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Feature Extraction of Multimodal Images Based on Tensor Decomposition and Mathematical Morphology (poster)

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Overview

Contribution: We extract **spatial morphological features** from a **hyper-spectral image (HSI)**, represent the data as **multi-modal arrays**, then process them using **tensor decomposition** to improve the quality of **feature extraction**.

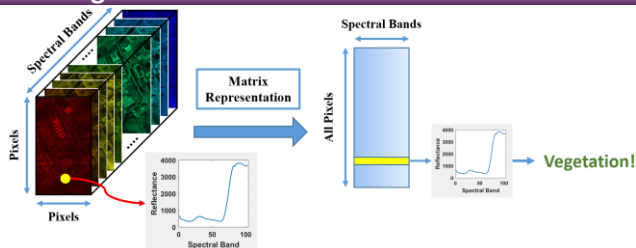
- HSIs naturally provide us with spectral features of the objects of the scene in order to understand its physical composition, but **spectral features are not enough**.
- We extract spatial neighborhood features through Morphology, but the state-of-the-art either mixes the two feature modalities or treats them independently => **Data are lost!**
- Solution: Tensor analysis** jointly accounts to the full data block and maintains the inter-feature relationships. This is explored in classification and blind separation of image data.

Background

HSIs can be represented as 2D arrays after rearranging the two pixel modes, then:

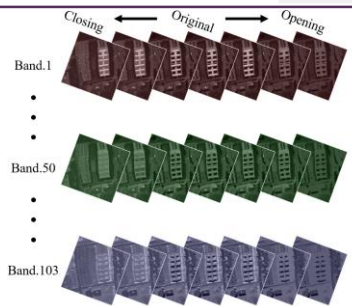
- **Pixels = Samples**
- **Spectral bands = Features**

These arrays are processed using matrix techniques.

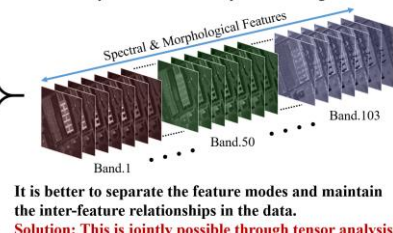


Morphological Filtering

provides meaningful **spatial features** related to pixel connectivity (e.g. size or brightness of objects).

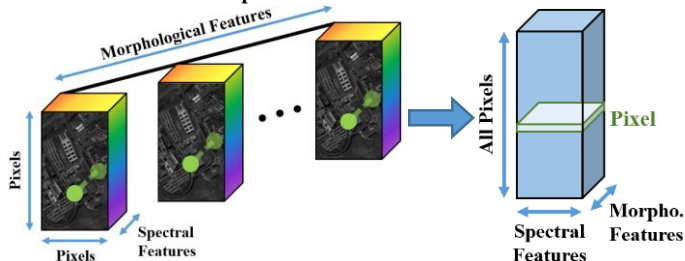


However, **classical morphological arrangement of HSIs mixes the features**. Then, the meaning and structure of the data is destroyed and the feature space is too large!



It is better to separate the feature modes and maintain the inter-feature relationships in the data. **Solution: This is jointly possible through tensor analysis!**

4th order HSI with separated features



Tensor Representation: By separating the features, we are able to extract meaningful patterns as well as observe some inter-feature relationships. Feature Extraction is done thanks to **CP Decomposition (CPD)**.

Proposed Framework: Morphology with Nonnegative CPD and AO-ADMM

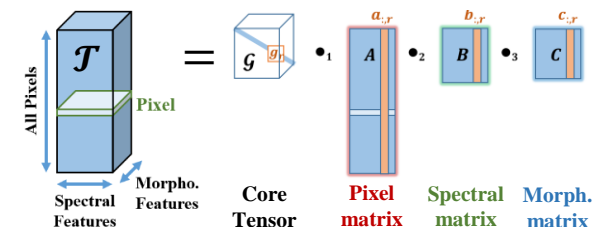
- Even though the image is vectorized, spatial information is not entirely lost thanks to using **small neighborhoods for morphological filtering**, which also ensures that the **rank stays low**.

- In order to extract the features, we use **CPD** with nonnegative constraints to ensure **physical interpretability**.

- Each **column triplet** $\{a_{:,r}, b_{:,r}, c_{:,r}\}$ of features represents a full material's **spatial highlight**, **spectral reflectance**, and **morphological pattern**.

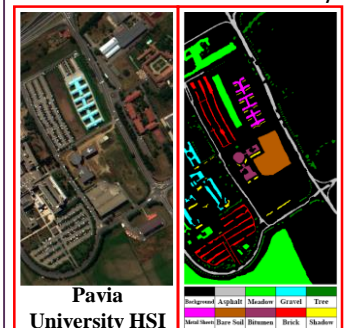
- CPD is **unique** under only mild conditions.

- We use AO-ADMM to minimize the cost function: $\|\mathcal{T} - (\mathbf{A}, \mathbf{B}, \mathbf{C})\|_F + \mathbf{r}(\mathbf{A}) + \mathbf{r}(\mathbf{B}) + \mathbf{r}(\mathbf{C})$ by solving for each matrix in an alternating ADMM way. The function $\mathbf{r}(\mathbf{H})$ represents the constraints applied only at \mathbf{H} => CPD is flexible with modal constraints.

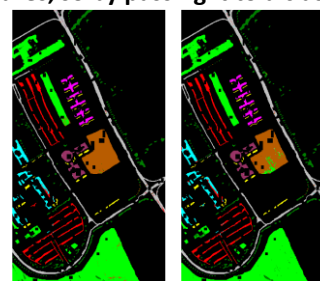


Experimental Validation: Scene Classification and Blind Source Separation (Spectral Unmixing)

Our HSI set is Pavia University:



A looks like a matrix of samples and features, so by passing it to a classifier:



AO = 97% AO = 96%
Sample Classification Maps,
Overall Accuracies (OA),
and Average Accuracies (AA)

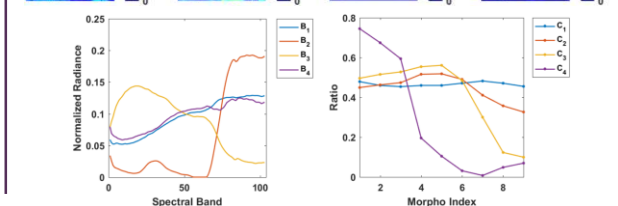
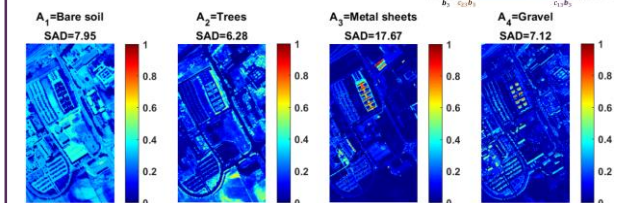
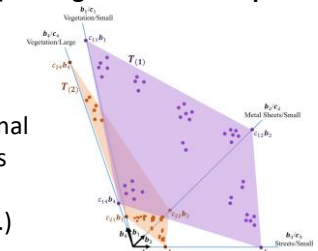
- We test different types of morphological operators and CPD parameters.

- Aside from classification accuracies that are comparable to the state of the art, CPD allows us to blindly & uniquely unmix the HSI data without loss.

Method	Features	OA %	AA %
PCA ₍₄₎	4	68.30	80.28
NMF ₍₄₀₎	40	77.01	87.65
EMAP	144	91.59	92.92
EMAP + PCA ₍₁₅₎	15	94.46	94.12
EMAP + TPCA _(4,4,3)	48	95.44	94.86
EMAP + CPD _(50,40)	40	97.06	98.60

Blind Source Separation (looking at 4 column triplets of features):

- It is possible to explain the features as a scatter plot in a multi-dimensional feature space. (Relations with ELMM for spectral unmixing and variability.)



References

- Comon, P. (2014). Tensors: a brief introduction. *IEEE Signal Processing Magazine*, 31(3), 44-53.
- Jouni, M., Mura, M. D., & Comon, P. (2020). Hyperspectral Image Classification Based on Mathematical Morphology and Tensor Decomposition. *Mathematical Morphology-Theory and Applications*, 4(1), 1-30.