BAND CLUSTERING AND SELECTION AND DECISION FUSION FOR TARGET DETECTION IN HYPERSPECTRAL IMAGERY

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ABSTRACT

A band clustering and selection approach based on a hyperspectral measure, spectral information divergence (SID) is presented in this paper. Hyperspectral image data is analyzed for target detection. Hyperspectral image data and spectral signatures of the targets are used to measure the SID. Virtual dimensionality (VD) is used to select optimal number of bands. For endmember extraction, vertex component analysis (VCA) is used. For decision fusion a new approach based on spectral discriminatory entropy (SDE) is proposed. A comparative study is conducted to show the effectiveness of new approach of band clustering and selection. Decision fusion is also compared with full band and individual SID detection schemes.

Index Terms— Hyperspectral image, remote sensing, band clustering, bands selection, decision fusion, endmember detection

1. INTRODUCTION

Hyperspectral remote sensors collect image data simultaneously in dozens or hundreds of narrow, adjacent spectral bands. These measurements make it possible to derive a continuous spectrum for each image cell. Hyperspectral data enables the analyst to detect more materials, objects and regions with more accuracy than previously possible. Where more information is carried by hundreds of bands of hyperspectral image data, there is a challenge of redundancy for analysis of hyperspectral image data. There is likely to be redundant among bands. Some bands may contain less discriminatory information than others. Dimension reduction is one way to overcome these problems. Methods of dimensionality reduction can be divided into two categories, feature extraction (based on transformation) [1] and band or feature selection. In hyperspectral imaging, feature or band selection is preferable to feature extraction for dimensionality reduction because of two main reasons [2]. First, feature extraction needs the whole (or most) of the original data representation to extract new features, forcing to obtain and deal with the whole initial representation of the data. Secondly, when dealing with physical measures that are represented in the hyperspectral image domain, critical information may have been compromised and distorted because the data are transformed. Band selection has the advantage of preserving the relevant original information from the data [3]. In the past, many band selection techniques have been proposed [4, 5]. These methods can be roughly categorized into four groups [3], Search-based Methods [5, 4], Transform-based Methods [6], ICA-based Band Selection [7], and Information-based Methods [5, 3].

A hyperspectral pixel is generally a mixture of different materials present in the pixel with various abundance fractions. These materials absorb or reflect within each spectral band. As a consequence, spectral characterization becomes crucial in hyperspectral image analysis. However, because of atmospheric effects, the spectral information of a pixel varies during data acquisition. We use an information-theoretic spectral measure, SID, to account for spectral similarity for band clustering. Bands are clustered using SID of data and target signatures. Hierarchical structure is used for clustering by using two linkage strategies, nearest neighbor (also called single link) and average. Finally once the bands are clustered, there is a need of some criteria for selection of band from each cluster. For this, we pick the bands having maximum SID from each cluster. A new concept of virtual dimensionality (VD) [8] is used for the estimation of minimum number of bands for preserving maximum information. For each technique vector component analysis (VCA) [9] is used for unmixing of the hyperspectral image.

Materials do not have maximum discriminatory probability within same bands therefore a single band clustering and selection technique is not effective for multiple targets. To over come this problem multiple techniques are used for band clustering and selection. For each technique same method is used for endmember extraction. Finally the decision fusion criteria is defined using spectral discriminatory entropy

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(SDE) [10, 11].

The organization of the paper is as follows. Section 2 develops new approach for clustering based band-selection. Section 3 describes the decision fusion technique. Experimental results are given in section 4. We conclude the paper in last section 5.

2. BAND CLUSTERING AND SELECTION BASED ON SID

Each band image of hyperspectral image contains valuable spectral information that can be used to account for pixel variability and similarity. Spectral Information Divergence (SID) [10, 11] is a measure of the similarity between two random vectors (band images). It measures the probabilistic discrepancy between two corresponding spectral signatures. The purpose of clustering is to group the band images such that the intracluster SID variance is minimum and intercluster SID variance is maximum. Let $\{X_k\}_{l=1}^{L}$ be all band images in hyperspectral image cube and *L* is the total number of bands. Assume that *p(X)* and *q(Y)* are the probability mass functions of band image vectors *X* and *Y*. *N* is the size of each band image vector. Then SID is defined as:

$$SID(X,Y) = \sum_{i=1}^{N} p(x_i) log \frac{p(x_i)}{q(y_i)} + \sum_{i=1}^{N} q(y_i) log \frac{q(y_i)}{p(x_i)} \quad (1)$$

Where $\sum_{i=1}^{N} p(x_i) log(\frac{p(x_i)}{q(y_i)})$ is the *relative entropy* or *Kullback Leibler distance* between *p(X)* and *q(Y)*. From above a similarity vector $\mathbf{Y} = \{y_i\}_{i=1}^{L(L-1)/2}$ of length $L(L-1)/2$ is obtained. Based on similarity measures, the linkage is created among the $L(L-1)/2$ elements of $\mathbf{Y}$ for creating the hierarchical structure. For hierarchical clustering tree, the following methods are used:

- **Average linkage** uses the average distance between all pairs of objects in any two clusters, defined as

$$d(i,j) = \frac{1}{n_i n_j} \sum_{r=1}^{n_i} \sum_{s=1}^{n_s} |x_{ir} - x_{js}| \quad (2)$$

  Where n_i and n_j is the number of objects in ith and jth clusters.

- **Single linkage** or **nearest neighbor**, uses the smallest distance between objects in the two clusters, defined as

$$d(i,j) = min(|x_{ik}, x_{jk}|) \quad (3)$$

  Where $i\epsilon\{12, ...n_i\}, j\epsilon\{1, 2, ...n_i\}$

Using the above similarity measurement methods and hierarchical clustering tree methods we get following two ways to cluster the bands. Hierarchical tree is constructed with average linkage and nearest neighbor by using SID of hyperspectral image for similarity measure. They are termed as SIDDA and SIDDS respectively. We also construct hierarchical tree using SID of target signatures for similarity measure. They are termed as SIDSA and SIDSS respectively.

In the following, we propose an algorithm for clustering band selection.

1. Calculate VD (number of bands);
2. Calculate SID for each band image ;
3. Group the band images into a binary hierarchical cluster tree using distances among each SID values to determine the proximity of band images to each other;
4. Prune branches off the bottom of the hierarchical tree according to the value of VD and assign all the objects below each cut to a single cluster;
5. Pick one band having maximum SID from each cluster.

3. DECISION FUSION

Materials do not have maximum discriminatory probability within the same band, therefore a single band clustering and selection technique is not effective for multiple targets. To over come this problem multiple techniques are used for band clustering and selection and for each technique same method is used for endmember extraction. Assume $\mathbf{S} = \{\mathbf{s}_i; i = 1, 2, \dots K\}$ is spectral library of K spectral signatures. If *t* is the target and $m(s_i, s_j)$ is the spectral measure (SID) among signatures s_i and s_j, power of a band selection technique is define as

$$RSDP_m(\mathbf{s}_i, \mathbf{s}_j; \mathbf{t}) = max\{\frac{m(\mathbf{s}_i, \mathbf{t}) m(\mathbf{s}_j, \mathbf{t})}{m(\mathbf{s}_j, t) m(\mathbf{s}_i, \mathbf{t})}\} \quad (4)$$

If for a target *t*, the SDE of a band selection technique is low then there is a better chance to identify the target. SDE is

$$SDE_m(\mathbf{S}; \mathbf{t}) = -\sum_{k=1}^{K} p_{S,t}^{m}(k) \log p_{s,t}^{m}(k) \quad (5)$$

where $p_{S,t}^{m}$ is the discriminatory probability mass function of signatures $\mathbf{S}$ with respect to target t.

$$p_{\mathbf{S},\mathbf{t}}^{m}(i) = \frac{m(\mathbf{s_i}, \mathbf{t})}{\sum_{i=1}^{K} m(\mathbf{s_i}, \mathbf{t})}, \text{ for } i = 1, 2, \dots K \quad (6)$$

Decision fusion is conducted on the basis of maximum value SDE_m of the band selection technique. The algorithm steps for decision fusion are described below

1. Get the selected bands of each band clustering and selection technique;
2. Compute SDE_m of each band clustering and selection technique for each target and select the technique with maximum SDE_m for each target;

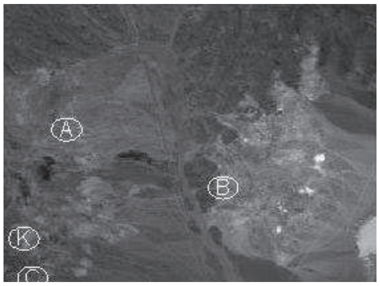


Fig. 1. Ground Truth of spatial positions of four pure pixels corresponding to following minerals: Alunite (A), Buddingtonite (B), Calcite (C), and Kaolinite

Table 1. Selected bands using different techniques

Criteria	Selected bands
SIDDA	26, 20,183, 186, 4, 6,176, 168, 33, 40, 14, 10, 67, 148, 1, 2,180, 135, 16,187, 188, 189
SIDDS	181, 182, 15, 6, 138, 176, 16, 180, 17, 18, 4, 183, 136, 184, 185, 2, 3, 186, 1, 188, 187,189
SIDSA	146, 7, 1, 2, 175, 174, 177, 177, 183, 181, 139, 14, 151, 101, 135, 161, 152, 173, 159, 160, 189,163
SIDSS	158, 154, 160, 152, 151, 168, 163, 2, 174, 173, 177, 177, 1, 162, 161, 176, 175, 153, 159, 181, 183, 189

3. Get results of VCA for each band clustering and selection technique;

4. Send output of the technique whose SDE_m is maximum for a particular target.

5. Pick one band having maximum SID from each cluster.

4. EXPERIMENTAL RESULTS

For a comparative study of proposed algorithm, a well-known Airborne Visible and InfraRed Imaging Spectrometer (AVIRIS) Cuprite image scene is used as shown in Fig. 1. It is available online [12] and was collected by 224 spectral bands with 10-nm spectral resolution over the Cuprite mining site, Nevada, in 1997. The selected image scene for experiments shown in Fig. 1 has a size of 350×350 pixels and is well understood mineralogically. Water absorption and low SNR bands 1-3, 105-115, and 150-170 have been removed prior to the analysis. The ground truth also provides the spatial locations of the four minerals Alunite (A), Buddingtonite (B), Calcite (C), and Kaolinite (K) which are encircled and labeled 'A', 'B', 'C' and 'K' respectively. These minerals can be used to verify endmembers extracted by an endmember extraction algorithm VCA. US Geological Survey (USGS) signatures of these four minerals are also shown in Fig. 2. The number of bands required to preserve maximum information, estimated by VD (with false alarm probability $P_f = 10^{-4}$), is 22.

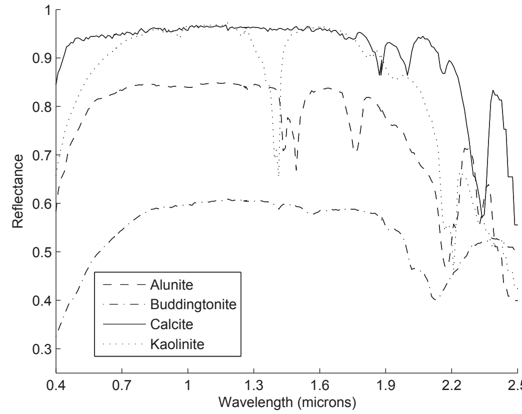
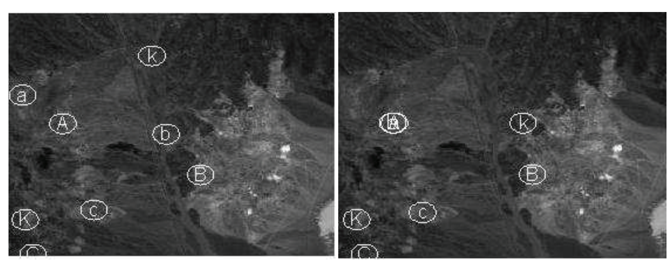


Fig. 2. USGS spectral signatures of Alunite (A), Buddingtonite (B), Calcite (C), and Kaolinite (K)

Fig. 3 shows the four endmembers extracted by VCA using full bands and data fusion of multiple band clustering and selection techniques using the bands tabulated in Table 1. The extracted endmembers are labeled 'a', 'b', 'c', 'k'. For comparison, ground truth endmember pixels are labeled as 'A', 'B', 'C', 'K'. Further more to get more details and to measure the spectral similarity among detected endmember pixels and the ground truth endmember minerals, spectral angle mapper (SAM) results are tabulated in Table 2. In Table 2 the coordinates included in the brackets for both 'a', 'b', 'c', 'k' and 'A', 'B', 'C', 'K' indicate the locations in the image scene. Results shows that the performance of proposed clustering-based band selection technique is better than full bands. All the endmember pixels are detected very well and have better spectral similarity values. Further more among our four submethods, the best one is SIDSA. Data fusion gives optimal detection as compared to any individual submethod.



(a) (b)

Fig. 3. Four endmember extracted by VCA using (a) Full Bands and (b) Decision Fusion

Table 2. Spectral similarity measurements (SAM) among found endmembers and the ground truth endmembers

	A (161,61)	B (234, 209)	C (298,22)	K (298, 22)
Full Band				
a (19,120)	0.0987	0.0973	0.1504	0.1300
b (172,176)	0.2022	0.0828	0.0468	0.2142
c (95,284)	0.1986	0.0868	0.0332	0.2033
k (157,64)	0.1043	0.1734	0.2165	0.0899
SIDDA				
a (304,23)	0.0398	0.1588	0.2070	0.0847
b (161,60)	0.1324	0.0562	0.0838	0.1475
c (232,126)	0.2301	0.1047	0.0599	0.2475
k (161,199)	0.1040	0.1787	0.2215	0.0348
SIDDS				
a (146,18)	0.0823	0.2147	0.2578	0.1136
b (292,174)	0.1913	0.0690	0.0632	0.1942
c (226,1456)	0.2051	0.0783	0.0590	0.2065
k (113,267)	0.0798	0.1527	0.1878	0.0402
SIDSA				
a (161,62)	0.0000	0.1576	0.2038	0.0961
b (146,18)	0.1412	0.0583	0.0827	0.1541
c (288,92)	0.1913	0.0690	0.0632	0.1942
k (226,145)	0.0798	0.1527	0.1878	0.0402
SIDSS				
a (18,124)	0.0674	0.1137	0.1653	0.0999
b (149,16)	0.1412	0.0583	0.0827	0.1541
c (288,92)	0.2124	0.0923	0.0320	0.2180
k (238,74)	0.0938	0.1379	0.1693	0.0472
Decision Fusion				
a (161,62)	0.0000	0.1576	0.2038	0.0961
b (161,60)	0.1324	0.0562	0.0838	0.1475
c (288,92)	0.2124	0.0923	0.0320	0.2180
k (161,199)	0.1040	0.1787	0.2215	0.0348

5. CONCLUSION

Experiments conducted with AVIRIS data set reveal that SIDSA is a better technique of dimension reduction of hyperspectral data for unmixing as well as for detection. SIDSA clusters the bands in such a way to keep intra-cluster SID variance minimum and inter-cluster SID variance maximum. It takes only seconds ,not hours, for band clustering and selection. Our proposed data fusion scheme based on SDE is indeed a promising target detection technique. Its performance is better than all individual target detection schemes.

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