Neurocomputing 169 (2015) 5–12

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Hyperspectral target detection via exploiting spatial-spectral joint sparsity

Yanfeng Gu*, Yuting Wang, He Zheng, Yue Hu

School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin, China

ARTICLE INFO

Article history:
Received 31 March 2014
Received in revised form
17 July 2014
Accepted 29 September 2014
Available online 19 May 2015

Keywords:
Hyperspectral image
Sparse representation
Matched subspace detector (MSD)
Target detection
Sparse model

ABSTRACT

In this paper, we propose a new spatial-spectral joint sparsity algorithm for target detection in hyperspectral imagery (HSI). The proposed algorithm embeds the sparse representation (SR) into the conventional subspace target detector in hyperspectral images. This algorithm is based on such an idea that a pixel in HSI rely on a low-dimensional subspace and can be represented as a sparse linear combination of the training samples. Substituting SR for the conventional subspace method, a sparse matched subspace detector (SMSD) is developed. Moreover, 3D discrete wavelet transform (DWT) and independent component analysis (ICA) are exploited to extract the spatial and spectral distribution information in the hyperspectral imagery and capture the joint spatial-spectral sparsity structure. By integrating the structured sparsity and the SMSD, the proposed algorithm is able to carry out target detection task in the hyperspectral images. Experiments are conducted on real hyperspectral image data. The experimental results show that the proposed algorithm outperforms both the conventional matched subspace detector (MSD) and the state-of-the-arts sparse detection algorithm.

1. Introduction

HSI is a dense and uniformly sampled version of the continuous spectral response, The spectral feature is not only beneficial to classification of different materials [1–3], but also to target detection. This characteristic of high spectral resolution makes differentiation of various materials on the earth possible [4]. Thus, target detection is one of the important applications of HIS [5]. It can be viewed as a binary classification problem where pixels are labeled as target (target present) or background (target absent) based on their spectral characteristics [6]. The most common model assumes that the spectra are represented by unique spatially non-overlapping materials. This model is called the linear mixing model [7]. Many statistical hypothesis testing techniques [8] have been proposed for hyperspectral target detection [9]. Among these approaches, spectral matched filters [10], matched subspace detectors [11,12], and adaptive subspace detectors [13] have been widely used to detect targets of interests.

Recently, a novel signal classification technique via sparse representation (SR) has been proposed for face recognition [14]. And a target detection algorithm based on sparse representation for HSI has also been proposed [15]. The sparsity model is based on the concept that spectral signatures of pixels from the same class lie in a low-dimensional subspace [16] and thus can be represented as a sparse linear combination of few atoms from an overcomplete dictionary built using the target and background subspaces [17]. Several techniques have been used in the literature for global background-subspace estimation [18,19]. The sparse code can reveal the class information if pixels from different classes lie in different subspaces [20].

Neighboring hyperspectral pixels usually consist of similar materials and have similar spectral characteristics [21]. Therefore, some algorithms which exploit the spatial correlation between neighboring pixels have been proposed, such as Laplacian constraint and joint sparsity model [22]. Another method is the three-dimensional discrete wavelet transform (3D-DWT), which can decompose a hyperspectral data cube at different scales, frequencies, and orientations. And the geometrical and statistical spatial-spectral structures can be captured. However, this step may result in generating a large number of features or high-dimensional features [23]. Thus, feature reduction has to be done.

In this paper, we combine the idea of sparse representation and matched subspace detector (MSD) to develop a new target detection algorithm for hyperspectral imagery, so-called sparsity-based matched subspace detector (SMSD) where we use sparse representation to replace the noise in matched subspace detector. Considering the spatial-spectral structures, we exploit 3D-DWT and independent component analysis (ICA) to solve the high-dimensional problem. The proposed algorithm is compared with

* Corresponding author. Tel.: +86 451 86403020.
E-mail address: guyf77@gmail.com (Y. Gu).

http://dx.doi.org/10.1016/j.neucom.2014.09.101

the state-of-the-art algorithm. Experimental results show that our algorithm has a better detection performance.

The rest of this paper is organized as follows. In Section 2, the subspace-based detection scheme is introduced. In Section 3, the proposed detection method is presented in detail. Datasets and experimental results are shown in Section 4. Conclusions are drawn in Section 5.

2. Subspace-based detection

In this section, we briefly introduce previously developed subspace-based detection scheme, such as matched subspace detector (MSD) and recently developed sparsity based target detection approach.

2.1. Linear subspace detection model

In some target detection applications, the target pixel vectors can be represented as a linear combination of the target spectral subspace and background spectral subspace. Similarly, the background pixel vectors can be represented as a linear combination of the background spectral subspace, which can also be called a linear subspace mixing model. Target detection can be expressed as two competing hypotheses H_0 and H_1.

$$\begin{aligned} &H_0 : x = B\alpha_b + n \quad &\text{target absent} \\ &H_1 : x = T\alpha_t + B\alpha_b + n \quad &\text{target present} \end{aligned} \tag{1}$$

where T and B represent matrices whose columns span the target and background subspace, respectively. α_t and α_b are unknown vectors whose entries are coefficients that account for the abundances of the corresponding column vectors of T and B, respectively. n represents Gaussian random noise with distribution $N(0, \sigma^2 I)$. To analyze the noise, several noise-estimation techniques can be employed, such as the ones proposed in [24–26]. $[T\ B]$ is a concatenated matrix of T and B. If x is a target pixel, it can be represented by the hypothesis H_1. If x is a background pixel, it can be represented by the hypothesis H_0. We can identify the input signal by checking whether it contains target subspace signals, or not.

2.2. Matched subspace detector

Given the linear subspace detection model, as shown in (1), we can obtain

$$\begin{aligned} n_0 &= x - B\alpha_b = (I - P_B)x \\ n_1 &= x - T\alpha_t - B\alpha_b = (I - P_{TB})x \end{aligned} \tag{2}$$

where we project the input vector onto a subspace to provide the least-squares solution to the linear subspace model. P_B is a projection matrix associated with the background subspace $\langle B \rangle$. P_{TB} is a projection matrix associated with the target-and-background subspace $\langle TB \rangle$.

The GLRT (Generalized Likelihood Ratio Test) for the linear subspace detection model is

$$D_{\text{MSD}}(x) = \frac{x^T(I - P_B)x}{x^T(I - P_{TB})x} \underset{H_0}{\overset{H_1}{\gtrless}} \eta_{\text{MSD}} \tag{3}$$

for a given threshold η_{MSD}, if the output $D_{\text{MSD}}(x) > \eta_{\text{MSD}}$, then x will be labeled as target; otherwise, it will be labeled as background.

2.3. Sparsity model

Sparsity model is assumed that each pixel can be regarded as a combination of just few atoms from a large dictionary. Just like the linear subspace mixing model.

Given a hyperspectral pixel x, which is a P-dimensional vector, where P is the number of spectral bands. Let $A = [a_1, a_2, a_3, \ldots, a_K] \in R^{P \times K} (P \ll K)$ be an over-complete dictionary. The pixel x can be represented as follows:

$$x = \sum_{i=1}^{K} a_i \alpha_i + n \tag{4}$$

where $\{\alpha_i\}$ is the decomposition coefficient. n is the noise.

For hyperspectral target detection, we assumed that a pixel is either a target pixel or background pixel. When the pixel x is a

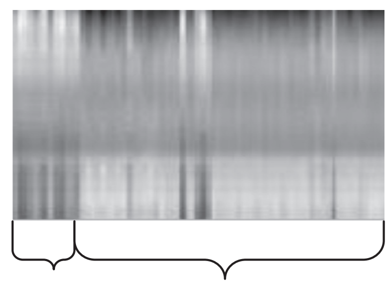

Fig. 2. Local structure dictionary.

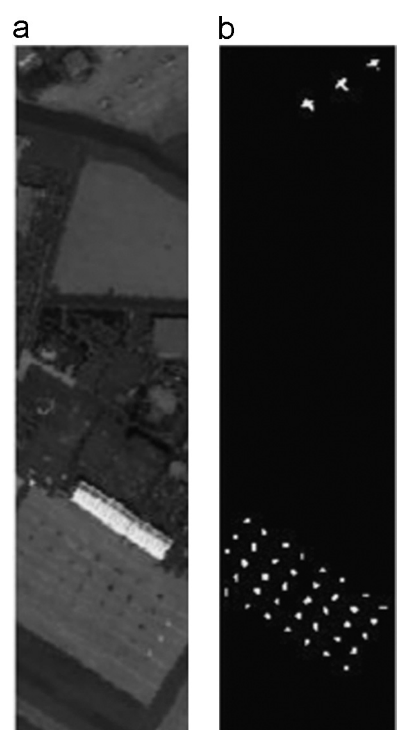

Fig. 1. Real HSI and corresponding distribution of targets from the scene of HIS. (a) The sixth band image. (b) Truth distribution.