SPATIAL-SPECTRAL DATA FUSION FOR RESOLUTION ENHANCEMENT OF HYPERSPECTRAL IMAGERY

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1. INTRODUCTION

Hyperspectral (HS) images are rich in spectral information but relatively poor in spatial resolution which usually varies from few to tens of meters. Many different algorithms for spatial resolution enhancement of HS images have been proposed in last decade [1-11]. Joint processing is the main idea in a considerable number of proposed methods in which the spatial information of a high resolution (HR) image is imposed onto the low resolution (LR) HS image [4, 5]. Some other approaches are indirect and are based on spectral mixture analysis (SMA) or subpixel classification [6, 7] and some articles suggest it through super-resolution mapping (SRM) and learning based methods like Hopfield neural network (HNN) [8-11].

Tackling the limitations of the mentioned techniques, i.e. the need for HR sources of information and high computational cost, has been the motivation of the proposed fast SRM algorithm in this paper.

2. OUTLINE OF THE PROPOSED METHOD

The proposed method consists of two main parts, namely, linear spectral unmixing and super-resolution mapping. In order to extract the fractional images (endmember abundances), the linear spectral unmixing is applied on the HS image after classifying it using the minimum noise fraction (MNF) and pixel purity index (PPI) techniques. This is carried out based on the developed linear mixture model (LMM) and fully constraint least squares (FCLS) algorithm which are discussed in section 3.

The proposed super-resolution mapping (SRM) algorithm is a learning-based tool which should be initially trained according to the developed spatial correlation model (section 4 and 5). To this end, a similar data from the same source of the HS image is used for training of the SRM algorithm (section 6). The trained SRM algorithm is applied on the fractional images and exploits the relation between the abundances of endmembers in each pixel and the abundances of the same endmembers in the neighboring pixels (section 7).

3. LINEAR SPECTRAL UNMIXING

LMM is a frequent assumption in HS remote sensing [12, 13]. Let L equal the number of endmembers in the spectral library with l ranging from 1 to L. Each spectrum in the library consists of M discrete wavelengths (λ_m) where m=1 to M. Let $S^l(\lambda_m)$ represent the spectral response of material l at wavelength λ_m. Each spectrum in the library is described by the following vector:

$$s^l = (S^l(\lambda_1), S^l(\lambda_2), ..., S^l(\lambda_M)) \tag{1}$$

For an unknown spectra $u = (u_1, u_2, ..., u_M)$ each vector component is composed of a linear combination of j endmembers from J. u is related to J by the estimation vector $x = (x_1, x_2, ..., x_L)$ and generally has to follow two constraints of nonnegativity and sum-to-one, based on physical considerations, i.e.,

$$0 \le x_l \le 1 \quad \text{and} \quad \sum_{l=1}^{L} x_l = 1 \tag{2}$$

For a mixture described by u, the spectral response at λ_m, $S^u(\lambda_m)$, would be as following:

$$S^u(\lambda_m) = \sum_l x_l S^l_{\lambda_m} \tag{3}$$

Among the proposed algorithm for handling the LMM according to (2), FCLS algorithm can efficiently meet both abundance constraints and is optimal in terms of least squares error [14].

4. BACKPROPAGATION NEURAL NETWORK (BPNN)

Backpropagation neural network was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions [15]. The generalization property of BPNN makes it possible to train it on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs. BPNNs often have one or more hidden layers of nonlinear neurons followed by an output layer of linear neurons.

5. SUPER-RESOLUTION MAPPING (SRM)

The basis for the proposed SRM technique is explained by Fig. 1. Fig. 1(a) shows a fractional image of a scene, obtained through linear spectral unmixing, with a possible contribution of one of the endmembers. Fig. 1(b), for example shows a possible random assignment in which the spatial correlation of the endmember is not taken into account and as a consequent it does not provide the optimum spatial dependence. In contrast, Fig. 1(c) depicts a much better mapping and the assigned subpixels are the best in term of spatial correlation of endmembers.

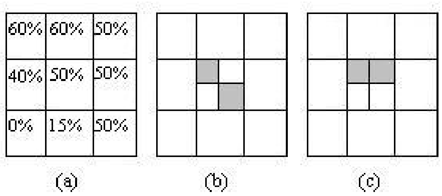

Fig. 1. The basis for the proposed SRM technique.

6. DATA

To determine the efficacy of the proposed algorithm, some real test HS images are chosen for experiment. The test images in the experiment include two remotely sensed HS images which were collected by the Airborne Visible/Infrared Imaging spectrometer (AVIRIS-II). One of the test images, namely Dataset-I is an AVIRIS-II HS data with 200 available bands. A hard classification map is available for this data too. The second test data, namely Sandiego is a 405 $\times$400 pixel area image with 126 available bands. A 100 $\times$ 100 region on the top left corner is chosen for our experiments (Dataset-II). As the training data, another part of Sandeigo, namely Dataset-III is chosen. Dataset-III is chosen from Sandiego to impose the maximum likelihood between the test image and the training data.

7. EXPERIMENTS AND RESULTS

Experiment on Dataset-II is carried out after training of the algorithm with subsampled and original Dataset-III (after unmixing) as the input and target vectors, respectively. The adherence of the resulted enhanced images to the HR images is compared through the root-mean-square error (RMSE) and correlation coefficient (CC) measures (table 1). Fig.2 shows the LR, enhanced, and HR fractional images for one of the endmembers (asphalt) resulted by the proposed technique. The efficiency of the proposed method is good and the computational time of SRM algorithm is about tens and few seconds with and without considering the initial training time, respectively.

(a) (b) (c)

Fig. 2. Experimental results on the Dataset-II. (a), (b), and (c) the LR, enhanced, and HR images for asphalt, respectively.

Table 1. RMSE and CC measures for enhances images by proposed method on Dataset-II

	Sand	Asphalt
RMSE	0.0729	0.0786
CC	0.9733	0.9813

8. CONCLUSION

The main advantages of the proposed technique are three: it doesn't need any secondary HR source of information, there is no need to a priori information about the test HS image, and it is fast so as makes it a proper choice for real-time applications such as target recognition.

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