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BAND REDUCTION FOR TARGET DETECTION IN HYPERSPECTRAL IMAGES

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ABSTRACT. Due to the high spectral resolution, hyperspectral images need large data storage and processing time. Indeed, its high dimensional structure requires high computational complexity, especially for target detection. In order to overcome these problems, band reduction methods have been proposed. In this paper, we compare PCA and SNR-based band reduction methods to improve target detection performance in hyperspectral images. Experimental results show that band reduction methods not only reduce processing time, but also increase accuracy rate.

1. INTRODUCTION

Hyperspectral imaging collects image data simultaneously in hundreds of narrow and adjacent spectral bands. Owing to narrow contiguous spectral bands, hyperspectral images have detailed information about scene. Because of having large quantity of spectral information, hyperspectral images are used in many applications including remote sensing, mineral identification, environmental studies, surveillance, object classification and target detection. Although high spectral information allows us to distinguish various types of materials in scene, it increases processing time on account of large data size. Furthermore, large number of spectral bands increases complexity. Since hyperspectral images contain highly correlated spectral bands, their unnecessary information is excessive. Thus, dimensionality reduction methods have been developed which reduce the number of bands without losing the information content and also segregate noise in the data [1]. Fig. 1 shows a flow diagram of the band reduction.

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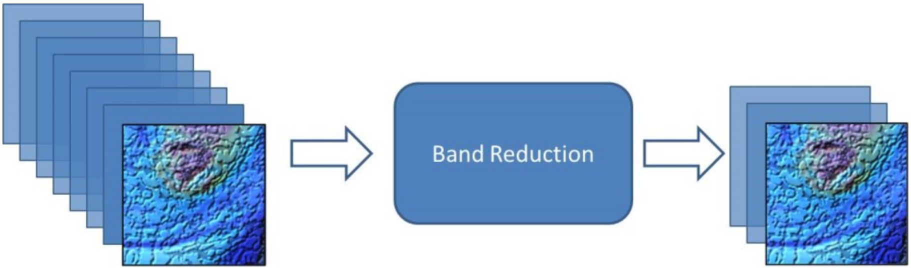


FIGURE 1. Band reduction flow diagram

Band reduction is an effective and necessary preprocessing phase for processing images in order to overcome problems caused by high size in hyperspectral images. Our aim is to obtain high accuracy percentage and low processing time with less data namely hyperspectral image band in target detection. Hyperspectral image is a three-dimensional data and consists of spectral bands each having a two-dimensional spatial image. Hyperspectral data cube used in the experimental studies is shown in Fig. 2.

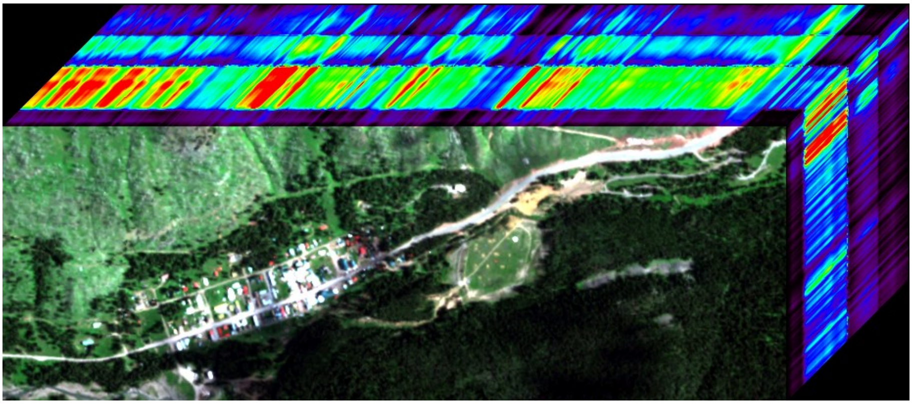
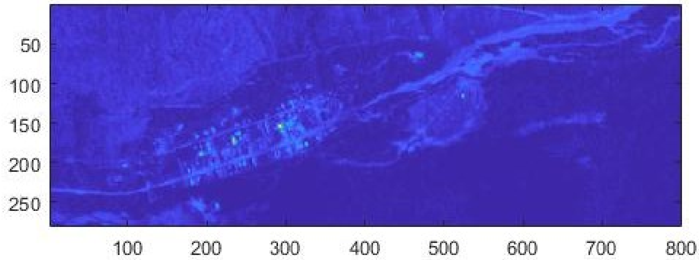
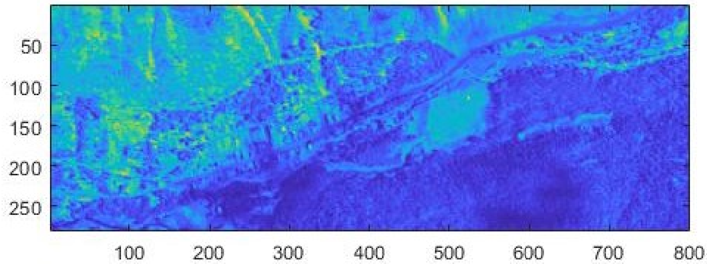


FIGURE 2. HyMap Hyperspectral Data Cube

Each band of hyperspectral image includes the responses of ground substances at a specific wavelength. Two spectral bands with different wavelengths of the hyperspectral image which is used in this study are shown in Fig. 3 [2].



(a)



(b)

FIGURE 3. Spectral band examples of hyperspectral image (a) 15^{th} band of hyperspectral image (b) 60^{th} band of hyperspectral image

In the next section, Principle Component Analysis (PCA) and Signal-to-Noise Ratio (SNR)-based band reduction techniques are discussed. Comparison of these techniques and effect on target detection are examined in section 3. In the last section, conclusion and discussion are given.

2. Band reduction approaches

There are several band reduction techniques for hyperspectral images each having different performance characteristics when combined with target detection methods. In this study, we consider two approaches, PCA and SNR-based band reduction methods, to increase target detection performance as well as to decrease processing time. In the following subsections PCA and SNR-based approaches are explained.

2.1. PCA Approach

In terms of remote sensing, PCA has been used in many areas. In this paper we use PCA for band reduction for target detection in hyperspectral images. The first small number of PCA bands generally include most of the information existing in hyperspectral image and therefore hyperspectral image bands and noise can be reduced effectively [3].

PCA utilizes the correlation which exists between neighboring spectral bands that generally contain the same information about the same object. PCA examines band dependence or correlation using statistical properties between the bands of hyperspectral image [4].

A hyperspectral image, which has *P* number of bands with *m* rows and *n* columns, namely B=mxn pixels, in each band, is defined as

$$\boldsymbol{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \dots, \boldsymbol{h}_B]^T \tag{1}$$

where $\boldsymbol{h}_i$ is a pixel vector of the hyperspectral image at spatial point *i* which is given as

$$\boldsymbol{h}_i = [h_1, h_2, h_3, \dots, h_P]_i^{\,T}, i = 1, \dots, B \tag{2}$$

where h_j, $\{j=1,\ldots,P\}$ are pixel values at each band. The mean vector of all pixel vectors is

$$\boldsymbol{\mu} = \frac{1}{B}\sum_{i=1}^{B}[h_1, h_2, h_3, \dots, h_P]_i^T. \tag{3}$$

Covariance matrix is calculated as

$$\boldsymbol{C_H} = \frac{1}{B}\sum_{i=1}^{B}(\boldsymbol{h}_i - \boldsymbol{\mu})(\boldsymbol{h}_i - \boldsymbol{\mu})^T. \tag{4}$$

PCA is based on eigenvalue decomposition of covariance. Covariance matrix can be written as

$$\boldsymbol{C_H} = \boldsymbol{ADA}^T \tag{5}$$

where $\boldsymbol{D} = \mathrm{diag}(\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_P)$ is the diagonal eigenvalue matrix where λ_j, $\{j=1,\ldots,P\}$ are eigenvalues and $\boldsymbol{A} = (\boldsymbol{a}_1, \boldsymbol{a}_2, \boldsymbol{a}_3, \dots, \boldsymbol{a}_P)$ is orthonormal eigenvector matrix with orthonormal vectors $\boldsymbol{a}_j$, $\{j=1,\ldots,P\}$. Each PCA pixel vector after the transformation can be calculated as follows [5]:

$$\boldsymbol{y}_i = \boldsymbol{A}^T \boldsymbol{h}_i, \quad i = 1,2,\ldots,B \tag{6}$$

Each of the transformed pixel vectors contains the compressed information of the entire data set. While first few PCA bands have the highest variance, last bands have the lowest variance. Therefore, the first PCA bands generally contain most of the information in the original hyperspectral images. Since PCA is used to reduce number of bands to be used, it enables more efficient and accurate analysis [2]. It also eliminates noise since last bands are mostly noisy.

2.2. SNR-based Band Reduction Method

Hyperspectral imaging is very useful for remote sensing, but hyperspectral data is characterized by narrow bands affected by low SNR [6]. In this paper, Minimum Noise Fraction (MNF) algorithm is used as SNR-based band reduction method.

MNF is used to determine the dimensionality of image data, isolate noise in the data, and reduce computational requirements for subsequent operations [7]. MNF is based on separation of noise from information content in the image. MNF mainly consists of two steps. The first step associates and re-scales the noise in the data based on an estimated noise covariance matrix. Then a standard PCA is applied to the noise-whitened data [8].

Assuming that hyperspectral image matrix $\boldsymbol{H}$ consists of the sum of signal and noise;

$$\boldsymbol{H} = \boldsymbol{S} + \boldsymbol{N} \tag{7}$$

where $\boldsymbol{S}$ and $\boldsymbol{N}$ are the uncorrelated signal and additive noise, respectively. Therefore, covariance matrices are referred by

$$\boldsymbol{C_H} = \boldsymbol{C_S} + \boldsymbol{C_N} \tag{8}$$

where $\boldsymbol{C_S}$ and $\boldsymbol{C_N}$ are noise and signal covariance matrices, respectively. MNF results in a new uncorrelated data set which is a linear transform of the original data $\boldsymbol{Y}$ which is given as

$$\boldsymbol{Y} = \boldsymbol{V}^T \boldsymbol{Z} \tag{9}$$

where $\boldsymbol{V}$ and $\boldsymbol{Z}$ are linear transformation matrix and zero-mean hyperspectral image, respectively. Row vectors in the zero-mean dataset $\boldsymbol{Z}$ are found by subtracting the row vectors of $\boldsymbol{H}$ from their means [9]. The first row vector of $\boldsymbol{Y}$ contains the signal components without noise. However, the other rows contain noisy signal components. In other words, as the number of lines increases, noisy signal components increase. SNR of each hyperspectral band can be written as

$$SNR_j = \frac{\boldsymbol{v}_j^T \boldsymbol{C_H} \boldsymbol{v}_j}{\boldsymbol{v}_j^T \boldsymbol{C_N} \boldsymbol{v}_j} - 1,\ j = 1, \dots, P \tag{10}$$

where $\boldsymbol{v}_j, j = \{1, \dots, P\}$ are orthonormal vectors of matrix $\boldsymbol{V}$.

3. Comparison of PCA and MNF band reduction methods with target detection algorithm

We use Adaptive Coherence Estimator (ACE) [10] target detection method alone and with PCA and then MNF to compare band reduction methods in terms of processing time and detection accuracy.

ACE is a target detection method that can be used in cases where background statistical parameters are not known. This method is derived from Generalized Likelihood Ratio (GLR) approach. Based on the assumption that the background covariance matrix is known, target detection criterion *D* is calculated for each $\boldsymbol{h}_i$ pixel vector as follows:

$$D(\boldsymbol{h}_i) = \frac{\left(\boldsymbol{g}^T \boldsymbol{C_H}^{-1} \boldsymbol{h}_i\right)^2}{(\boldsymbol{g}^T \boldsymbol{C_H}^{-1} \boldsymbol{g})(\boldsymbol{h}_i{}^T \boldsymbol{C_H}^{-1} \boldsymbol{h}_i)} \tag{11}$$

where $\boldsymbol{g}$ is the target spectrum. In equation (11), ACE algorithm estimates the detection statistics and obtains a separation between the target and the background.

For experimental studies, we use hyperspectral data set which was collected by HyMap sensor and supplied by Rochester Institute of Technology. Hyperspectral data set has 3-meter spatial resolution per pixel and 126 spectral bands. Also, data set includes spectral signature of red small carpet [2].

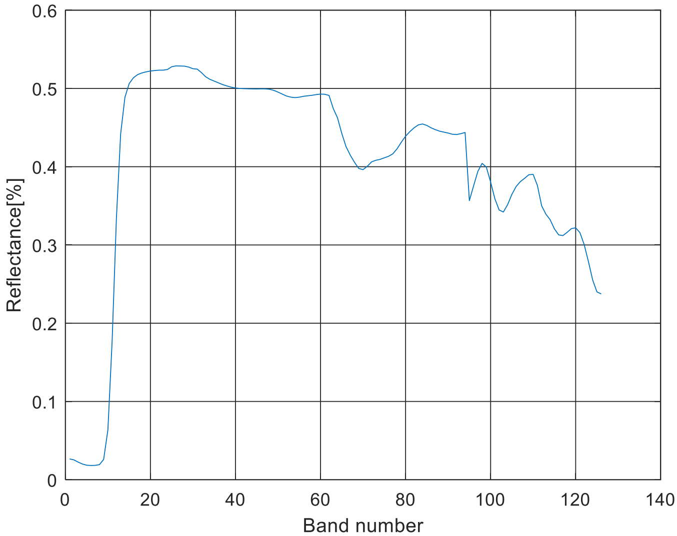
For the evaluation purpose, we use PCA in conjunction with ACE called PCA-ACE method and then MNF with ACE, named MNF-ACE method on hyperspectral data set with spectral signature of 3x3 meter red carpet.

Experimental tests are performed on a computer with the specifications of Intel Core i5 2450M 2.5 GHz processor and 4GB RAM. The higher the detection accuracy, the greater the detection performance is. The best detection result is given with detection accuracy of 1. Using band reduction improves detection performance.
The results for all methods are given in Tab. 1. As it can be seen in Tab. 1, accuracy and processing time are the best for ACE target detection algorithm with MNF band reduction method.

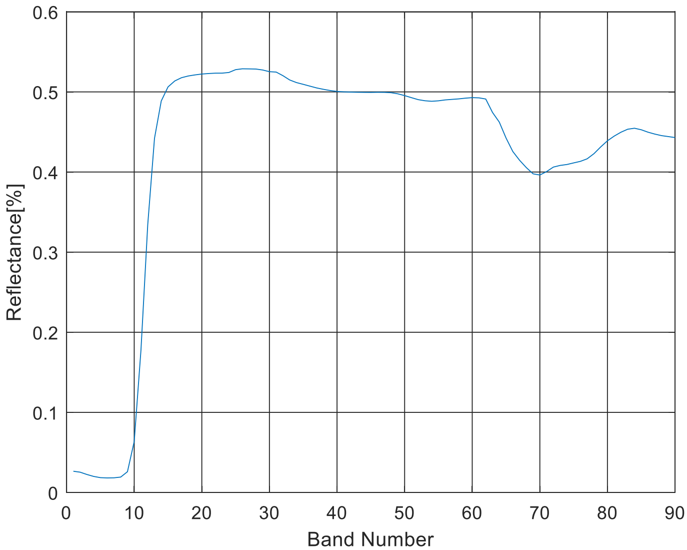
Table 1. Comparison of band reduction methods for effect on target detection algorithm in terms of processing time and detection accuracy.

Method	Processing Time (second)	Detection Accuracy
ACE	6.65	0.6892
PCA-ACE	2.55	0.6927
MNF-ACE	2.40	0.8164

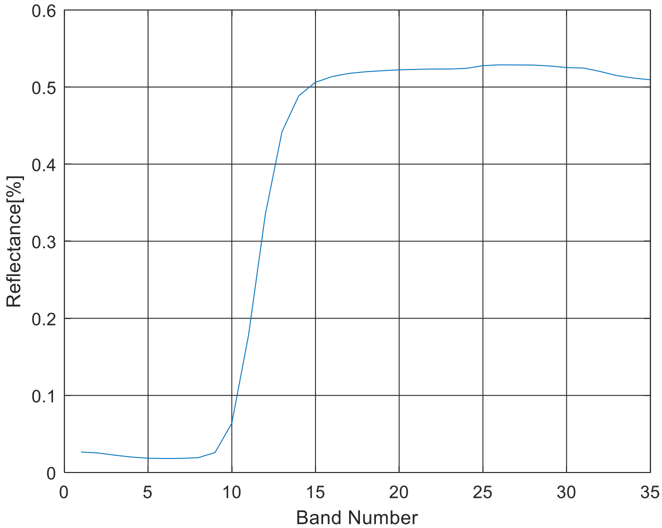
In order to demonstrate the effect of band reduction methods, PCA and MNF, target pixel spectrum and results of target detection are shown in Fig. 4. The spectrum in Fig. 4 (a) is the target signature, which is also detected by ACE without band reduction. In Fig. 4 (b), target spectrum which is detected by ACE with PCA band reduction method is shown. In this method resulting number of bands is 90. Other spectrum with 35 bands given in Fig. 4 (c) is detected by ACE with MNF band reduction method. MNF reduction results in the least number of bands used in target detection with the highest detection accuracy.


Reflectance[%]
Band number
0
0.1
0.2
0.3
0.4
0.5
0.6
0
20
40
60
80
100
120
140

(a)


Reflectance[%]
Band Number
0
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50
60
70
80
90

(b)



(c)

FIGURE 4. Comparison of detected target spectra (a) Original target signature which is detected by ACE without any band reduction application, (b) detected target spectrum by ACE with PCA band reduction, (c) detected target spectrum by ACE with MNF band reduction

4. CONCLUSION

In this study, a comparative framework was developed for band reduction approaches for target detection in hyperspectral images. We specifically investigated PCA and MNF band reduction algorithms when used with ACE algorithm for target detection in hyperspectral images. ACE alone gives the worst results in terms of processing time and detection accuracy when used without band reduction. Conversely, the results demonstrate that band reduction increases target detection performance since noisy bands are eliminated. Particularly, MNF band reduction algorithm with ACE leads to better detection accuracy and processing time than PCA with ACE. It is possible to extent future works with other target detection and band reduction methods, more targets with spectral signatures and hyperspectral images.

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