NOISE-ROBUST SUBBAND DECOMPOSITION BLIND SIGNAL SEPARATION FOR HYPERSPECTRAL UNMIXING

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1. INTRODUCTION

Hyperspectral remote sensing data open up new opportunities for analyzing areas characterized by a large variety of spectrally distinct surface materials. In many cases, limited spatial resolution and the heterogeneous nature of target surfaces make the spectra measured from a single pixel to be contributed by more than one material. Therefore, the mixed pixel should be decomposed into a collection of constituent spectra as an important preprocessing step for various hyperspectral applications. Unsupervised unmixing approaches that consider hyperspectral unmixing as a blind source separation (BSS) problem, are developed fast recently. Among them, independent component analysis (ICA) and its extensions have been proved effective and successful [1].

The standard ICA model assumes that the source signals are mutual independent or spatial-temporally uncorrelated. As for hyperspectral unmixing, due to the physical constraints in the data acquisition process, this assumption is not fully satisfied. The extended ICA algorithms and other BSS approaches are proposed to weaken this limitation [2, 3, 4].

Recently, a new ICA/BSS technique, called subband decomposition ICA/BSS (SD-ICA/BSS) [5], is proposed to relax ICA's limitation. It assumes that the wide-band source signals are generally dependent but some narrow-band subcomponents of the sources are independent [6]. SD-ICA has been applied to speech separation, image restoration and so on, but its application in hyperspectral unmixing is very little. For SD-ICA/BSS, subband decomposition and subband selection are two key problems. The existing methods emphasize the "independence" of sub-components, but ignore the impact of their "noise". In order to obtain noise-robust blind separation results, this paper presents a noise-robust SD-ICA/BSS method, in which wavelet package (WP) transform is used for multiscale subband decomposition, and a joint measure of independence and noise is used as subband selection criterion.

2. LINEAR SPECTRAL MIXTURE MODEL AND SD-ICA/BSS

Linear spectral mixture process models an observed spectral imagery cube to be linear mixtures of endmember's spectra, so the pixel with coordinate (i, j) can be written as

$$X_{ij} = A_{ij}S + n_{ij} \tag{1}$$

where $\mathbf{n}$ is the noise produced by sensors and environment. Under linear spectral mixture model, spectral unmixing is an inversion problem that finds $\mathbf{A}$ and $\mathbf{S}$ using various constraints. ICA finds a demixing matrix $\mathbf{W}$ which gives the independent

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components $\mathbf{Y}$ that is an approximation of endmember signatures $\mathbf{S}$

$$\mathbf{Y} = \mathbf{W}\mathbf{X} \tag{2}$$

Most of ICA/BSS algorithms require the assumption of the independence/uncorrelatedness of the source signals. As for hyperspectral unmixing, there are many factors making endmember spectra not to be fully independent. SD-ICA solves this problem with the concept of subband filtering. The source signals can be represented as the sum of several sub-components as

$$S_p = S_{p,1} + S_{p,2} + \cdots + S_{p,K} \tag{3}$$

SD-ICA assumes that the filtered source sub-components can be divided into two groups: source-independent sub-components and source-dependent sub-components. There exist some subband filters such that the source-independent sub-components pass through them and the source-dependent sub-components are attenuated. As spectral unmixing model and subband filter are both linear operators, an ICA/BSS algorithm can be applied to any one independent sub-component instead of the original source

$$F_k[X_{ij}] = A_{ij}F_k[\mathbf{S}] + F_k[n_{ij}] \tag{4}$$

$$F_k[\mathbf{Y}] = \mathbf{W}F_k[\mathbf{X}] \tag{5}$$

We can obtain either an estimation of the demixing matrix $\mathbf{W}$ or an estimation of the endmember abundance $\mathbf{A}$, and then endmember signatures can be obtained by applying $\mathbf{W}$ to the original observed data $\mathbf{X}$

$$\mathbf{S} \approx \mathbf{Y} = \mathbf{W}\mathbf{X} \tag{6}$$

3. NOISE-ROBUST SD-ICA/BSS

In practice, the high-frequency sub-components are often found to be more mutually independent than low-frequency sub-components. However, for hyperspectral unmixing, the unmixing performance with high-frequency sub-components is not always better than that with low-frequency ones. This may arise out of the facts that: high spectral-resolution sensors extract many unknown interfering signatures in addition to endmember signatures, noises mainly distribute in high-frequency bands, and ICA/BSS algorithms are sensitive to noise.

Multiscale subband decomposition can produce a rich frequency menu, and multiple resolutions in spatial (time) domain, which not only has more opportunities of selecting independent sub-components from it, but has different strengths of noise at different scales as well. Wavelet packet (WP) transform represents a generalization of the method of multiscale decomposition, and comprises the entire family of subband coded (tree) decompositions. ICA/BSS can applied to any node k in WP tree

$$\mathcal{WP}_k(X_{ij}) = A_{ij}\mathcal{WP}_k(S) + \mathcal{WP}(n_{ij}) \tag{7}$$

For subband selection, we propose a new criterion, which considers independence and noise simultaneously, and reaches a tradeoff between them. It is defined as

$$Q[\mathcal{WP}_k(X)] = \alpha I[\mathcal{WP}_k(X)] + (1-\alpha)N[\mathcal{WP}_k(X)] \tag{8}$$

where $I(\mathcal{WP}_k)$ is the measure of independence, $N(\mathcal{WP}_k)$ is the measure of noise. α is the weight of independence in the measure, which is given a value of 0.5 in our experiments. Mutual information [7] and noise fraction [8] are employed to measure independence and noise respectively.

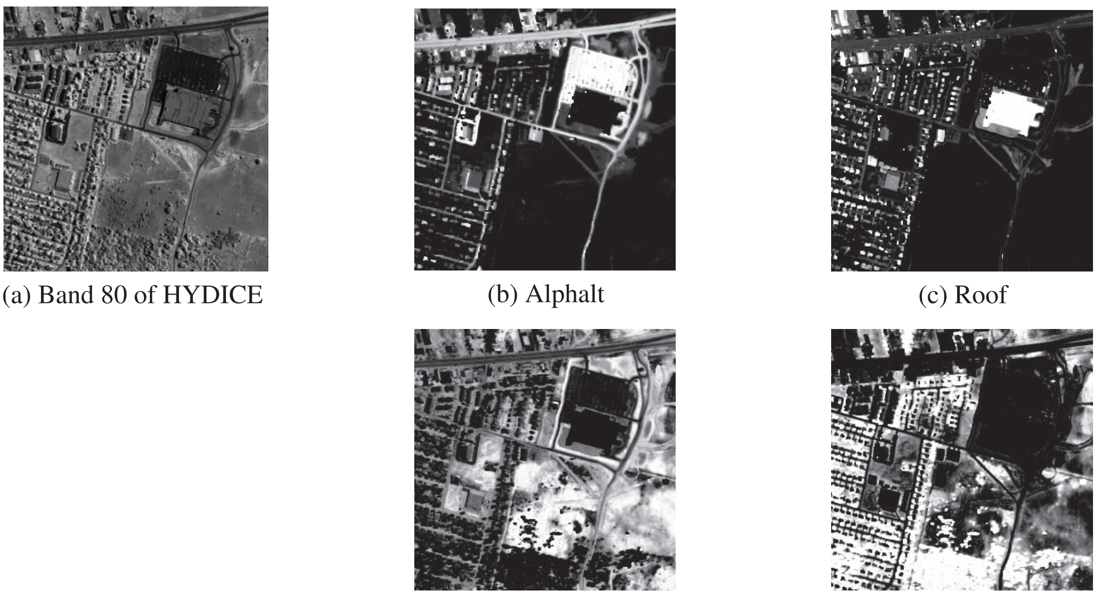
Table 1. RMSE scores of ICA and CNMF methods with raw spectra, D1 subband spectra (selected by I), AA2 subband spectra (selected by Q).

Method	Endmember				
	asphalt	grass	roof	tree	
ICA	0.344	0.213	0.218	0.247	Raw
	0.360	0.263	0.290	0.290	D1
	0.340	0.246	0.278	0.281	AA2
CNMF	0.290	0.267	0.253	0.190	Raw
	0.280	0.195	0.209	0.180	D1
	0.117	0.135	0.125	0.113	AA2

4. EXPERIMENTAL RESULTS

We apply the proposed method to a remote sensing data set collected by the HYperspectral Digital Imagery Collection Experiment (HYDICE) sensor. Fig.1(a) shows its image of band 80. In order to show the effectiveness of noise-robust SD-ICA/BSS, it will be compared with standard ICA/BSS. The ICA/BSS algorithms applied here are ICA and CNMF [4]. The performance of unmixing is evaluated by the root mean square error (RMSE) [2], which is used to evaluate the similarity of true endmemeber abundances $\hat{A}$ versus the estimated abundances A.

In the experiments, the spectral signal of each pixel is decomposed into the two-level WP tree, i.e., there are six tree nodes (subbands), A1 (low-pass) and D1 (high-pass) in the first level, and AA2, AD2 (decomposed from A1), DA2, DD2 (decomposed from D1) in the second level. Table 1 gives some experimental results. AA2 and D1 are the selected subbands by Q and I respectively. It can be found that the performance of hyperspectral uxmixing with AA2 sub-components are better as a whole than that with D1 or with the raw spectral signals, which demonstrates Q is a suitable criterion for subband selection. Fig.1(b-e) shows the separated abundances of each endmember by CNMF with AA2 subband.



(a) Band 80 of HYDICE

(b) Alphalt

(c) Roof

(d) Grass

(e) Tree

Fig. 1. (a) Original image. (b-e) Endmember abundances produced by CNMF with AA1 subband.

5. REFERENCES

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