Single-Shot Hyperspectral Imaging via Deep Chromatic Aberration Deconvolution

Corey Zheng | Austin Barton | Mohammad Taher | Abdulaziz Memesh
czheng45@gatech.edu | abarton40@gatech.edu | mtaher3@gatech.edu | a.memesh@gatech.edu

Introduction

Hyperspectral imaging captures the unique wavelength emission and reflectance spectra of objects within the field of view. However, hyperspectral images are difficult to acquire with their three-dimensional nature, two spatial dimensions and a spectral dimension. Thus, we present our work: Single-shot Hyperspectral Imaging via Deep Chromatic Aberration Deconvolution. We explore using deep U-Net networks to perform hyperspectral volume reconstruction from a single chromatically-aberrated monochromatic image

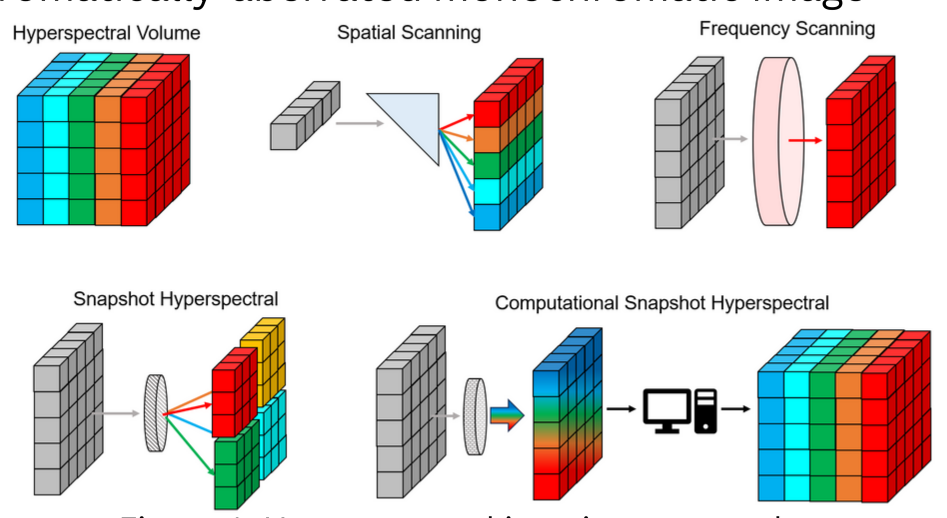


Figure 1: Hyperspectral imaging approaches

Background

Chromatic aberration approaches that take advantage of a uniquely varying wavelength dependent point-spread function (PSF) have been used to encode spectral information into the spatial blur of an image in a similar vein as depth-from-defocus approaches. Existing approaches include Classic Iterative Deconvolution [4] and pairing complex DOE with U-Net [5]

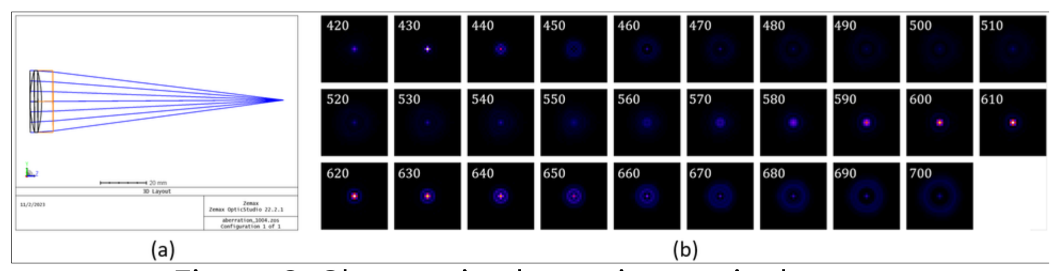


Figure 2: Chromatic aberration optical system

U-Net Architecture

- Encoder-Decoder Convolutional Neural Network
- Contracting path encodes monochromatic images
- Symmetric expanding path reconstructs hyperspectral images
- Precise localization, Detail Preservation, Efficient

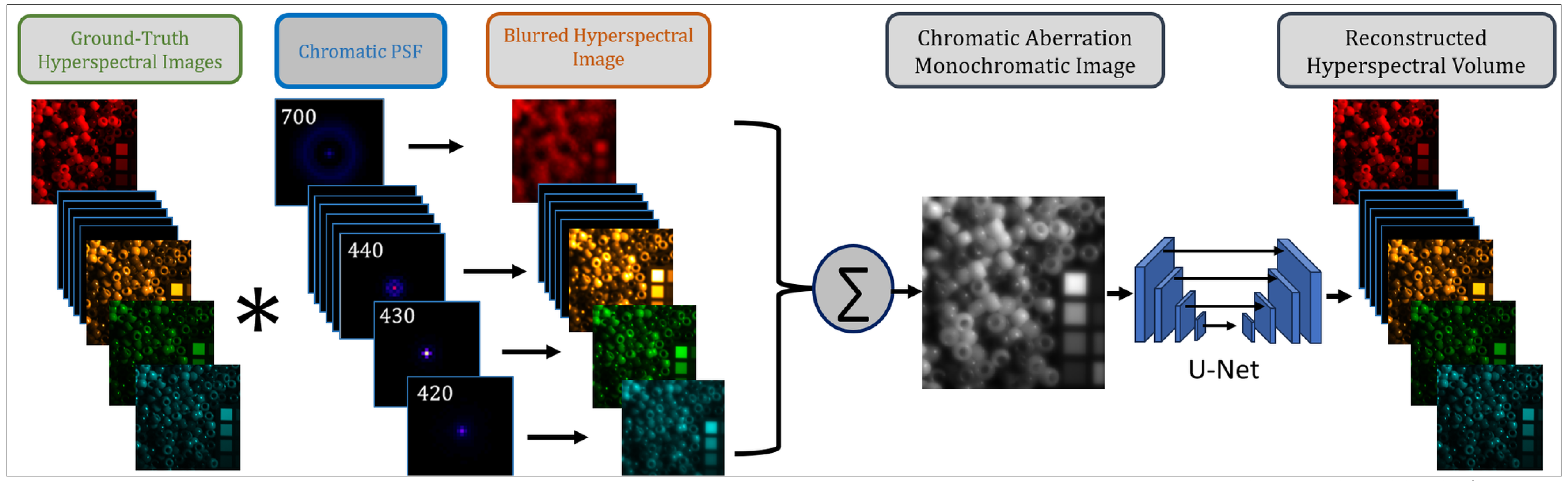
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
      EncoderBlock-1           [N, 29, 64, 64]            8004
      EncoderBlock-2          [N, 128, 32, 32]          181632
      EncoderBlock-3          [N, 256, 16, 16]          886272
      EncoderBlock-4            [N, 512, 8, 8]         3542016

          BottleNeck           [N, 1024, 8, 8]        14161920

      DecoderBlock-1          [N, 512, 16, 16]         9178624
      DecoderBlock-2          [N, 256, 32, 32]         2295552
      DecoderBlock-3          [N, 128, 64, 64]          574336
      DecoderBlock-4         [N, 29, 128, 128]           37758
================================================================
Total params: 30,866,114
Trainable params: 30,866,114
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.06
Forward/backward pass size (MB): 1118543.84
Params size (MB): 117.74
Estimated Total Size (MB): 1118661.65
----------------------------------------------------------------
```

Figure 3: U-net Model Parameters

Main System Process



Goal: Restore ground truth hyperspectral data

Simulate chromatic aberration on 29 channel hyperspectral ground truth

Input: 1x128x128 pixel monochromatic image

Output: 29x128x128 hyperspectral images (10nm wavelength band from 420 - 710 nm)

Results

- HyperUnet and HyperUnetLR demonstrated superior performance in terms of various metrics.
- Importantly, our deep learning models consistently outperformed Richardson-Lucy deconvolution, which struggled to maintain spectral discrimination and preserve multiple color channels.
- HyperUnetLR achieved predictions with considerably lower SSIMLoss but the qualitative improvement in deblurring was negligible and its spectral recovery capabilities were significantly inferior to HyperUnet.
- Consequently, HyperUnet was chosen as the most effective network among the various experiments.

Model	PSNR(dB)	SSIM
Baek et al. [1]	27.96	0.75
Jeon et al. [2]	28.81	**0.81**
Baek et al. [3]	**29.31**	**0.81**
HyperUnet	**25.029**	0.8681
HyperUnet_{LR}	24.945	**0.8991**
HyperUnet_{SSIM}	14.887	0.5187
$\text{HyperUnet}_{Reduced}$	22.292	0.7870
Richardson-Lucy Deconvolution	14.713	0.8615

Figure 4: Comparison of our HyperUnet experiments to other approaches

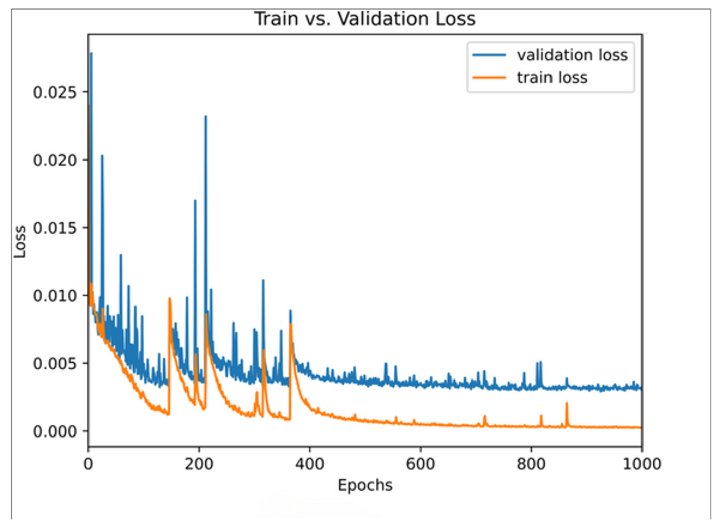


Figure 5: HyperUnet Loss curves

Figure 6: Evolution of HyperUnet performance over training

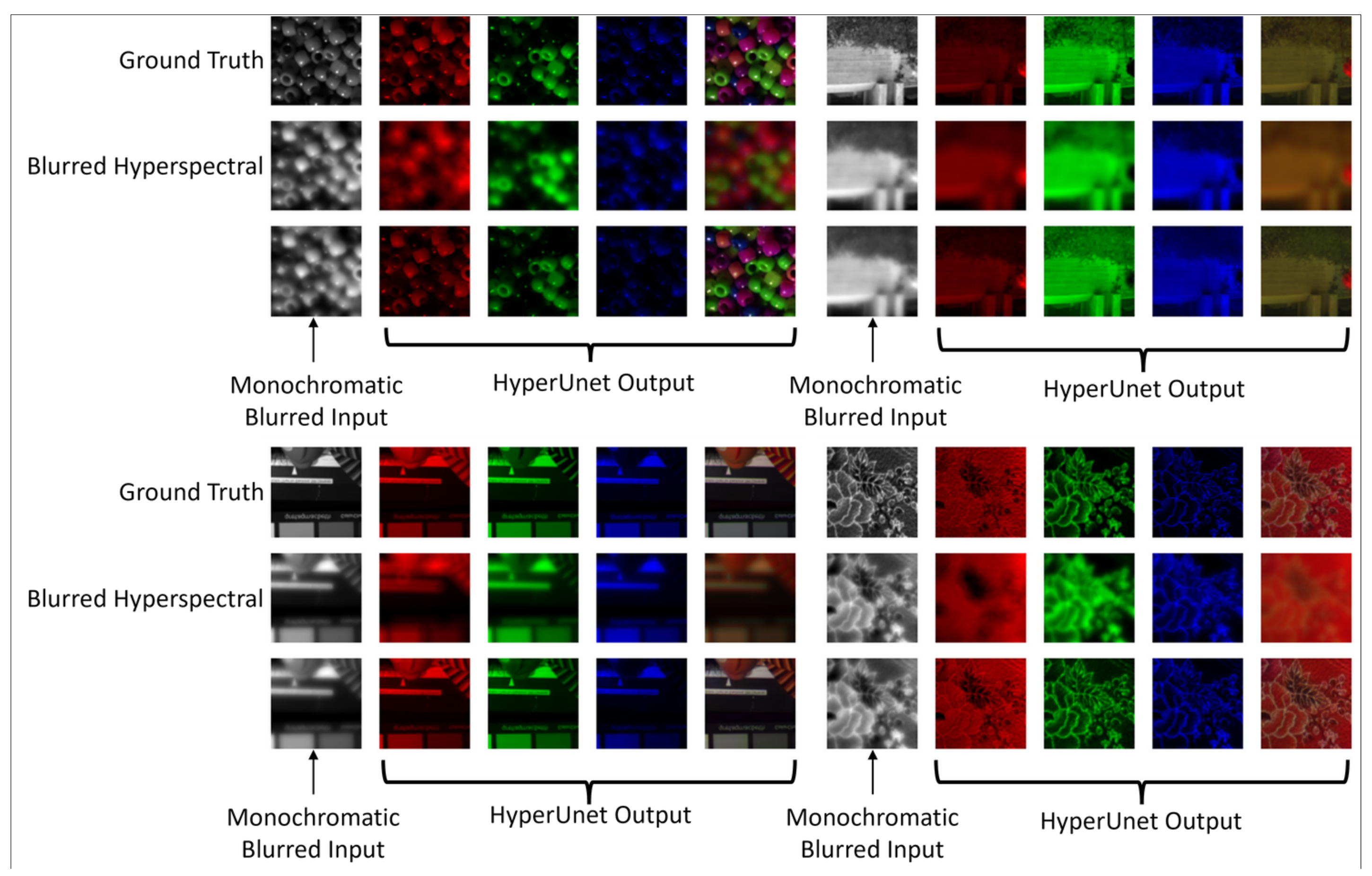


Figure 7: 4 exemplary test set sample hyperspectral reconstructions via HyperUnet. Columns, in order, are monochromatic image, 700nm channel, 560nm channel, 420nm channel, and pseudoRGB image

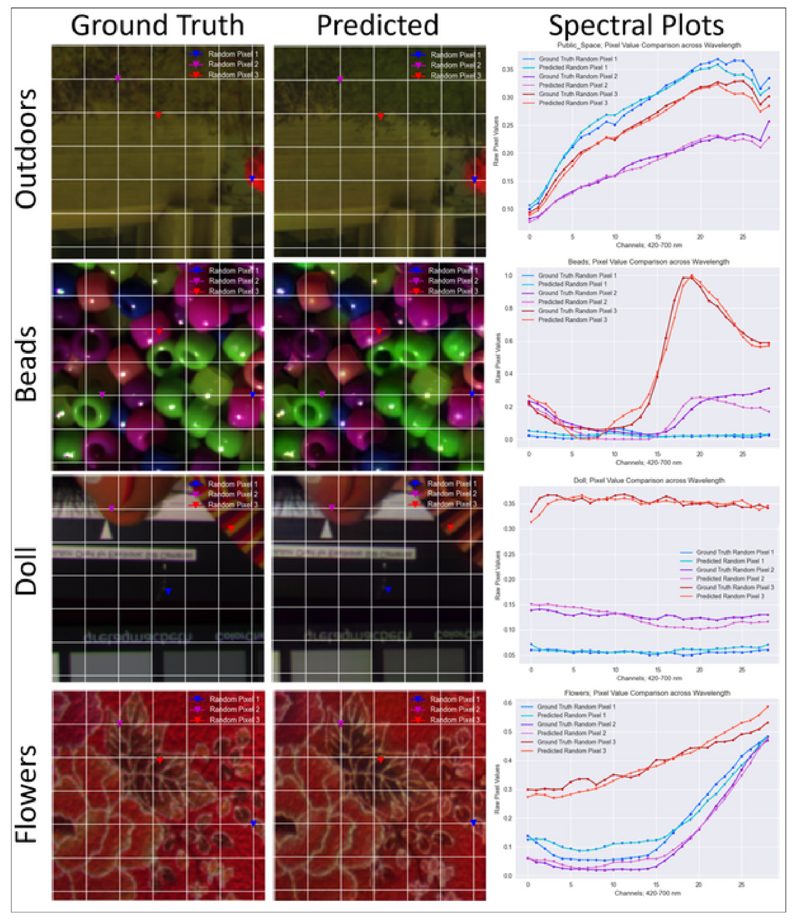


Figure 8: 4 exemplary test set samples featuring pixelwise spectra at 3 locations

Discussion

- We demonstrate an effective blind approach to deconvolution via deep learning in our best performing model, HyperUnet.
- Training these models is highly unstable and sensitive to the initialization of the model.
- Network instability led to mode collapse (Figure 9) resulting in lost wavelength bands.
- Our approach enables far more accessible snapshot hyperspectral imaging with a higher theoretical throughput.

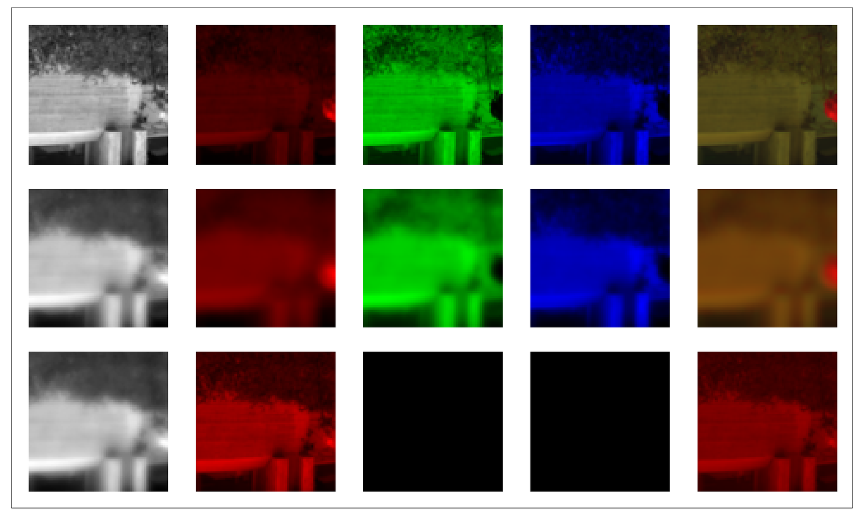


Figure 9: Results of HyperUnet with MSE + SSIM loss function that resulted in mode collapse.

Future Work

- Reproducing these results across different datasets would be challenging due to the sensitivity of the models to weight initialization.
- Our models consistently suffered from overfitting, even the best-performing one, indicating the need for further experimentation.
- Overfitting may not be solely due to model size, encouraging exploration of more sophisticated and well-tuned architectures for this task.
- Given our suspicion that the PSF's nature contributes to network failures, investigating asymmetric PSFs achievable with conventional optics rather than custom elements becomes crucial for making snapshot hyperspectral imaging more accessible.

References

[1] Baek et al., ACM TOG, 2017
[2] Jeon et al., 2019
[3] Baek et al., IEEE/CVF, 2021
[4] Shuyue et al., MDPI, 2019
[5] Daniel et al., 2019