BLIND UNMIXING USING A DOUBLE DEEP IMAGE PRIOR

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Background

❖ Motivations

- Most blind unmixing networks are based on Autoencoder-like structure.
- 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.

❖ Blind unmixing (BU) problem

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

Where,

$Y \in R^{p \times n}$ is the hyperspectral data cube;
$E \in R^{p \times r}$ is the endmember signature matrix;
$A \in R^{r \times n}$ is the abundance matrix;

- Goal of BU is to estimate E and A given Y.

❖ DIP techniques[2]

- Given an inverse problem

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

Where, x_0 is noisy image, R is regulariser.

- DIP propose to solve the problem

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

where $f_\theta(z)$ is a neural network parameterized by θ, with a random input z. After learning, network would output the restored image by $x^* = f_{\theta^*}(z)$.

❖ Unmixing using DIP (UnDIP) [3]

- Existing method such as SiVM generate $\tilde{E}$, then (1) reduce to abundance estimation and can be solved via:

$$\theta^* = \text{argmin}_\theta \frac{1}{2} \left\| Y - \tilde{E} f_\theta(Z) \right\|_F^2$$

The abundance would be given by $\hat{A} = f_{\theta^*}(Z)$.

[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.

[2] V. Lempitsky, A. Vedaldi and D. Ulyanov, "Deep Image Prior," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 9446-9454, doi: 10.1109/CVPR.2018.00984.

[3] B. Rasti, B. Koirala, P. Scheunders and P. Ghamisi, "UnDIP: Hyperspectral Unmixing Using Deep Image Prior," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5504615, doi: 10.1109/TGRS.2021.3067802.

Methods

❖ Endmember estimation via DIP (EDIP)

- Given an estimation of abundance $\tilde{A}$, (1) reduce to Endmember estimation problem, which can be solved using a DIP:

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

The endmember would be given by $\hat{E} = f_{\hat{\theta}_E}(z_E)$.

❖ Abundance estimation via DIP (EDIP)

- Given an estimation of endmember $\tilde{E}$, (1) reduce to abundance estimation problem, which can be solved using a DIP:

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

The abundance would be given by $\hat{A} = f_{\hat{\theta}_A}(z_A)$.

❖ Overall structure

After obtaining $\hat{E}$ and $\hat{A}$, using EDIP and ADIP respectively, we can generate a reconstruction of HSI image as follows:

$$\hat{Y} = \hat{E}\hat{A}$$

Thus, the overall structure of the proposed network, named BUDDIP, is obtained by assembling EDIP and ADIP, as shown in Fig.1.

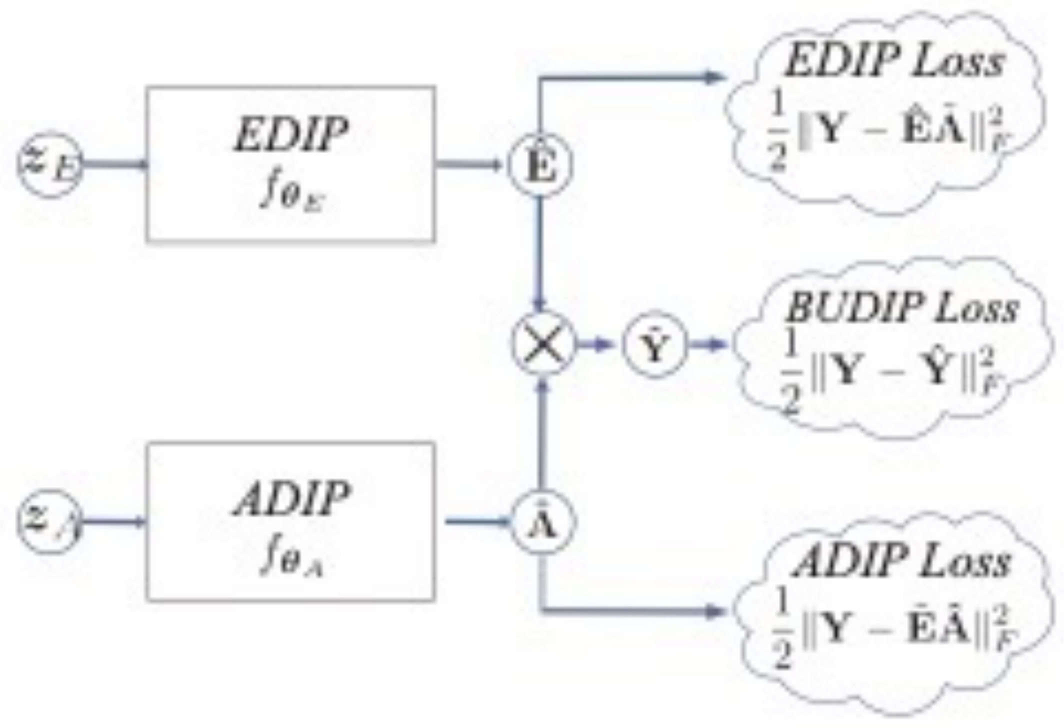


Fig.1 BUDDIP

❖ We also propose a new composite loss function:

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

where,

$$L_{EDIP} = \frac{1}{2} \left\| Y - f_{\theta_E}(z_E) \tilde{A} \right\|_F^2$$
$$L_{ADIP} = \frac{1}{2} \left\| Y - \tilde{E} f_{\theta_A}(z_A) \right\|_F^2$$
$$L_{BU} = \frac{1}{2} \left\| Y - \hat{Y} \right\|_F^2$$

$(\tilde{E}, \tilde{A})$ is the guidance generated by existing methods such as SiVM+FCLS.

Results

❖ Experiment on synthetic data

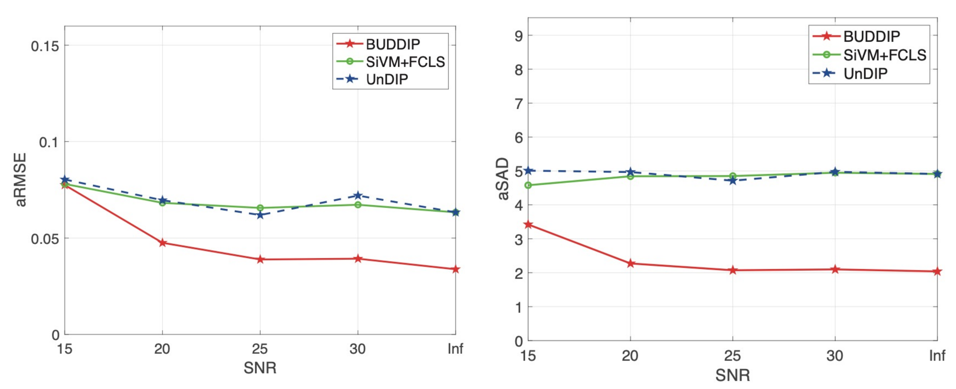
- We use the procedure in [4] to generate a synthetic HSI image of size 100 x 100 pixels.
- We use default setting up

α_1	0.1
α_2	0.01
α_3	1.0
optimiser	ADAM
Learning rate	1e-4
Epoch	4500

[4] Q. Qian, F. Xiong and J. Zhou, "Deep Unfolded Iter- ative Shrinkage-Thresholding Model for Hyperspectral Unmixing," *IGARSS 2019*, Yokohama, Japan, 2019, pp. 2151-2154.

➢ Performance vs. SNR

We use default setting except SNR vary in $\{15,20,25,30, inf\}$ dB.

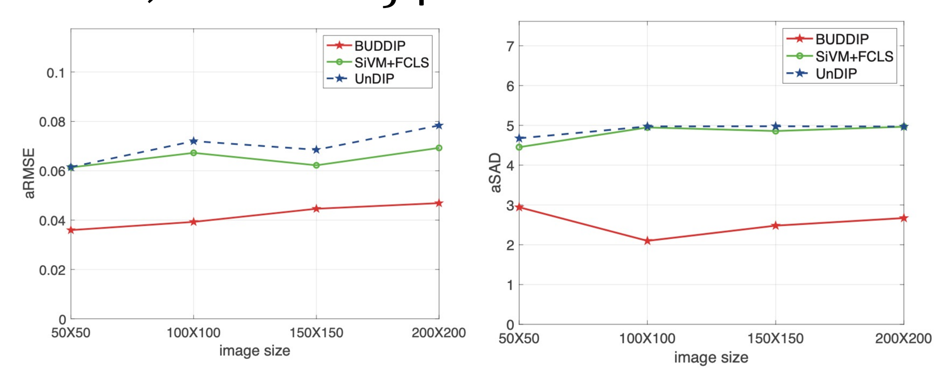


(a) aRMSE vs. SNR (b) aSAD vs. SNR

Fig.2 BU performance vs. SNR

➢ Performance vs. training size

We use default setting except training size vary in $\{50\times50, 100\times100, 150\times150, 200\times200\}$ pixels.



(a) aRMSE vs. image size (b) aSAD vs. image size

Fig.3 BU performance vs. training size

❖ Experiment on Real data

- We use the Jasper Ridge Dataset, and the default setting except $\alpha_1 = \alpha_2 = \alpha_3 = 1.0$ and epoch=24000.

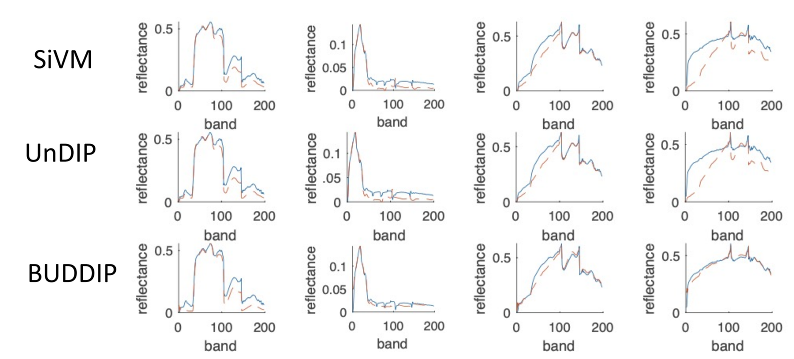


Fig.4. endmember estimation. Solid blue line is true value, While dot line is estimated value.

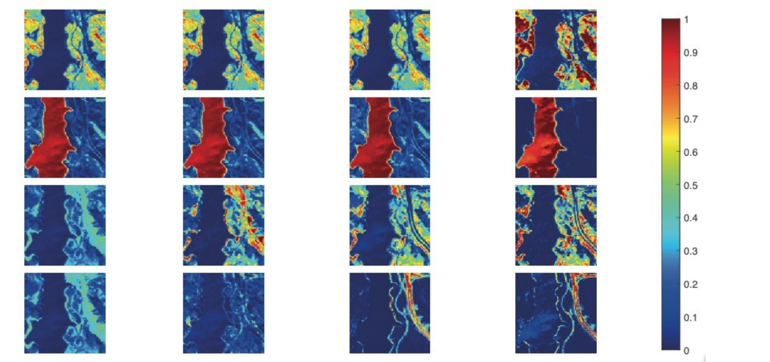


Fig.5. abundance estimation. From left to right: SiVM+FCLS, UnDIP, BUDDIP, reference.

Table 1. Unmixing performance by Different Algorithms.

	SiVM+FCLS	UnDIP	BUDDIP
aRMSE	0.1480	0.1748	**0.1023**
aSAD	11.3492	11.3493	**6.8489**