Overviews: Hyperspectral Image Analysis using Sparse Representation

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# I. Introduction

**(Definition)** (1) Hyperspectral remote sensing is concerned with the extraction of information from objects or scenes lying on the Earth surface, based on their radiance acquired by airborne or spaceborne sensors (2) Application of Hyperspectral sensing (3) In hyperspectral imaging, also termed imaging spectroscopy, the sensor acquires a spectral vector with hundreds or thousands of elements from every pixel in a given scene.

**(Characteristic)** (1) spectrally smooth and spatially piece-wise smooth (2) An equivalent interpretation of an HSI is given by the acquisition of a stack of images representing the radiance in the respective band (wavelength interval). (3) the spectral information is often highly correlated and thus lives in a low dimensional manifold.

**(Data description)** (1) the obtained spectrum is the average of the material’s reflectance within this field of view (2) The spectral resolution is determined by the bandwidth of the spectral bands. (3) Different forms of representation: spatial representation, spectral representation, spatial-spectral representation

**(HIS difficulties)** Hyperspectral images are not applicable to effectively differentiate objects composed of the same material (i.e., objects with the same spectral characteristics). For example, roofs and roads that are made of the same material exhibit the same spectral characteristics, which makes the discrimination of such categories in the feature space a very difficult task.

**(Factors make analysis of HSI complex)** (1) spectral mixing (2) high dimensionality and size of the data

Sparse representation (SR) has recently drawn significant interest in computer vision and image processing due to its enhanced performance in many applications. The main idea of SR theory lies in the fact that an image signal can be represented as a linear combination of the fewest possible atoms or transform basis primitives in an over-complete dictionary. Sparsity means that only a small number of atoms are required to accurately reconstruct a signal, i.e., the coefficients become sparse. Over-completeness indicates that the number of atoms in the dictionary is larger than the dimension of the signal. Thus, these atoms in an over-complete dictionary permit an accurate sparse representation of signals.

One of the advantages of the sparse representation method is that it can reduce the data dimension, the dependence between the dimensions of the feature vector after sparse representation becomes lower, more independent. Furthermore, sparse representation adds sparse constraints, so that each "base" obtained after calculation has the same importance for interpreting data, the purpose of which is to try to find the explanatory factor hidden behind the data.

It has been demonstrated that natural images can be sparsely represented from the perspective of the properties of visual neurons. For example, the sparse representation- based classification (SRC) method first assumes that the test sample can be sufficiently represented by samples from the same subject. Specifically, SRC exploits the linear combination of training samples to represent the test sample and computes sparse representation coefficients of the linear representation system, and then calculates the reconstruction residuals of each class employing the sparse representation coefficients and training samples. The test sample will be classified as a member of the class, which leads to the minimum reconstruction residual. Generally, we can use some greedy algorithms.

In the greedy strategy approximation for solving sparse representation problem, the target task is mainly to solve the sparse representation method with l0-norm minimization. While the fact that this problem is an NP-hard problem, the greedy strategy provides an approximate solution to alleviate this difficulty. The greedy strategy searches for the best local optimal solution in each iteration with the goal of achieving the optimal holistic solution. For the sparse representation method, the greedy strategy approximation only chooses the most k appropriate samples, which are called k-sparsity, to approximate the measurement vector.

(HIS analysis via sparse representation)

(structure)

# II. Representation learning

Via a joint sparsity model where hyperspectral pixels in a small neighborhood around the test pixel are simultaneously represented by linear combinations of a few common training samples, which are weighted with a different set of coefficients for each pixel. The proposed sparsity-based algorithm is applied to several real hyperspectral images for classification.

Considering that hyperspectral imagery (HSI) is intrinsically defined in both the spectral and spatial domains, we further establish two variants of feature learning procedures for sparse spectral feature learning and multiscale spatial feature learning.

Inspired by the success of previous works, we believe that feature learning is a more potential and robust way for HSI classification. With this motivation, we establish a novel spectral–spatial feature learning framework for HSI classification based on the stacked sparse autoencoder model (SSAE). Considering that HSI is intrinsically defined both in the spectral and spatial domains, we further establish two variants of feature learning procedures for spectral feature learning and spatial feature learning.

# III. Unmixing

**(Reasons of mixing)** low spatial resolution of the scanner or to the presence of intimate mixtures in the scene, the spectral vectors acquired by the hyperspectral scanners are actually mixtures of the spectral signatures of the materials present in the scene. (Description of unmixing) Spectral unmixing aims at estimating the number of reference materials, also called endmembers, their spectral signatures, and their fractional abundances.

**(unmixing based sparse regression)**

# IV. Detection

HSI image target detection relies on the binary hypothesis model of an unknown sample induced by sparse representation. The sample can be sparsely represented by the training samples from the background-only dictionary under the null hypothesis and the training samples from the target and background dictionary under the alternative hypothesis. The sparse vectors in the model can be recovered by a greedy algorithm, and the same sparsity levels are employed for both hypotheses. Thus, the recovery process leads to a competition between the background-only subspace and the target and background subspace, which are directly represented by the different hypotheses. The detection decision can be made by comparing the reconstruction residuals under the different hypotheses.

# V. Classification

Sparse representation has also been applied to HSI image classification, relying on the observation that hyperspectral pixels belonging to the same class approximately lie in the same low-dimensional subspace. Thus, an unknown test pixel can be sparsely represented by a few training samples (atoms) from a given dictionary, and the corresponding sparse representation vector will implicitly encode the class information.

# VI. Anomaly detection

A novel method for anomaly detection in hyperspectral images (HSIs) is proposed based on low-rank and sparse representation. The proposed method is based on the separation of the background and the anomalies in the observed data. Since each pixel in the background can be approximately represented by a background dictionary and the representation coefficients of all pixels form a low-rank matrix, a low-rank representation is used to model the background part. To better characterize each pixel's local representation, a sparsity-inducing regularization term is added to the representation coefficients. Moreover, a dictionary construction strategy is adopted to make the dictionary more stable and discriminative. Then, the anomalies are determined by the response of the residual matrix. An important advantage of the proposed algorithm is that it combines the global and local structure in the HSI. Experimental results have been conducted using both simulated and real data sets. These experiments indicate that our algorithm achieves very promising anomaly detection performance.

# VII. Data fusion

**(Definition)** Data fusion combines data from multiple sources to improve the potential values and interpretation performances of the source data, and to produce a high-quality visible representation of the data. **(Application)** object detection, recognition, identification and classification, to object tracking, change detection, decision making, etc. **(method)**

# VIII. Conclusion

**(summarize of HSI analysis based sparse)**

**(the challenge and the future)**