BLIND UNMIXING USING A DOUBLE DEEP IMAGE PRIOR

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1 Motivation

2 Previous work

3 Proposed algorithm

4 Results

❖ HSI linear unmixing model

$$Y = EA + N \quad (1)$$

where,

(Y, E, A) is (HSI reflectance spectrum, material reflectance /endmember signature matrix, abundance matrix);

N is generally additive Gaussian noise;

❖ Goal

Given Y, estimate A and E.

$$\hat{E}, \hat{A} = \underset{E,A}{argmin} \frac{1}{2} \|Y - EA\|_F^2 + R(A)$$
$$s.t., E \geq 0, A \geq 0, A^T 1_r = 1_n$$

❖ Previous methods

- Most network based blind unmixing methods cannot guarantee to generate physically meaningful unmixing results due to the lack of effective guidance[1].
- The performance of most unmixing networks with training guidance is limited by the quality of the guidance.

❖ Motivation

- Can we propose a new network that can surpass the performance limitation imposed by training guidance?

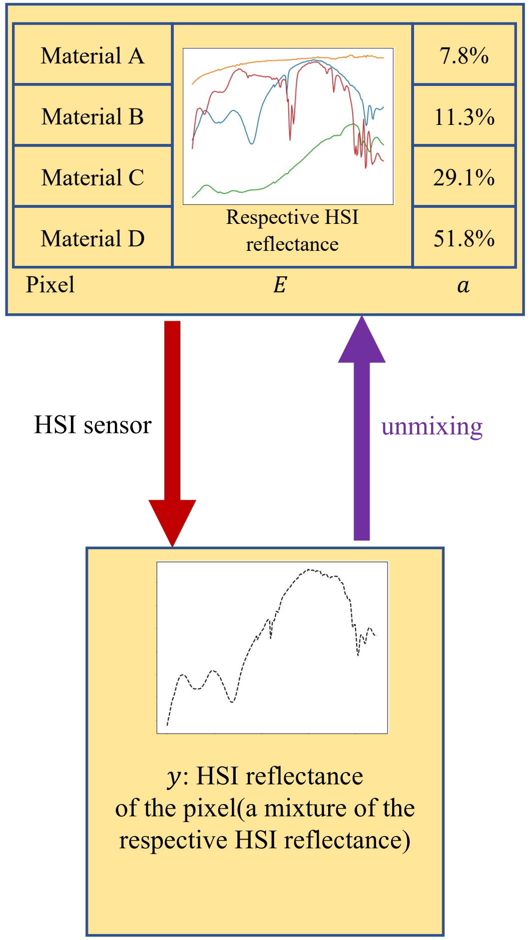

Fig.1 HSI unmixing Problem

[1] D. Hong et al., "Endmember-Guided Unmixing Network (EGU-Net): A General Deep Learning Framework for Self-Supervised Hyperspectral Unmixing," in IEEE Transactions on Neural Networks and Learning Systems, doi: 10.1109/TNNLS.2021.3082289.

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Unmixing using Deep Image Prior (UnDIP)

❖ DIP[2]

➢ Problem setting

Consider the image inverse problem, such as denoising, given by:

$$x^* = \underset{x}{\operatorname{argmin}} \|x - x_0\|_2^2 + R(x) \qquad (1)$$

where,

x_0 is the noisy image;

R is a regularizer on x.

➢ DIP technique

DIP propose to solve it by:

$$\theta^* = \underset{x}{\operatorname{argmin}} \|f_\theta(z) - x_0\|_2^2 \qquad (2)$$

where,

$f_\theta(z)$ is a neural network parameterized by θ with a random input z.

➢ Note

❖ After learning, the network f_θ can replace the regularizer R.

❖ The restored image is given by $x^* = f_{\theta^*}(z)$.

[2] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky, "Deep image prior," *International Journal of Computer Vision*, vol. 128, no. 7, pp. 1867–1888, Mar 2020.

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Unmixing using Deep Image Prior (UnDIP)

Cons:
- **No E itself;**
- **Limited by $\hat{E}$.**

❖ UnDIP[3]

Suppose some existing methods give $\tilde{E}$,

$$\hat{E}, \hat{A} = \mathrm{argmin}_{\mathrm{E,A}} \frac{1}{2}\|Y - EA\|_F^2 + R(A) \quad (3)$$
$$s.t., E \geq 0, A \geq 0, A^T 1_r = 1_n$$

given $\tilde{E}$

$$\hat{A} = \mathrm{argmin}_{\mathrm{A}} \frac{1}{2}\left\|Y - \tilde{E}A\right\|_F^2 + R(A) \quad (4)$$
$$s.t., A \geq 0, A^T 1_r = 1_n$$

DIP

$$\theta^* = \mathrm{argmin}_\theta \frac{1}{2}\left\|Y - \tilde{E} f_\theta(z)\right\|_F^2 \quad (5)$$
$$\hat{A} = f_{\theta^*}(z)$$

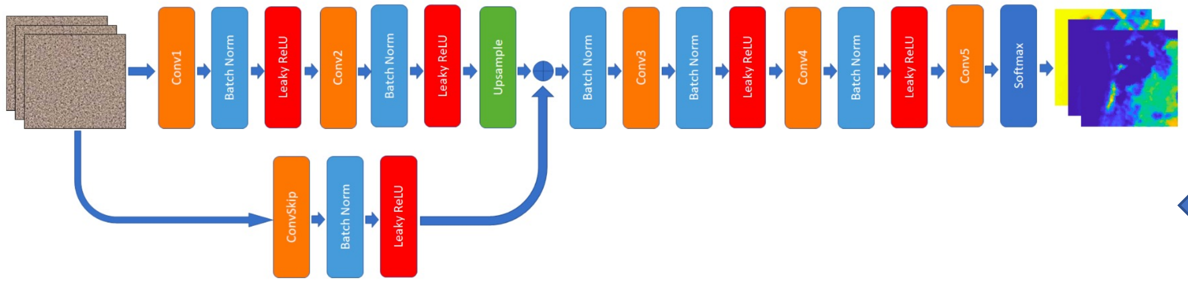

Fig. 2. Proposed convolutional network architecture with one skip connection. This network is used as f_θ for UnDIP in the experiments. Different layers in the network are shown with specific colors.

[3] Rasti, B., Koirala, B., Scheunders, P., & Ghamisi, P. (2021). UnDIP: Hyperspectral Unmixing Using Deep Image Prior. *IEEE Transactions on Geoscience and Remote Sensing*, 1–15. https://doi.org/10.1109/TGRS.2021.3067802

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❖ Endmember estimation via EDIP

Like UnDIP, suppose an estimation of abundance $\tilde{A}$ is given by existing methods, then (1) would reduce to endmember estimation problem:

$$\hat{E} = \underset{E}{argmin} \frac{1}{2} \left\| Y - E\tilde{A} \right\|_F^2$$
$$s.t., E \geq 0$$

According to DIP technique, we propose to solve it via

$$\hat{\theta}_E = \min_{\theta_E} \frac{1}{2} \left\| Y - f_{\theta_E}(z_E)\tilde{A} \right\|_F^2$$

Where, $f_{\theta_E}(z_E)$ is the network with learnable parameters θ_E and random input z_E。

- Last layer of f_{θ_E} is sigmoid to impose $E \geq 0$.
- Endmember given by $\hat{E} = f_{\hat{\theta}_E}(z_E)$.

❖ Abundance estimation via EDIP

Similarly, suppose an estimation of endmember $\tilde{E}$ is given by existing methods, then (1) would reduce to abundance estimation problem:

$$\hat{A} = \underset{E}{argmin} \frac{1}{2} \left\| Y - \tilde{E} A \right\|_F^2$$
$$s.t., A \geq 0, A^T 1_r = 1_n$$

According to DIP technique, we propose to solve it via

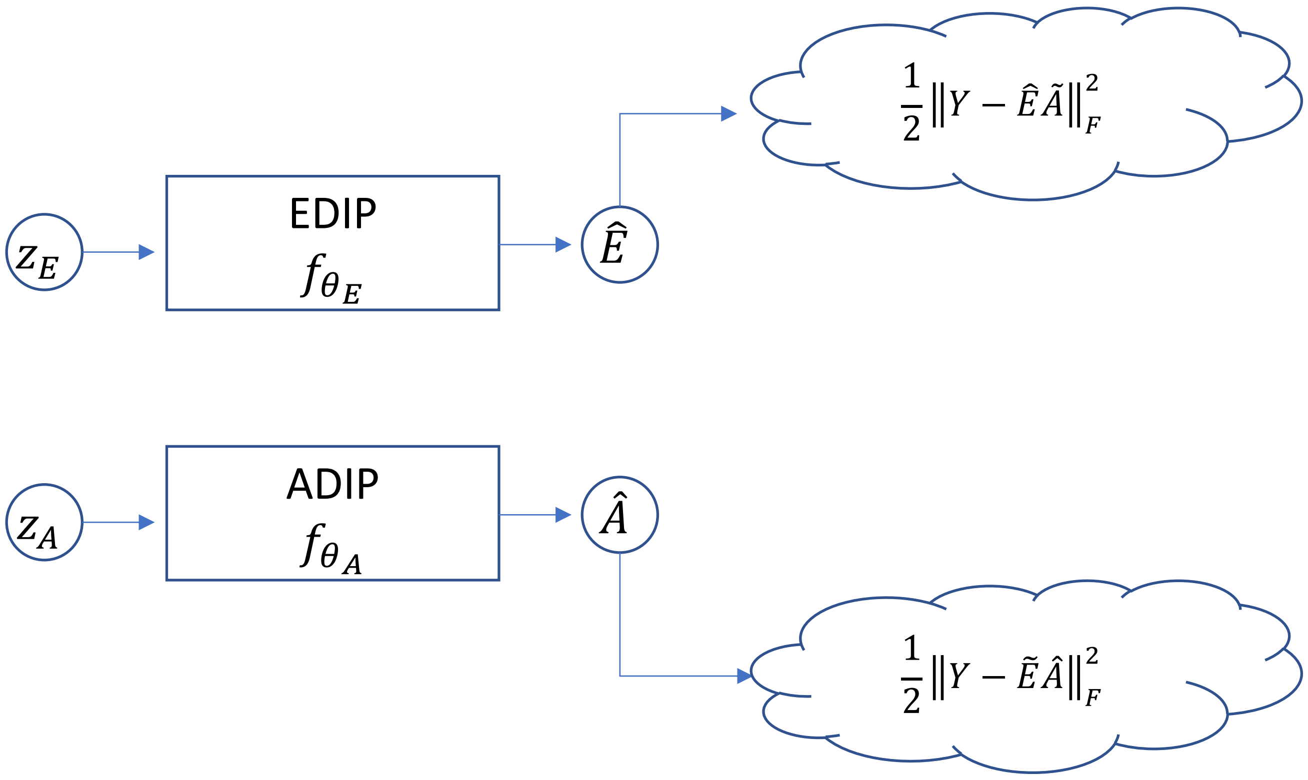
$$\hat{\theta}_A = \min_{\theta_A} \frac{1}{2} \left\| Y - \tilde{E} f_{\theta_A}(z_A) \right\|_F^2$$

Where, $f_{\theta_A}(z_A)$ is the network with learnable parameters θ_A and random input z_A。

- Last layer of f_{θ_A} is softmax to impose $A \geq 0, A^T 1_r = 1_n$.
- Abundance given by $\hat{A} = f_{\hat{\theta}_A}(z_A)$.

❖ Unmixing using Double DIP (BUDDIP)

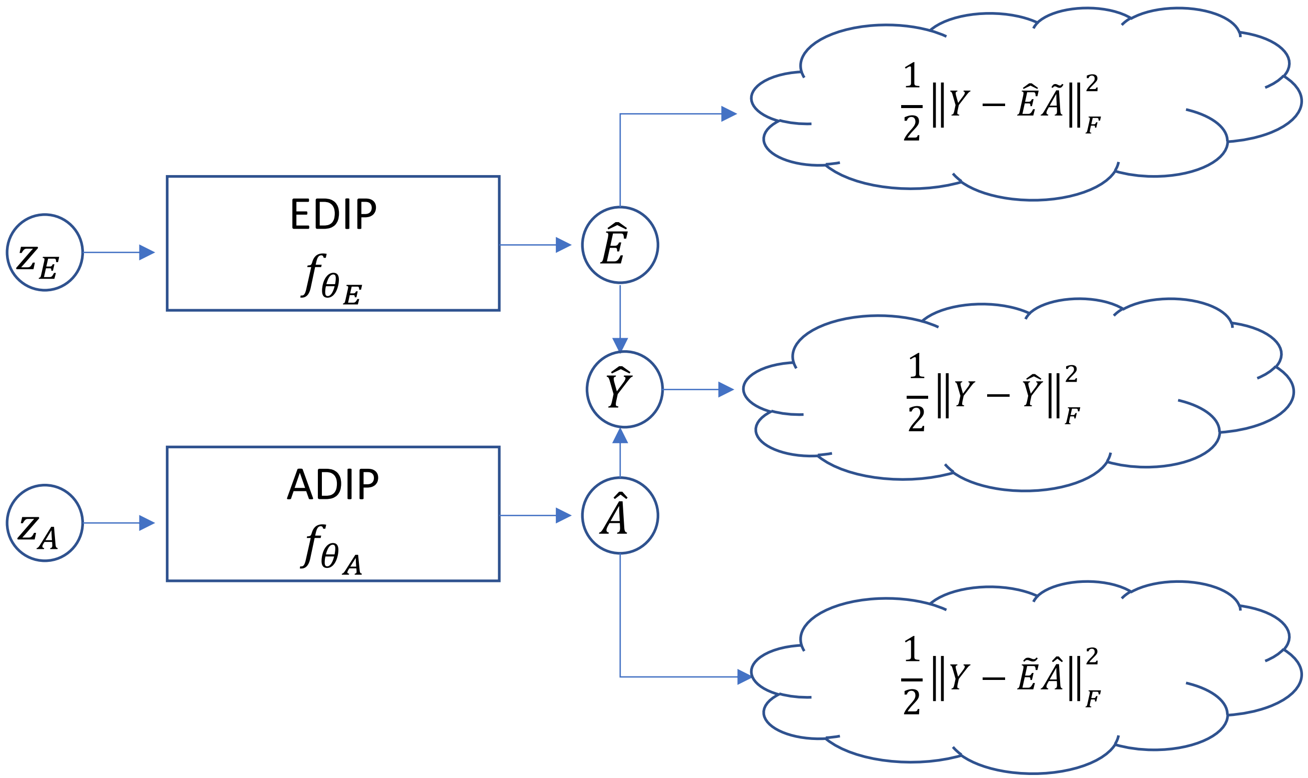
- EDIP + ADIP



can estimate E now;
but still limited by $(\tilde{E}, \tilde{A})$.

❖ Unmixing using Double DIP (BUDDIP)

➢ EDIP + ADIP



✓ We also propose the third loss:

Blind unmixing loss: $L_{BU} = \frac{1}{2}\|Y - \hat{Y}\|_F^2$

✓ Final loss

$L = \alpha_1 L_{EDIP} + \alpha_2 L_{ADIP} + \alpha_3 L_{BU}$

✓ New interpretation

Based on the guidance $(\tilde{E}, \tilde{A})$, find a better solution.

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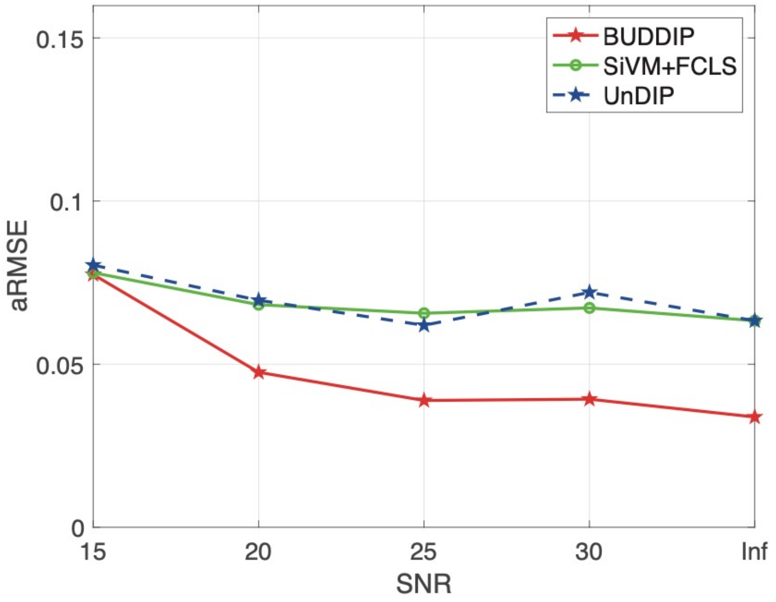
Experiment on Synthetic Data

data	generate according to [4].
competitors	UnDIP[3]; SiVM[5]+FCLS[6].
metrics for endmember	average Spectral Angle Distance (aSAD) $$aSAD(E,\hat{E}) = \frac{1}{r}\sum_{i=1}^{r}\frac{180}{\pi}\cos^{-1}(e_i,\hat{e}_i)$$
metrics for abundance	average Root mean square error (aRMSE) $$aRMSE(A,\hat{A}) = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{1}{r}\|a_i-\hat{a}_i\|_2^2}$$
optimizer	ADAM
Learning rate	1e-4
epochs	4500
hyper-parameters	$\alpha_1 = 0.1, \alpha_2 = 0.01, \alpha_3 = 1.0$

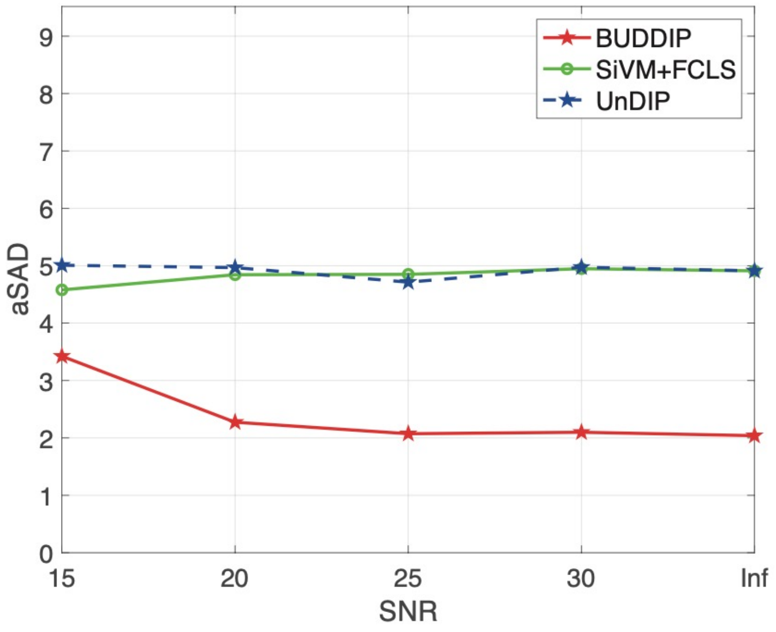
[4] S. Jia and Y. Qian, “Constrained nonnegative matrix factorization for hyperspectral unmixing,” IEEE Trans. Geosci. Remote Sens., vol. 47, no. 1, pp. 161–173, Jan. 2009.
[5] Rob Heylen, Dzˇevdet Burazerovic, and Paul Scheun- ders, “Fully constrained least squares spectral unmix- ing by simplex projection,” *IEEE Transactions on Geo- science and Remote Sensing*, vol. 49, no. 11, pp. 4112– 4122, 2011.
[6] D. C. Heinz and Chein-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.

Performance vs. SNR

We use default setting except SNR vary in $[15,20,25,30, inf]$ dB.



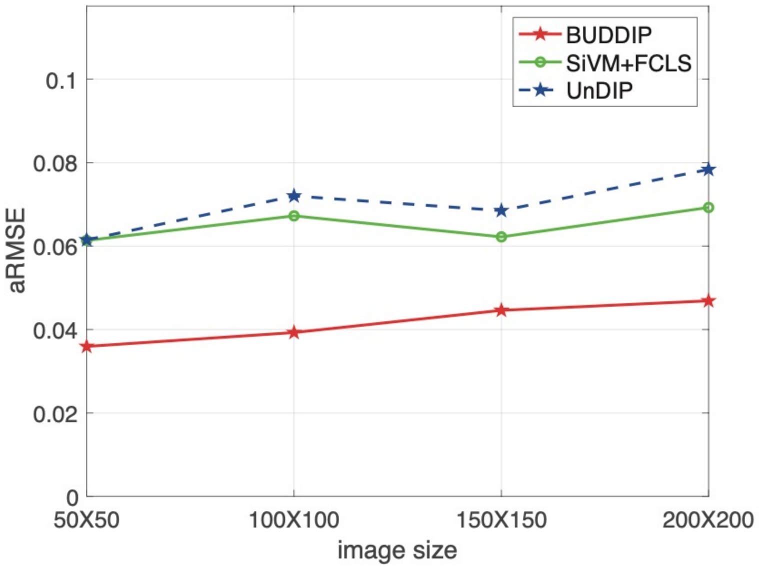
(a) aRMSE vs. SNR



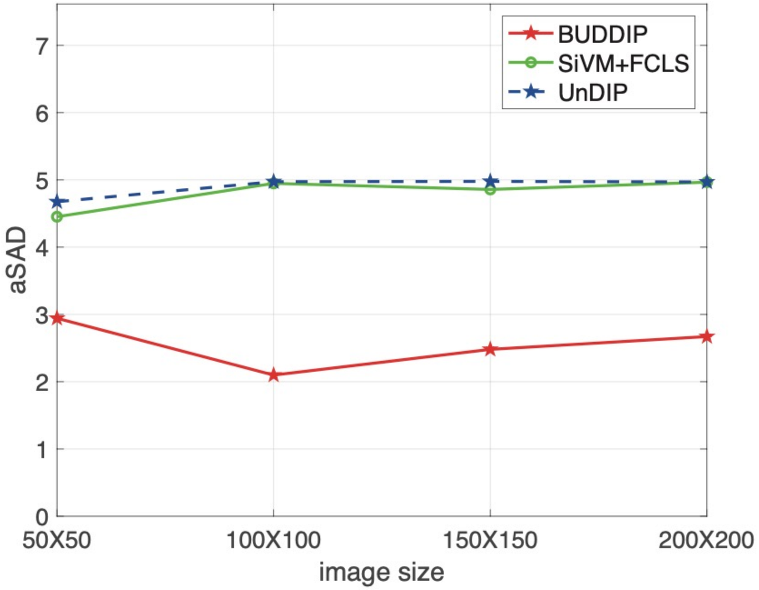
(b) aSAD vs. SNR

Performance vs. HSI image size

We use default setting except training size vary in {50×50,100×100,150×150,200×200} pixels.



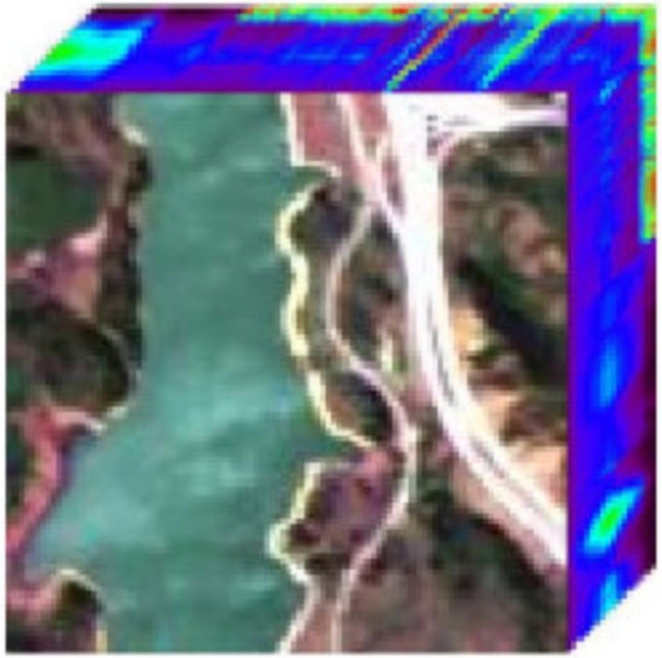
(a) aRMSE vs. image size



(b) aSAD vs. image size

Experiment Real Data

Jasper Ridge[1]

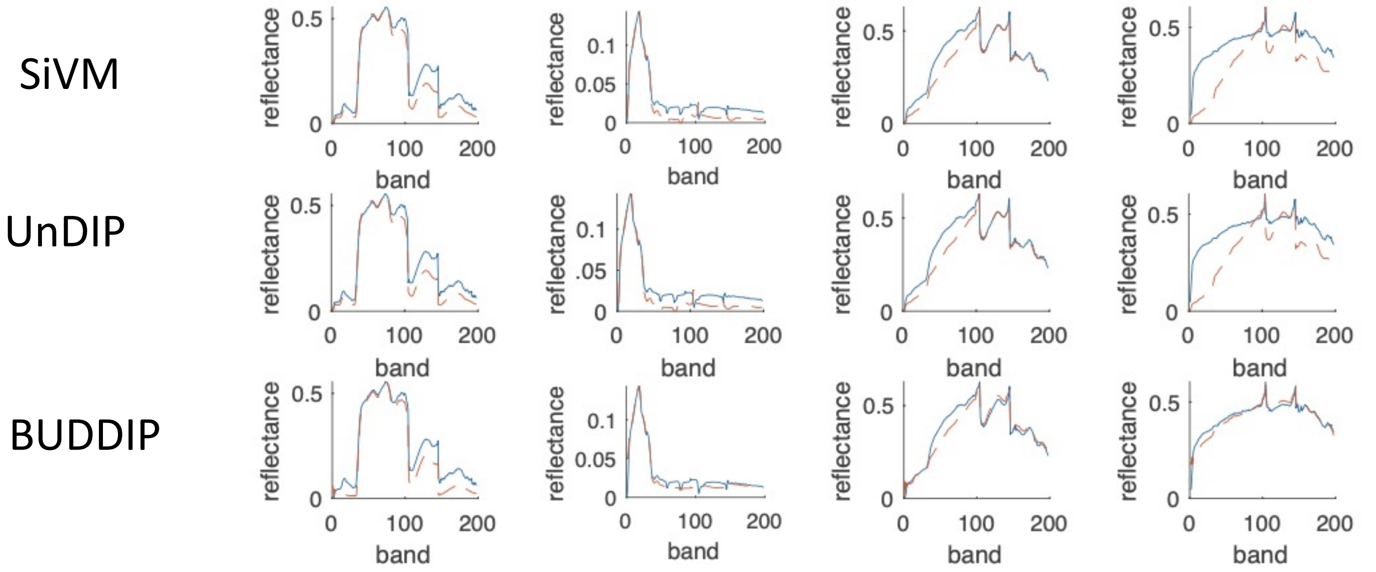


term	value
pixels	100 x 100
channels	198
endmembers	Road, Soil, Water, Tree

[1] F. Zhu, Y. Wang, S. Xiang, B. Fan, and C. Pan, "Structured Sparse Method for Hyperspectral Unmixing," *ISPRS J. Photogrammetry Remote Sens.*, vol. 88, pp. 101–118, 2014.

Performance: Endmember estimation

We use default setting except $\alpha_1 = \alpha_2 = \alpha_3 = 1.0$ and epoch=24000.

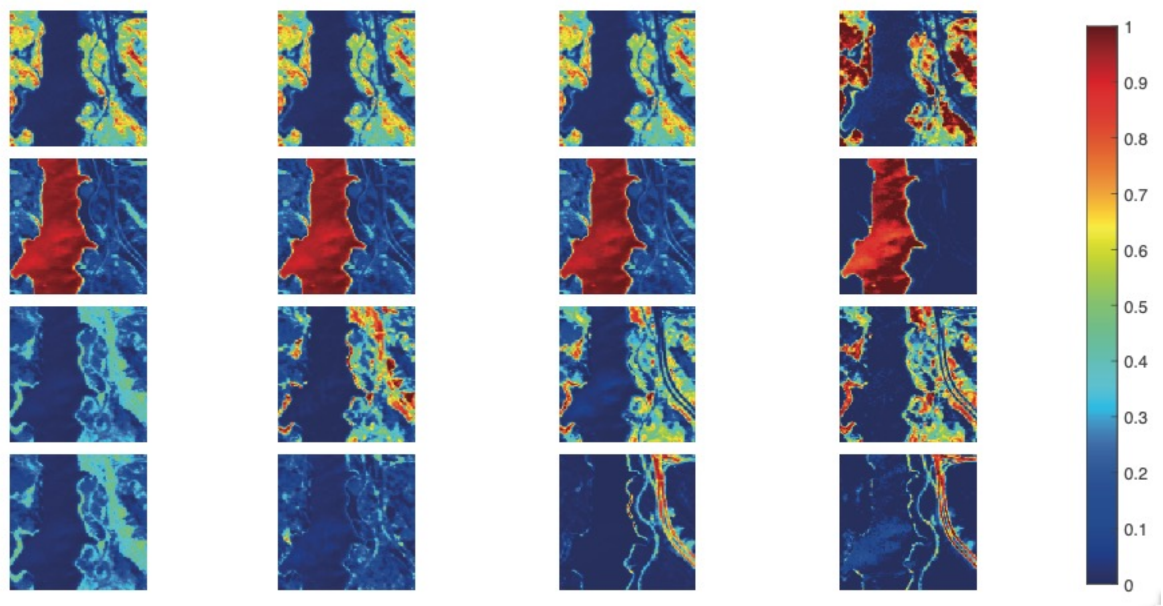


Solid blue line is true value, while dot line is estimated value.

	SiVM +FCLS	UnDIP	BUDDIP
aSAD	11.349	11.349	6.8489

Performance: Abundance estimation

We use default setting except $\alpha_1 = \alpha_2 = \alpha_3 = 1.0$ and epoch=24000.



SiVM+FCLS. UnDIP. BUDDIP. reference.

	SiVM +FCLS	UnDIP	BUDDIP
aRMSE	0.1480	0.1748	0.1023


Thank you!