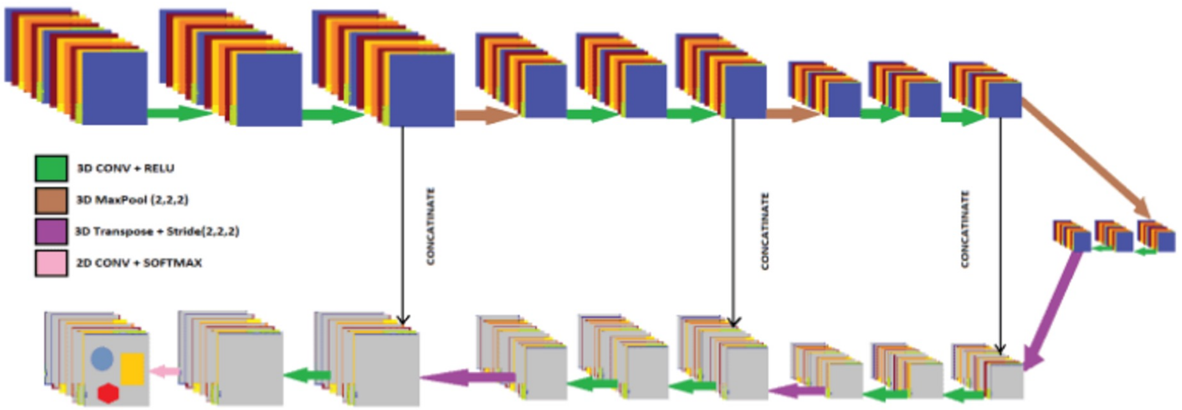
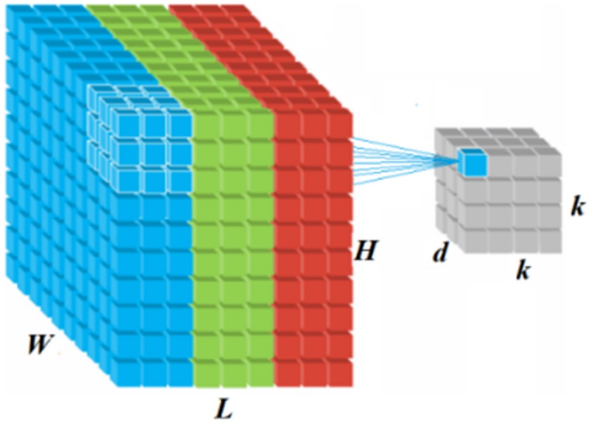
Deep Learning Segmentation

We adapt the **3D Hyper-UNET*** for geospatial hyperspectral and multispectral imaging proposed by *Nischal et al.* to the realm of biomedical hyperspectral imaging

Combines both **spatial** and **spectral** information using 3D kernel convolutions





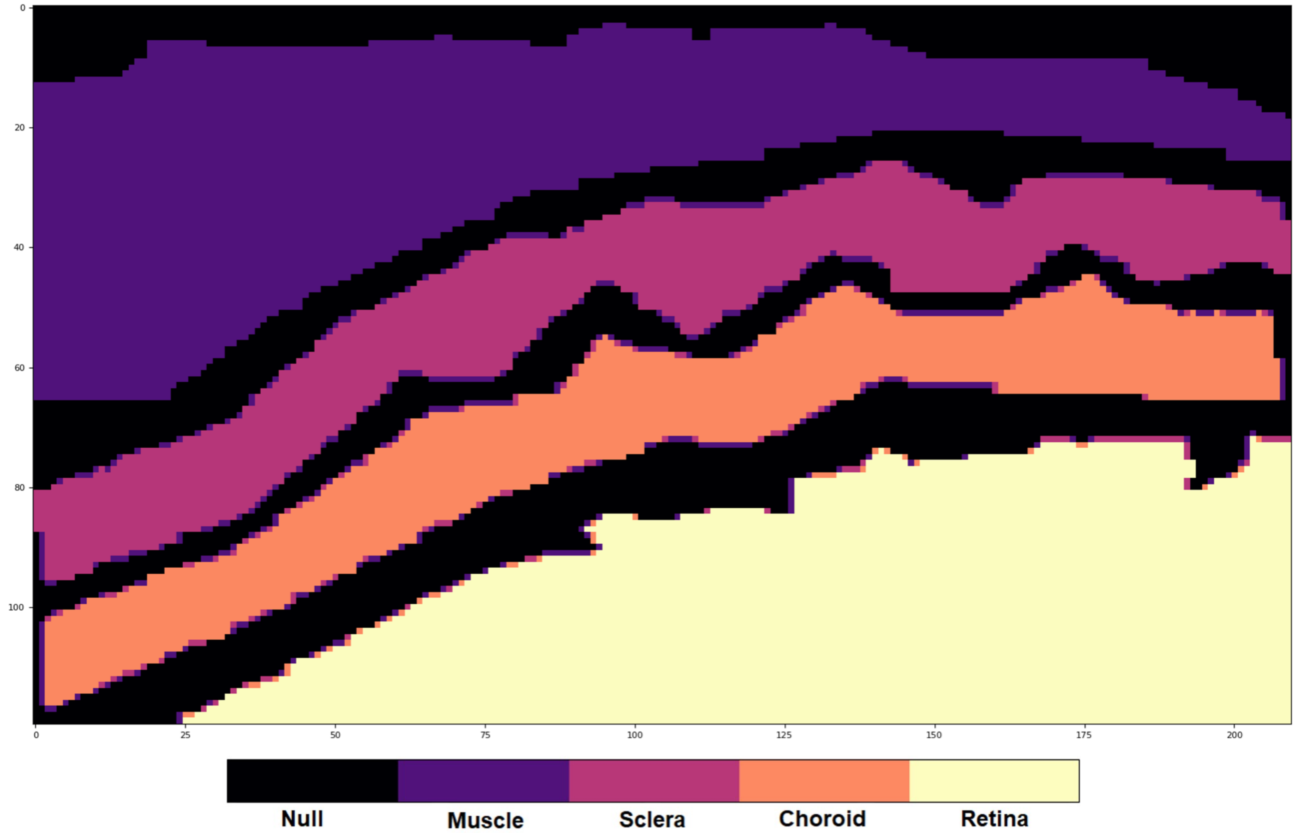
FIELDS

J. Nishchal, S. Reddy, N. Navya Priya, V. R. Jenni, R. Hebbar and B. S. Babu, "Pansharpening and Semantic Segmentation of Satellite Imagery," 2021 Asian Conference on Innovation in Technology (ASIANCON), 2021, pp. 1-9, doi: 10.1109/ASIANCON51346.2021.9544725.

Deep Learning Segmentation Results

```
unet = U_Net(dataset = 'biomedical_image', num_epochs=1000, reduced_size_x_y=144, n_features=5)
```

```
Trainable params: 5,028,101
Non-trainable params: 1,344
```



IoU: 0.8054
Loss: 0.0386

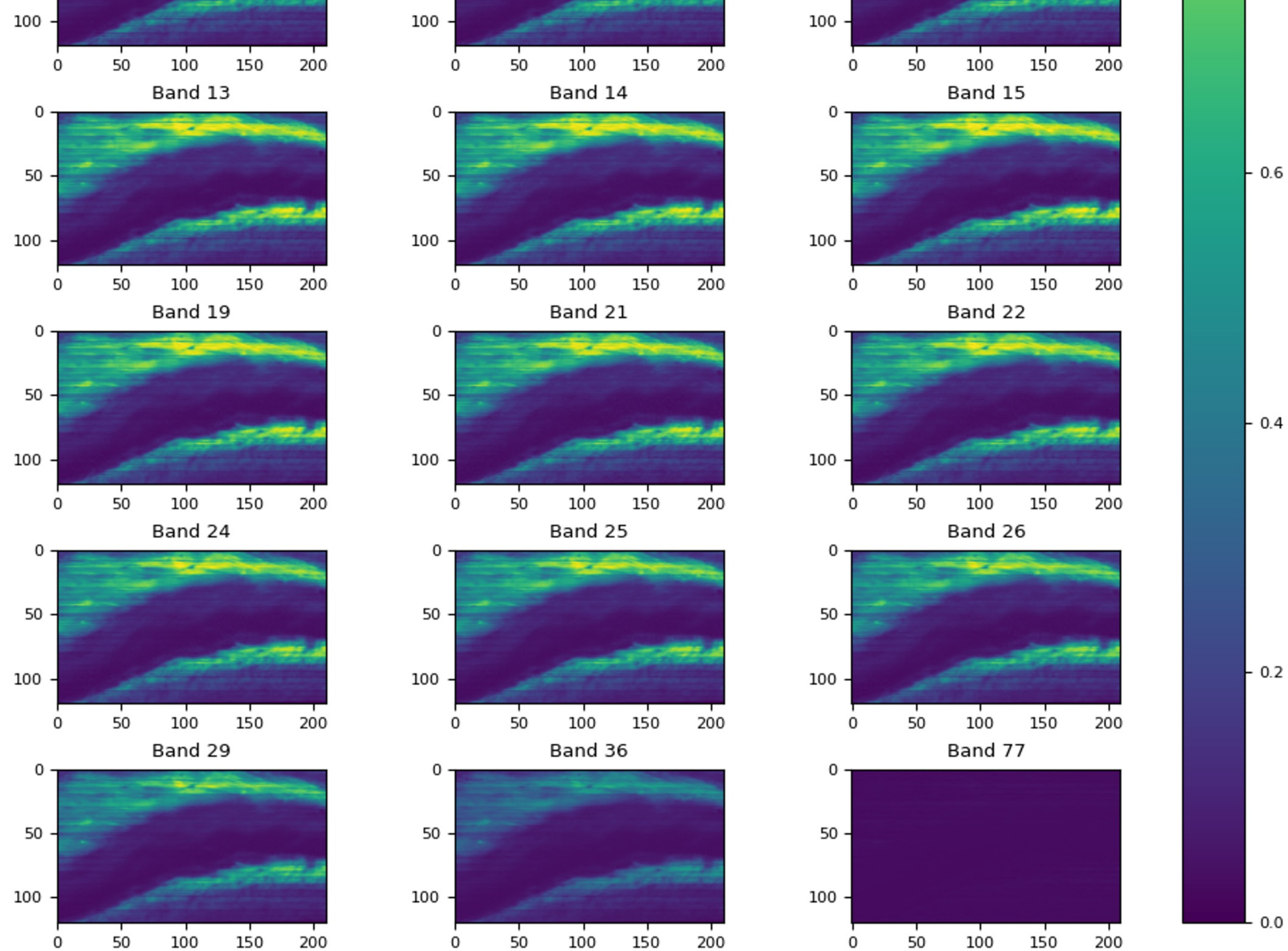
Dimension Reduction

- Linear Predictor Band Selection

Linear Ban

Motivation:
As the band width is so
the hyperspectral image
We do not gain that muc
keeping adjacent bands
choose only the most re
our unmixing and segme

Algorithm*:
Start with an initial set o
linear predictor model us
next band with the great
the model for **Φ**, Repeat
bands are found or erro



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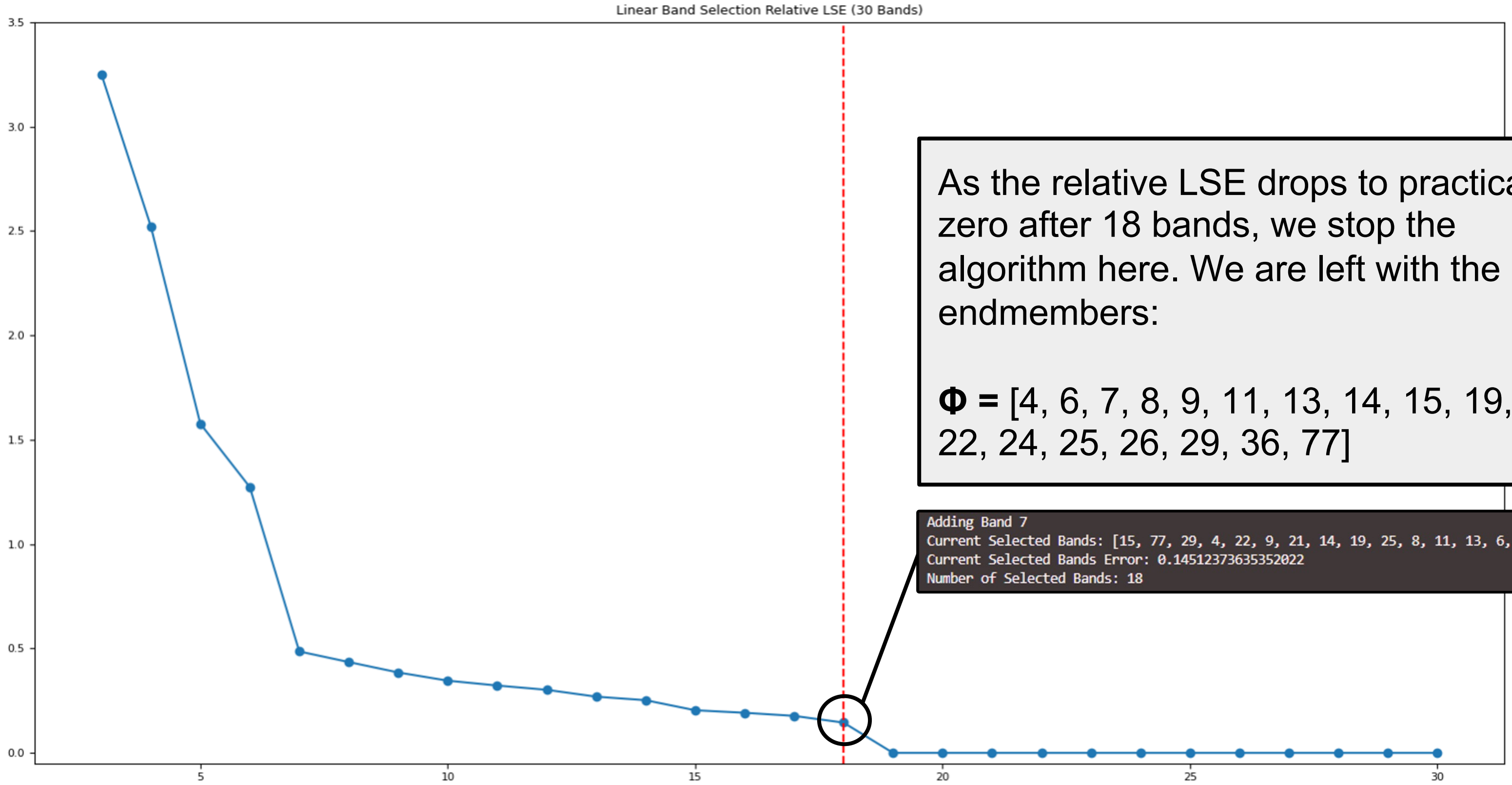
t 9

[*]Du, Q., & Yang, H. (2008). Similarity-Based U
Analysis. IEEE Geoscience and Remote Sensing

FIELDS

Linear Band Selection Results

LSE with respect to previous selected bands



Number of Bands Selected by Algorithm

As the relative LSE drops to practically zero after 18 bands, we stop the algorithm here. We are left with the endmembers:

Φ = [4, 6, 7, 8, 9, 11, 13, 14, 15, 19, 21, 22, 24, 25, 26, 29, 36, 77]

```
Adding Band 7
Current Selected Bands: [15, 77, 29, 4, 22, 9, 21, 14, 19, 25, 8, 11, 13, 6, 26, 36, 24, 7]
Current Selected Bands Error: 0.14512373635352022
Number of Selected Bands: 18
```

FIELDS

Acknowledgments

We want to thank the following:

Fields Institute for supporting us and this project

Dr. Na Yu and **Dr. You Liang** at TMU for their support and guidance in this project

Dr. Yeni Yucel at St Michaels for the motivation behind this project, the biomedical data we could show you today, and valuable suggestions from biomedical point of view

Janak Bhanushali at TMU for his help at the beginning of the project

What We've Accomplished

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Unsupervised Methods: UFCLSU

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Semi-Supervised: SAM, SIDSAM, JMSAM, NS3, K Means

Dimension Reduction:

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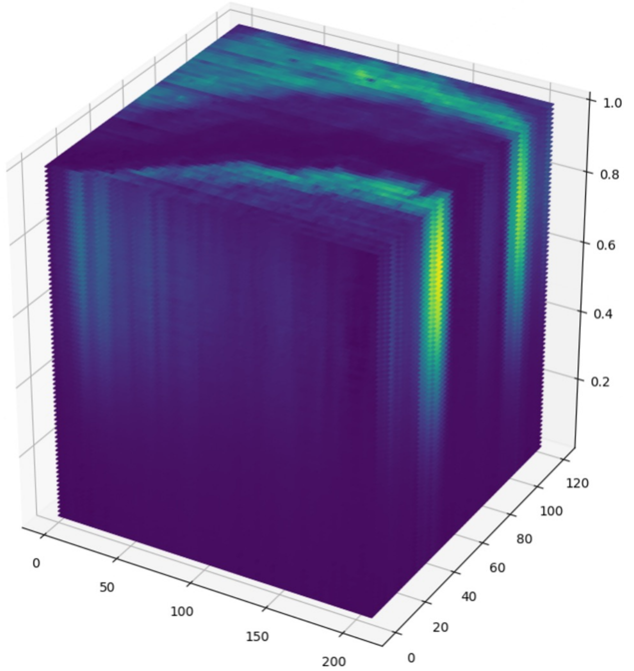
General Layer Plots for Unmixing and Segmentation



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Questions?