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Article

Local Prototype Space-based Band Selection for Hyperspectral Subpixel Analysis

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Summary: In this paper, two unsupervised local band selection (BS) methods in the prototype space (PS) for improving subpixel analysis performance are proposed. Here, the PS is a two dimensional space which is constituted of the target spectrum and that of the local background. The proposed methods benefit from local background characterization through image clustering. These BS methods select the discriminative bands in two ways: 1) selecting the bands which form a convex hull in the PS, and 2) using a cluster-based approach in the PS to select bands. An experiment applied to real-world hyperspectral data showed that the proposed BS methods improve the performance of constrained energy minimization (CEM) and adaptive matched filter (AMF) subpixel detection methods in terms of the number of false alarms.

Zusammenfassung: *Verbesserung der Subpixelanalyse von Hyperspektraldaten durch Verwendung des so genannten „Prototyp-Raumes“.* Mit dem Ziel einer verbesserten Subpixel-Analyse werden in diesem Artikel zwei unüberwachte Methoden zur Auswahl spektraler Bänder im so genannten „Prototype-Raum“ (PS) untersucht. In dieser Studie ist der PS ein zweidimensionaler Raum, der aus den Signalen des Targets sowie des lokalen Hintergrunds aufgebaut ist. Dabei erweist sich die Ableitung des lokalen Hintergrunds mittels Clusteranalyse als geeignet. Zwei Methoden werden vorgeschlagen, die geeigneten Bänder abzuleiten: 1) Auswahl der Bänder, die im PS das Gerüst der konvexen Hülle bilden, und 2) Auswahl der Bänder aus den Ergebnissen einer Clusteranalyse im PS. Die Anwendung anhand eines Hyperspektraldatensatzes zeigt, dass die beiden vorgeschlagenen Methoden zur Auswahl spektraler Bänder die Ergebnisse der Constrained Energy Minimization (CEM) und des Adaptive Matched Filter (AMF), zweier Detektionsmethoden von Targets auf Subpixelebene, hinsichtlich ihrer Falsch-Positiv-Rate verbessern.

1 Introduction

Algorithms used in hyperspectral applications can be divided into four categories (Manolakis et al. 2001): target/anomaly detection, change detection, classification, and spectral unmixing. Very high spectral resolution of hyperspectral data increases discrimination between materials with similar spectral responses (Melgani & Bruzzone 2004). There are, however, several challenges in hyperspectral data analysis including the curse of dimensionality. Therefore, automatic analysis of hyperspectral data is not a trivial task (Melgani & Bruzzone 2004). One possible way to mitigate these problems is dimension reduction of the hyperspectral data. Dimension reduction methods can be grouped into two main categories: 1) feature selection, i.e. band selection, and 2) feature extraction. The former identifies a subset of the original bands without affecting their physical meanings, whereas in the latter case each feature is a combination of the original data (Kaewpijit et al. 2003). In target detection applications maintaining the physical meaning of the bands is mandatory.

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Therefore, in this paper, we focus on band selection (BS) methods. Because spectral signatures of targets are affected by the materials in their neighbourhood rather than by the globally extracted endmembers (Matteoli et al. 2009), the proposed methods aim at applying BS in a local background. We refer the interested reader to Jain & Zongker (1997), Bruzzone & Serpico (2000), Mitra et al. (2002), and Chang & Wang (2006) for more details on BS methods.

In this paper, we present two unsupervised local BS methods to improve target detection performance. To this end, we first project the data into the prototype space (PS) (Mojaradi et al. 2009). To select informative bands in the PS, two solutions are proposed: 1) choosing the bands which form a convex hull, and 2) choosing the bands by band clustering in the PS. After dimension reduction, the constrained energy minimization (CEM) (Harsanyi 1993), adaptive cosine/coherent estimate (ACE) (Kraut et al. 2005) and adaptive matched filter (AMF) (Robey et al. 1992) target detectors are used. The ultimate goal of the proposed BS methods is improving target/background discrimination via minimizing the redundancy in the hyperspectral image (HSI) data. Experiments were conducted on a hyperspectral image acquired by the HyMap sensor and the results confirmed the validity of the proposed methods. This paper is outlined as follows. The proposed methods are described in section 2. Dataset description and final results are discussed in section 3. In section 4, we present the conclusions and final remarks.

2 PS-based Band Selection

Conventional target detectors, e.g. CEM, ACE, and AMF, characterize the background globally in full dimension, i.e. using all bands. However, by using the proposed BS algorithms, target detection methods can be applied locally to data with reduced dimension. In fact, the idea behind these algorithms is that for a given target and a local background, a set of bands can be selected. The main processing steps of the proposed methods are shown in Fig. 1 and described in the following subsections.

2.1 *Pre-Processing*

1) *Image partitioning*: The image is partitioned into eight equal sub-images (Fig. 1a). The justification for partitioning the image is due to two operational considerations: (1) to avoid memory shortage in the processing systems, and (2) to make the implementation of the proposed methods in parallel processing systems feasible.
2) *Data clustering in each partition*: The proposed methods are applied locally. Each image partition is made up of several endmembers. So, each partition is clustered using the fuzzy c-means (FCM) method (Bezdek et al. 1984) (Fig. 1b). The number of clusters in each partition is determined by the signal subspace dimension using the HySime method (Bioucas-Dias & Nascimento 2008).
3) *PS formation*: In this paper, we propose the use of the PS for band representation. Each point in the PS corresponds to one band in the spectral space. Moreover, target detection is a binary hypothesis testing problem in which we choose between two possible cases: (1) target is present, or (2) target is absent, i.e. the pixel under test is considered as background. Therefore, the dimension of the PS can be set to two. Target spectrum forms the first dimension of the PS. To represent the second dimension of the PS, i.e. background, the mean spectrum of each cluster in a given image partition is used (Fig. 1c). In sum, the PS can be formed using the spectra of target and background (Fig. 1d).

To illustrate the idea behind PS, assume that the spectral signatures of target and background are shown as column vectors t and m, respectively. To form the PS, we use the concatenation of t and m which is expressed as E.

$$E = \left[\boldsymbol{t}\ \boldsymbol{m}\right]^{\mathrm{T}} = \begin{bmatrix} t_1 & \dots & t_l \\ m_1 & \dots & m_l \end{bmatrix}, \qquad (1)$$

where l is the number of bands. Each column of E corresponds to one point in the PS.

Since we follow a partition-based approach for BS, the PS is formed for each cluster in a given partition. For instance, if a partition is made up of five clusters, then five separate PSs for each target will be formed.

2.2 *Band Selection*

Two BS methods in the PS are proposed: 1) convex-based method, and 2) cluster-based method (Fig. 1e).

1) *Convex-based BS*: "A set S is convex if for every pair of points p, $q \in S$, the line segment pq is contained in S" (LATECKI et al. 1995), and the smallest convex set containing S is called a convex hull. Inspired by this definition, we select discriminative bands in the PS, which are the points forming the convex hull. In the convex-based BS, non-boundary points of the convex region in the PS, i.e. bands inside the convex hull, can be considered as combinations of the points which form the convex hull. We refer the interested reader to ANDREW (1979) for a more detailed introduction to convex hulls in two dimensions.

2) *Cluster-based BS*: In this method, the bands in the PS are clustered by the FCM method. Having clustered the bands, the band with the shortest Euclidean distance to the cluster centroid is chosen as the representative of that band cluster. The issue that needs to be addressed is the number of band clusters. To estimate the number of band clusters, a cluster validity index (CVI) is used. CVIs estimate the number of clusters by comparing the clustering performance for different number of clusters. To estimate the number of band clusters in the PS, the Calinski-Harabasz (CH) index (CALIŃSKI & HARABASZ 1974) is employed. The CH index can be written as

$$CH = \frac{B}{W}\frac{(n-k)}{(k-1)}, \tag{2}$$

where B and W are the between-cluster and within-cluster sum of squares, respectively, n is the number of points, and k is the number of clusters (CALIŃSKI & HARABASZ 1974). Maximum value of the CH index determines the optimal number of clusters. In other words, one possible approach

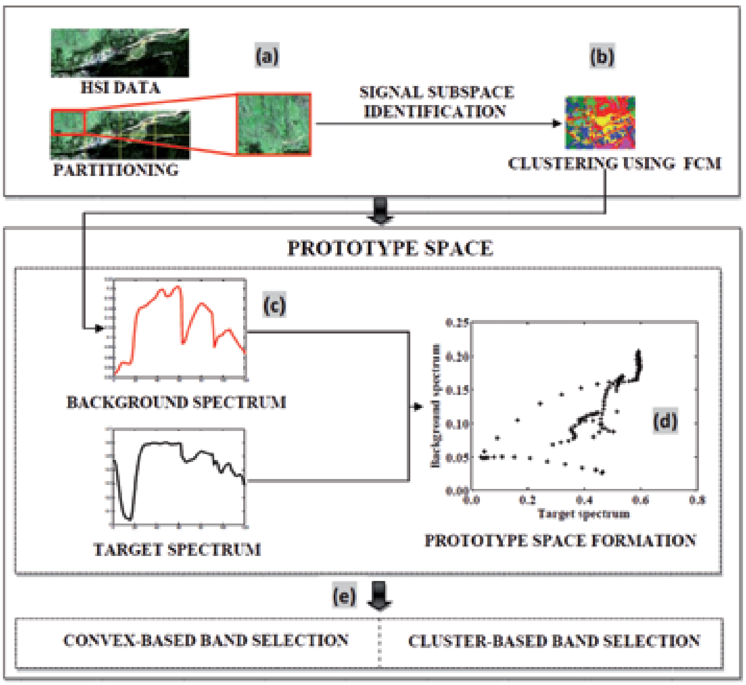

Fig. 1: Block diagram of the proposed local band selection approaches in the PS: (a) image partitioning, (b) data clustering, (c) determining the background spectra, (d) prototype space formation, and (e) band selection.
Note: only one instance of the background spectra, target spectra, and PS are shown here.

to determine the number of band clusters (k) is to find a k, $1 > k \leq M$, with the largest CH value. For our experiment, the upper bound (M) was set equal to the estimated signal subspace dimension in each image partition. It is also noteworthy that the CH index is used when the number of bands is not pre-determined. The cluster-based BS method can also be straightforwardly used for application with pre-determined number of bands by simply skipping the application of the CH index.

The ultimate goal of the proposed BS methods is to characterize a local background which guarantees discrimination of all targets from their surroundings. So, the union of the selected bands for all targets in each cluster is taken as the final set of bands for that cluster. The merit of the proposed BS methods is their unsupervised nature, i.e. they do not need any prior knowledge except the target spectrum.

3 Experimental Results

3.1 *Dataset Description*

To test the proposed BS methods, a HyMap reflectance data of Cooke City, MT, USA acquired in 2006 with the spatial resolution of 3 metres is used (Snyder et al. 2008). The image size is 280 pixels × 800 pixels and the number of bands in the original dataset is 126 (before pre-processing) covering the 0.45 µm – 2.5 µm region with 15 nm – 20 nm-wide bands. It should be noted that in this study noisy bands were removed from the original data. Several fabric panels, i.e. targets, were placed in the study area during data acquisition (see Fig. 2). Target characteristics are reported in Tab. 1. As can be seen, the size of some of these fabric panels is less than the spatial resolution of the data. The dataset also includes the spectral library of the target panels in the study area.

3.2 *Band Selection*

As an illustration of BS in the PS, selected bands for target F3 (1 m × 1 m) are shown in Fig. 3 (these bands correspond to one of the image clusters). The spectrum of the pixel containing target F3 (1 m × 1 m) as well as the mean spectrum of its eight neighbouring pixels are shown in Fig. 4. As can be seen, the high degree of similarity between the spectrum of the pixel containing target F3 and that of the neighbouring pixels can hamper robust detection, so selecting optimal bands is of vital importance.

Fig. 2: True colour representation of the HyMap dataset. The red box represents the target area.

Tab. 1: Target characteristics in the HyMap image.

Target name	Fabric	Number of fabric panels	Size
F1	Red cotton	1	3 m × 3 m
F2	Yellow nylon	1	3 m × 3 m
F3	Blue cotton	2	2 m × 2 m, 1 m × 1 m
F4	Red nylon	2	2 m × 2 m, 1 m × 1 m

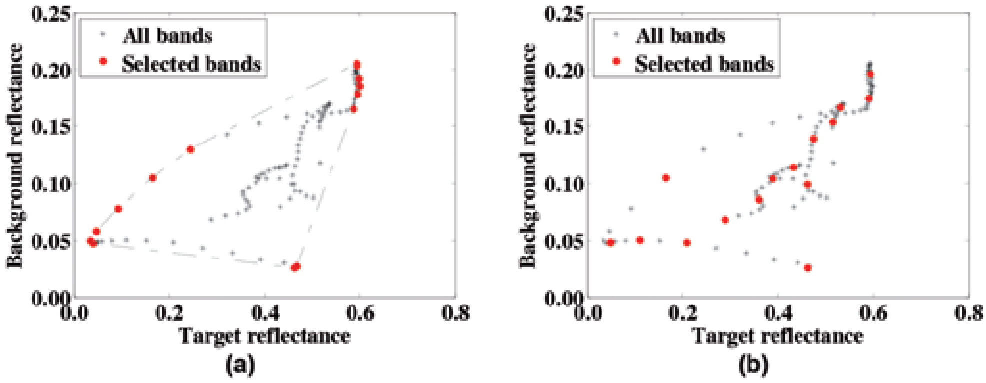

Fig. 3: An illustration of the selected bands in the PS: (a) convex-based band selection, and (b) cluster-based band selection. Red dots show the selected bands.

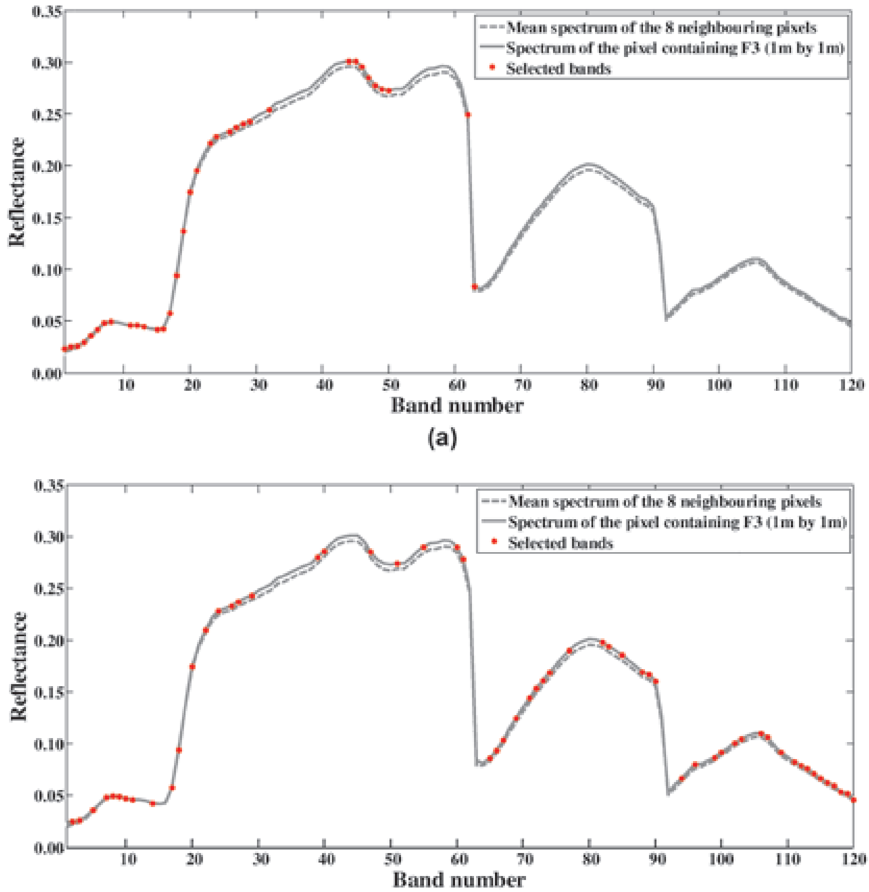

Fig. 4: Representing selected bands in the spectral space: (a) convex-based band selection, and (b) cluster-based band selection. Red dots show the selected bands.

The results from the convex-based method (Fig. 4a) show that all 34 selected bands fall within the bands 1 to 63 even though there are bands in other regions of the spectrum which may support more target/background separation. To alleviate this problem, a cluster analysis of the bands in the PS is applied and correlated bands are represented by clusters in the PS. Having clustered the bands by FCM, a band with minimum Euclidean distance to each cluster centre is selected. In FCM, the number of iterations and the weighting exponent are set to 100 and 2, respectively. In total, 58 bands are selected (see Fig. 4b). Distribution of the selected bands in the spectral space indicates that unlike the convex-based method, the cluster-based method finds a set of bands which maximize the overall discrimination between the target and background in all regions of the spectrum and thus the physical structure of the spectrum is preserved. The run time of the convex-based method and the cluster-based method on an Intel Core2 Duo 2.53 GHz processor with 4 GB of RAM is 9 and 172 seconds, respectively. This indicates high computational cost of the cluter-based method.

3.3 *Detection Evaluation*

To investigate the impact of the proposed BS methods on target detection performance, the CEM, ACE, and AMF algorithms are employed. These algorithms are developed for the case that the only available knowledge is the signature of the targets.

The performance of target detectors can be evaluated using the receiver operating characteristic (ROC) curve. The number of target pixels in the dataset used in this study is limited; therefore, results obtained from the ROC curve are not reliable. Consequently, to evaluate the detection performance, we use the approach proposed by Matteoli et al. (2011), which counts the number of false alarms (#FAs) for each target. Target detection results obtained from the CEM, ACE, and AMF detectors using the proposed BS methods and without BS, i.e. full dimension, are reported in Tab. 2. In this table, the #FAs for three scenarios are given: 1) no dimension reduction, i.e. using all bands, 2) using the convex-based method, and 3) using the cluster-based method. Due to random behaviour of the FCM algorithm at its first iteration, it may behave differently from run to run. Consequently, the median of 30 runs of the cluster-based method is presented here.

As is evident from Tab. 2, dimension reduction improves the detection performance of CEM and AMF detectors. In all experiments, the cluster-based method achieves lower or the same #FAs compared to the convex-based BS. This may be due to the fact that the cluster-based BS selects the discriminative bands in

Tab. 2: Detection results in terms of #FAs for CEM, ACE, and AMF methods (#FA = number of false alarms, CEM = constrained energy minimization, ACE = adaptive cosine / coherent estimate, AMF = adaptive matched filter).

Target	BS method	#FAs of each detection method		
		CEM	ACE	AMF
F1	Full dimension	14	0	13
	Convex-based	0	0	13
	Cluster-based	0	0	3
F2	Full dimension	0	0	0
	Convex-based	0	1	0
	Cluster-based	0	0	0
F3	Full dimension	29	0	100
	Convex-based	3	0	13
	Cluster-based	0	0	2
F4	Full dimension	20	0	20
	Convex-based	8	1	12
	Cluster-based	0	0	1

all regions of the spectrum. The cluster-based method shows the best performance by reducing the total #FAs from 63 to 0 for CEM, and 133 to 6 for AMF. It should be noted that the #FAs of the ACE detector is 0 without dimension reduction. Regarding the size of the targets, they can be divided into two groups: 1) easy targets, i.e. targets F1 and F2, and 2) difficult targets, i.e. targets F3 and F4. In case of easy targets, two BS methods yield perfect detection results with low #FAs. For difficult targets, higher #FAs is obtained, especially after applying the convex-based BS. In sum, by examining the obtained results we can conclude that: 1) the cluster-based method is more robust than the convex-based method and results in lower #FAs; however, its computational cost is higher, and 2) compared to the convex-based method, the cluster-based method identifies more discriminative bands.

4 Conclusion

In this paper, two local BS methods for improving detection performance were proposed. Conventional target detection algorithms have two main shortcomings: 1) they characterize the background globally, and 2) they use all bands of the HSI data. To resolve the first issue, the image was partitioned, and then each partition was clustered using FCM. These image clusters were used to characterize the background locally. To overcome the second shortcoming, two new BS methods in the PS were proposed. The first BS method forms a convex hull in the PS to select discriminative bands, whereas the second method clusters the bands in the PS to reduce the dimensionality of the data. Detection results revealed that both methods were able to select discriminative bands to improve the performance of CEM and AMF detection methods. In particular, the cluster-based method yielded the best detection results in terms of the number of false alarms.

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