Pattern Recognition Letters 32 (2011) 114–119

Contents lists available at ScienceDirect

Pattern Recognition Letters

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

Kernel-based regularized-angle spectral matching for target detection in hyperspectral imagery

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ARTICLE INFO

Article history:
Received 26 October 2009
Available online 8 October 2010
Communicated by A. Shokoufandeh

Keywords:
Hyperspectral imagery
Target detection
Spectral matched filter
Spectral angle mapper
Kernel methods

ABSTRACT

Target detection is one of the most important applications of hyperspectral imagery in the field of both civilian and military. In this letter, we firstly propose a new spectral matching method for target detection in hyperspectral imagery, which utilizes a pre-whitening procedure and defines a regularized spectral angle between the spectra of the test sample and the targets. The regularized spectral angle, which possesses explicit geometric sense in multidimensional spectral vector space, indicates a measure to make the target detection more effective. Furthermore Kernel realization of the Angle-Regularized Spectral Matching (KAR-SM, based on kernel mapping) improves detection even more. To demonstrate the detection performance of the proposed method and its kernel version, experiments are conducted on real hyperspectral images. The experimental tests show that the proposed detector outperforms the conventional spectral matched filter and its kernel version.

1. Introduction

Analysis of hyperspectral images has played an important role in many fields of remote sensing applications. Examples:

- Crop estimate in agriculture (Landgrebe, 2002; Bannari et al., 2006).
- Environment inspection (Andrew and Ustin, 2008).
- Soil resource reconnaissance (Lagacherie et al., 2008).
- Mine exploitation (Debba et al., 2006).
- Target detection in military (Manolakis et al., 2001; Manolakis and Shaw, 2002).

The most prominent characteristic of hyperspectral images, which makes hyperspectral remote sensing more attractive, is high spectral resolution. The hyperspectral images with high spectral resolution show a huge potential for the task of target detection and classification, being able to use fine spectral signature to discriminate and identify different materials or targets (Richards and Jia, 1999; Manolakis et al., 2001; Landgrebe, 2002; Manolakis and Shaw, 2002).

Target detection aims at searching the pixels of a hyperspectral data cube for "rare" pixels with known spectral signatures (Manolakis et al., 2001). For the past decades, a number of methods have been proposed to perform this important task, such as spectral angle mapper (SAM) (Richards and Jia, 1999), adaptive spectral matched filters (ASMF) (Robey et al., 1992), constrained energy minimization (CEM) (Harsanyi, 1993) and orthogonal subspace projection (OSP) (Harsanyi 1993). Spectral matched filter (SMF) is a representative spectral target detection algorithm. It assumes that the spectral signature of the target and the covariance matrix of background clutter are known. Generally, the priori target signature can be obtained from a standard spectral library or from training data. The covariance matrix of the background clutter is estimated with the same training data. To realize adaptive target detection, the covariance matrix of the background clutter is estimated with a small number of sample pixels present in the neighborhood of the pixel to be recognized in ASMF. Namely, the estimation of the background clutter covariance matrix is adaptive to the local statistics (Nasrabadi, 2008). However, serious interference from background clutters is always an open challenge in the field of target detection with hyperspectral images. To show the best performance of a detector, a reasonable approach is to use detection algorithms with good and well-understood theoretical properties (Manolakis et al., 2009).

In the past years, a novel machine learning algorithm, so-called 'Kernel Methods', has been widely investigated and applied for hyperspectral images. The applications of the kernel methods to hyperspectral images not only are involved in feature extraction and classification, but also in target recognition/detection, anomaly detection, change detection, etc. (Kwon and Nasrabadi, 2004; Nasrabadi and Kwon, 2005; Kwon and Nasrabadi, 2006; Gu et al., 2008; Manolakis et al., 2009). Recently, nonlinear versions of the conventional spectral target detection/recognition algorithms aforementioned have been proposed one after the other, for

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doi:10.1016/j.patrec.2010.09.022

instance, Kernel spectral matched filter (KSMF) (Kwon and Nasrabadi, 2004; Nasrabadi and Kwon, 2005), Kernel matched subspace detector (KMSD) (Kwon and Nasrabadi, 2006), in which kernel methods are used to improve nonlinear ability to detect targets. These kernel-based target detection algorithms show better performance than the corresponding conventional detection algorithms.

In this letter, we focus on spectral matching detection of the full pixel target (that is composed of target spectra) which is different from mixed pixel target (that is spectral mixture of target and non-target materials). The aim of this research is to construct a detector with good ability to suppress background and form its kernel version. First, we analyze two conventional spectral matching algorithms and compare their computational forms of the detectors. According to the geometric interpretation concerning the conventional detectors, we propose an angle-regularized spectral matching (AR-SM) algorithm. The proposed AR-SM adopts a whitening procedure to sphere the original hyperspectral data and defines a new form of detector for full pixel target detection, which utilizes a more reasonable and effective manner to measure the spectral similarity between the test pixel and the desired target. Furthermore, we introduce kernel methods to kernelize the whitening operator. Integrating the kernel-whitening operator and the AR-SM detector, we propose a new nonlinear full-pixel method for target detection in hyperspectral imagery which is called Kernel Angle-Regularized Spectral Matching (KAR-SM) algorithm.

The paper is organized as follows. An introduction to kernel methods is provided in Section 2. In Section 3, conventional spectral matched filters are reviewed and their disadvantages are analyzed. The proposed AR-SM detector is described in detail and the kernel form of the proposed detector is deduced in Section 4. Numerical experiments are conducted on two real hyperspectral data and given in Section 5. In this section, detection performance of four methods and comparison between different kernels are provided in detail. In Section 6, some conclusions are drawn.

2. An introduction to kernel methods

Kernel methods offer a general framework for converting some linear algorithms into their nonlinear forms by means of kernel mapping. Generally, these linear algorithms for machine learning problems, such as classification, density estimation and regression, have a distinct or indistinct inner product operation. When a well-established linear algorithm is available, kernel methods map the data from input space into a higher dimensional Hilbert space $\mathcal{H}$ or feature space $\mathcal{F}$ first, and then construct a corresponding linear algorithm in the feature space $\mathcal{F}$. By the kernel mapping, the original data with complicated nonlinear statistical characteristics are converted into a relatively simple data. Thus, the linear algorithm can be more effectively performed on the data mapped into feature space $\mathcal{F}$ (Schölkopf et al., 1999; Müller et al., 2001; Kwon and Nasrabadi, 2005).

Suppose that the input sample set is represented by $\mathcal{X}$ in an L-dimensional input space ($\mathcal{X} \subseteq \mathcal{R}^L$) and $\boldsymbol{\Phi}$ is the nonlinear mapping function. We have

$$\boldsymbol{\Phi} : \mathcal{X} \to \mathcal{F} \tag{1}$$

Let $\boldsymbol{x}$ be a pixel sample from $\mathcal{X}$, then $\boldsymbol{x}$ in input space $\mathcal{X}$ corresponds to $\Phi(\boldsymbol{x})$ in feature space $\mathcal{F}$. When realizing the conventional linear algorithms in feature space, kernel methods use kernel matrix $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ as an element of operation rather than directly computing the $\Phi(\boldsymbol{x})$ in feature space $\mathcal{F}$. The so-called kernel matrix is given by

$$K_{ij} = K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \langle \boldsymbol{\Phi}(\boldsymbol{x}_i), \boldsymbol{\Phi}(\boldsymbol{x}_j) \rangle \tag{2}$$

There are three kernel functions generally used, i.e., Gaussian radius basis function (RBF), polynomial kernel and sigmoid kernel. Among them, the Gaussian RBF kernel is more widely adopted because of its merits, for example, it is translation-invariant and the Fourier transform of this kernel is also Gaussian, etc.

3. Conventional spectral matched filter methods

A main assumption of the matched filter-based target detection algorithms is that the input test pixel can be modeled as a linear combination of the desired target spectral signature and the background noise given by

$$\boldsymbol{x} = a\boldsymbol{s} + \boldsymbol{n} \tag{3}$$

where $\boldsymbol{x} = [x_1, x_2, \ldots, x_L]^T$ is the observation of spectral sample with L spectral bands, i.e., the test pixel, $\boldsymbol{s} = [s_1, s_2, \ldots, s_L]^T$ is the spectral signature of the desired target, a is a constant and can be called target abundance (that is real proportion of target in a pixel) measure, and $\boldsymbol{n}$ is the background noise. When $a = 0$, the target is absent, and when $a > 0$, the target is present.

SAM is the simplest one of 'spectral matched' methods and given by

$$D_{SAM}(\boldsymbol{x}) \triangleq \frac{\boldsymbol{s}^T\boldsymbol{x}}{\|\boldsymbol{s}\| \cdot \|\boldsymbol{x}\|} = \frac{\boldsymbol{s}^T\boldsymbol{x}}{(\boldsymbol{s}^T\boldsymbol{s}) \cdot (\boldsymbol{x}^T\boldsymbol{x})} \tag{4}$$

SAM uses the cosine of the angle between spectral signatures of the test pixel and the desired target as the decision criterion, measuring the similarity of two spectral vectors. SAM provides adequate performance only for full-pixel targets having well separated distributions with small dispersions. There is not any optimality properties associated with the SAM algorithm, even for multivariate normally distributed classes (Manolakis and Shaw, 2002).

Being another conventional method for target detection in hyperspectral images, SMF models a Finite Impulse Response (FIR) filter to obtain the optimum weight under the condition of making the energy of output to a minimum as the output of target pixel is 1 and the output of background pixel is 0. The FIR filter is given by

$$y = \boldsymbol{w}^T\boldsymbol{x} \tag{5}$$

The design of the matched filter $\boldsymbol{w}$ can be converted to a constrained minimization problem as follows:

$$\min_{\boldsymbol{w}} \left(\sum_{i=1}^{N} y_i^2 \right), \quad s.t.\ \boldsymbol{w}^T\boldsymbol{s} = 1 \tag{6}$$

Substituting (5) into (6), the further simplification is

$$\sum_{i=1}^{N} y_i^2 = \sum_{i=1}^{N} (\boldsymbol{w}^T\boldsymbol{x})^T(\boldsymbol{w}^T\boldsymbol{x}) = \boldsymbol{w}^T \left(\sum_{i=1}^{N} \boldsymbol{x}\boldsymbol{x}^T \right) \boldsymbol{w} = N \cdot \boldsymbol{w}^T \boldsymbol{\Gamma}_b \boldsymbol{w} \tag{7}$$

where $\boldsymbol{\Gamma}_b$ is the covariance matrix of the input background data (mean-removed).

By means of Lagrange multiplier method

$$L(\boldsymbol{w}, c) = \boldsymbol{w}^T\boldsymbol{\Gamma}_b\boldsymbol{w} - c(\boldsymbol{w}^T\boldsymbol{s} - 1) \tag{8}$$

where c is the Lagrange multiplier.

The solution of the optimum weight is

$$\boldsymbol{w}^* = \frac{\boldsymbol{\Gamma}_b^{-1}\boldsymbol{s}}{\boldsymbol{s}^T\boldsymbol{\Gamma}_b^{-1}\boldsymbol{s}} \tag{9}$$

So the SMF detector is given by

$$D_{SMF}(\boldsymbol{x}) \triangleq (\boldsymbol{w}^*)^T\boldsymbol{x} = \frac{\boldsymbol{s}^T\hat{\boldsymbol{\Gamma}}_b^{-1}\boldsymbol{x}}{\boldsymbol{s}^T\hat{\boldsymbol{\Gamma}}_b^{-1}\boldsymbol{s}} \tag{10}$$