ITERATIVE METHOD FOR HYPERSPECTRAL PIXEL UNMIXING LEVERAGING LATENT DIRICHLET VARIATIONAL AUTOENCODER

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Introduction

Hyperspectral Images (HSIs) contain an order of magnitude more information than a typical RGB color image. HSI pixels contain hundreds of bands and capture integrated reflectances from materials or objects within the instantenous field-of-view subtended by that pixel. HSI images, therefore, present exciting opportunities for a number of downstream tasks involving materials, objects or scene analysis, segmentation, and classification [1, 2]. Concomittantly, HSI images pose unique challenges in terms of algorithms and system design due to their sheer scale [3]. Oftentimes multiple materials contribute to the observed pixel intensity and in these circumstances a pixel can be thought of as a mixture of these materials where both the materials in question and their mixing ratios are unknown. This is especially true for low-resolution Hyperspectral Images (HSIs) that are captured in a remote sensing setting where each pixel may cover a large region of space [2]. Therefore, in terms of methods and theory for HSI analysis, the problem of pixel unmixing has recieved extensive attention in the hyperspectral research community [4]. Pixel unmixing aims to identify the various materials and extract their mixing ratios represented within a given HSI pixel.[1] Pixel unmixing is essential for a number of downstream tasks, such as those that aim to understand the composition, heterogeneity, and proportions of various materials using hyperspectral imaging [3, 5, 6, 7]. Within this context, this paper develops Iterative Latent Dirichlet Variational Autoencoder (ILDVAE), a novel method for hyperspectral pixel unmixing that aims to recover the "pure" spectral signal of each material (hereafter referred to as endmembers) and their mixing ratios (abundances) in a pixel given its spectral signature.

[1]Since HSI pixels record spectra, the problem of pixel unmixing is perhaps more correctly referred to as spectral unmixing.

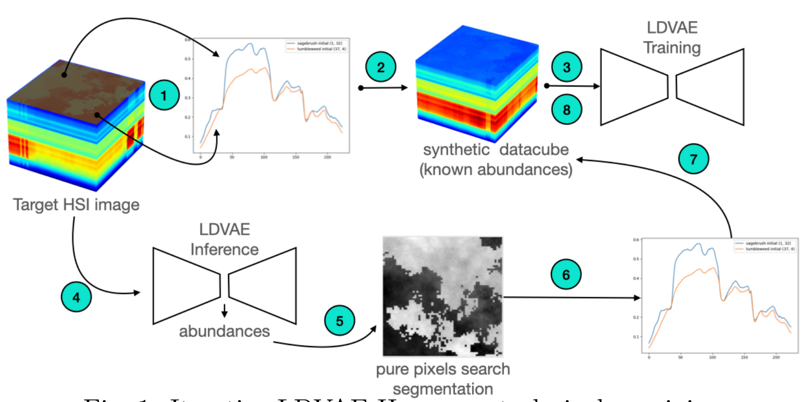

Fig. 1. Iterative LDVAE Hyperspectral pixel unmixing.

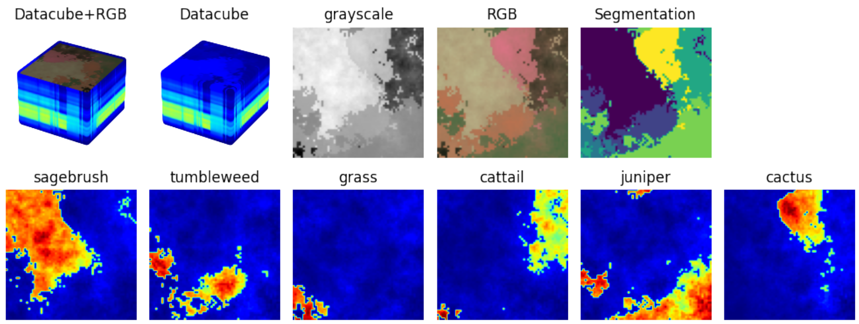

Fig. 2. First row, from left to right: Datacube with RGB projection, Datacube, HSI to grayscale, HSI to RGB, Segmentation results; Bottom row from left to right: abundance maps for each material (pixel unmixing).

Method Sketch

The work builds upon our prior work that requires pixel-level ground truth labels during training [8]. The current method employs an analysis-synthesis loop and relaxes the assumptions about pixel-level ground truth labels. We have evaluated this approach on synthetic dataset and our initial results are promsing. The method is outlined below.

ILDVAE Outline (see Figure 1)

1. Extract two random pixels from the target HSI image (assume these are the initial endmembers)
2. Generate a synthetic datacube with only two materials and known abundances
3. Train LDVAE on the synthetic datacube
4. Run LDVAE inference on the target HSI
5. Compute abundance maps of the target HSI, search for pure pixels endmembers (pure pixel threshold $\tau > 0.8$ from the n-simplex Dirichlet sample)
6. Extract new endmembers candidates
7. Generate new synthetic datacube
8. Retrain LDVAE with new synthetic datacube

Stopping Criterion

The iterative process stops when the error between endmembers of two consecutive iterations is smaller than a threshold ϵ:

$$\sum_{i=1}^{N} |\hat{e_{i,j}} - \hat{e}_{i,j-1}| \leq \epsilon$$

where $\hat{e}_{i,j}$ is the intensity value of a predicted endmember at band i and iteration j and N is the number of bands in the HSI.

Results

We evaluated the performance of our method with respect to abundances estimation (average $RMSE = 0.03464$), endmember extraction (average $SAD = 0.0876$), and semantic segmentation ($accuracy = 0.8105$). A qualitative assessment of segmentation can be visualized in the last figure of the first row of Figure 2, while abundance results can be visualized in the bottom row of Figure 2.

Contributions

We propose a new self-supervised method for pixel unmixing (endmember extraction and abundance estimation). The proposed method tightly couples analysis and synthesis and does not require ground truth data for training. We also show how the proposed method can be used for HSI semantic segmentation.

1. REFERENCES

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