High-Quality Hyperspectral Reconstruction Using a Spectral Prior

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Light and Color Imaging

Continuous spectra of light

Bayer pattern

RGB imaging
Hyperspectral Imaging (HSI)

Hyperspectral imaging

Compressive hyperspectral imaging
Compressive Hyperspectral Imaging

Scene spectra → Shear → Mask → Unshear → Projection

Reconstruction is an inverse problem of optical imaging
Straightforward Approach

• Learning a regression function using a CNN
The Regression Network Fails

ground truth  regression
Our Approach

Hyperspectral reconstruction

Nonlinear representations

Encoder

Decoder
Our reconstruction
Our reconstruction
Related Work

- Hyperspectral Imaging
- Compressive Hyperspectral Reconstruction
HSI without Reconstruction

Bandpass filter [Mansouri et al. 2007]

LCTF (liquid crystal tunable filter) [Attas et al. 2003]

Pushbroom [Brusco et al. 2006]
HSI with Reconstruction

CASSI [Wagadarikar et al. 2008]
DD-CASSI [Gehm et al. 2007]
SS-CASSI [Lin et al. 2014]

[Jeon et al. 2016]
Image Formation

\[ i = \Phi h \]

Observation (2D)  Light modulation (3D to 2D)
Hyperspectral Reconstruction

\[ \min_h \| i - \Phi h \|_2^2 \]

“Find a hyperspectral image \( h \) that satisfies the image formation”

\# equations \( \ll \) \# unknowns

underdetermined system
Reconstruction using TV-L1 Prior

- TV-L1 is very common in computational photography

\[
\min_h \left\| i - \Phi h \right\|_2^2 + \left\| h \right\|_1
\]

TwIST [Bioucas-Dias and Figueiredo 2007]
SpaRSA [Wright et al. 2009]
Reconstruction using Sparse Coding

- Use an overcomplete dictionary and a sparse code to represent a data

\[ h = D \alpha \]

\( D: \) a dictionary
\( \alpha: \) a sparse code

For all overlapping image patches

\[
\min_{\alpha} \left\| i - \phi D \alpha \right\|_2^2 + \left\| \alpha \right\|_1
\]

[Lin et al. 2014]
Autoencoder
- For Our Deep Spectral Prior
Autoencoder

[Hinton and Salakhutdinov 2006]
Nonlinear Representation

Nonlinear representation

x_1, x_2, x_3, x_4 → y_1, y_2, y_3, y_4
Autoencoder: Encoder and Decoder

Nonlinear representation

Encoder: generate nonlinear representation

Decoder: produce data from representations
Hyperspectral Reconstruction

- Learning a Spectral Prior
- Reconstruction with Alpha-fidelity
Overview of Our Reconstruction

Learning hyperspectral image prior

Hyperspectral image datasets → Convolutional autoencoder

Hyperspectral reconstruction

Compressive sensor input → Optimization → Reconstructed hyperspectral image

Encoder / decoder
Autoencoder of Hyperspectral Images

\[ A(h) = D(E(h)) \approx h \]

Convolutional autoencoder of hyperspectral images

Encoder

Decoder

Nonlinear representation
Autoencoder of Hyperspectral Images

- 3 x 3 convolution without pooling
- ReLU activation function
- 64 feature maps
Training Data

Columbia dataset
[Yasuma et al. 2006]

Harvard dataset
[Chakrabarti and Zickler 2011]
Validating Autoencoder

ground truth

reconstruction
(44.24 dB / 0.98)

reflectance

GT
gray patch
red flower

wavelength [nm]

0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
420 470 520 570 620 670
Our Reconstruction - Data Term

\[ i = \Phi h \]

- **Observation (2D)**
- **Light modulation (3D to 2D)**
- **Spectra (3D)**
- **Spectra**
- **Shear**
- **Mask**
- **Unshear and project**
- **Observed image**
Our Reconstruction - Data Term

\[ i = \Phi h = \Phi D(\alpha) \]
Our Reconstruction

\[
\min_{\alpha} \left\| i - \Phi D(\alpha) \right\|_2^2 + \sum_1 \left\| D(\alpha) \right\|_1
\]

\[\therefore h = D(\cdot)\]
How can we utilize the encoder?

**Decoder** $D(\alpha)$
- produce $h$ (hyperspectral images)
  from (nonlinear representations)
- a prior on $h$
- know how $h$ looks like

**Encoder** $rE(\cdot)$
- generate from $h$
- a prior on
- know how $h$ looks like
Our Reconstruction with fidelity Prior

\[
\min_{\alpha} \left\| i - \phi D(\alpha) \right\|_2^2 + \left\| D(\alpha) \right\|_1^2 + \left\| \alpha - E(D(\alpha)) \right\|_2^2
\]

“The nonlinear representation should be close to what the encoder knows.”
Impact of fidelity Prior

Yellow feather

w/o $\alpha$-prior

w/ $\alpha$-prior

GT

reflectance

wavelength [nm]

420 470 520 570 620 670

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
Results

- Our Dataset
- Synthetic Results
- With a Real Compressive Imager
Our High-Quality Dataset

Download from
http://vclab.kaist.ac.kr
Synthetic Result with Our High Quality Dataset


Ground truth

34.20dB / SSIM:0.95  32.03dB / SSIM:0.95  32.29dB / SSIM:0.92  39.21dB / SSIM:0.97

Reflectance

GT
TwIST (0.006)
SpaRSA (0.010)
SC (0.019)
Ours (0.006)
**Synthetic Result** with Columbia Dataset

[Yasuma et al. 2010]

- TwIST [Kim 2012]
- SpaRSA [Wright 2009]
- Sparse coding [Lin 2014]
- Ours

**Columbia Dataset**

- Ground truth

Reflectance vs. wavenumber graph:
- GT
- TwIST (0.058)
- SpaRSA (0.062)
- SC (0.039)
- Ours (0.016)
Synthetic Result with Our High Quality Dataset

Our reconstruction
Synthetic Result with Our High Quality Dataset

Our reconstruction
Our DD-CASSI Result

[Gehm et al. 2007]
Our DD-CASSI Result

Compressive Input

Our reconstruction

[Graph showing a comparison between GT and Ours for different wavelengths (nm)]

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Applications

- Spectral Interpolation
- Hyperspectral Demosaicing
Changing Modulation Matrix

Our reconstruction:

$$\min_{\alpha} \left\| \mathbf{i} - \Phi D(\alpha) \right\|_2^2 + \tau_1 \left\| \mathbf{\alpha} - E(D(\alpha)) \right\|_2^2 + \tau_2 \left\| \nabla_{xy} D(\alpha) \right\|_1$$

$\Phi$ for super-resolution: blurring + downsampling

Note: the observation $\mathbf{i}$ should be modified accordingly
Spectral Interpolation
Spectral Interpolation

16 channels (52 %)
Spectral Interpolation

8 channels (26 %)
Spectral Interpolation

3 channels (10%)
Spectral Interpolation

Ground Truth

reflectance

wavelength [nm]

GT

52% (0.011)
16 channels

26% (0.014)
8 channels

10% (0.077)
3 channels
Hyperspectral Demosaicing

Bayer image

450 nm  520 nm
580 nm  650 nm
Hyperspectral Demosaicing

Ground truth
Hyperspectral Demosaicing

Demosaiced

31.04dB / SSIM:0.89

reflectance

wavelength [nm]

GT

Bayer (0.020)
Conclusion
Conclusion

• Learned a spectral prior using a convolutional autoencoder

• Proposed a novel hyperspectral reconstruction using the learned prior

• Demonstrated interesting applications

• Published a high quality hyperspectral dataset
Acknowledgments

• Seung-Hwan Back, Incheol Kim, Adrian Jarabo, and Paz Hernando

• Min H. Kim acknowledges
  • Korea NRF grants (2016R1A2B2013031, 2013M3A6A6073718)
  • Giga Korea Project (GK17P0200)
  • MCST
  • Samsung Electronics (SRFC-IT1402-02)
  • ICT R&D program of MSIT/IITP of Korea (R7116-16-1035)

• Diego Gutierrez acknowledges
  • ERC under EU’s Horizon 2020 research
  • CHAMELEON project (682080)
  • The Spanish Ministerio de Economia y Competitividad (TIN2016-78753-P)