ISPRS Journal of Photogrammetry and Remote Sensing 114 (2016) 32–39

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

Clever eye algorithm for target detection of remote sensing imagery

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ARTICLE INFO

Article history:
Received 20 January 2015
Received in revised form 20 October 2015
Accepted 21 October 2015
Available online 12 February 2016

Keywords:
Hyperspectral data
Target detection
Matched filter
Constrained energy minimization

ABSTRACT

Target detection algorithms for hyperspectral remote sensing imagery, such as the two most commonly used remote sensing detection algorithms, the constrained energy minimization (CEM) and matched filter (MF), can usually be attributed to the inner product between a weight filter (or detector) and a pixel vector. CEM and MF have the same expression except that MF requires data centralization first. However, this difference leads to a difference in the target detection results. That is to say, the selection of the data origin could directly affect the performance of the detector. Therefore, does there exist another data origin other than the zero and mean-vector points for a better target detection performance? This is a very meaningful issue in the field of target detection, but it has not been paid enough attention yet. In this study, we propose a novel objective function by introducing the data origin as another variable, and the solution of the function is corresponding to the data origin with the minimal output energy. The process of finding the optimal solution can be vividly regarded as a clever eye automatically searching the best observing position and direction in the feature space, which corresponds to the largest separation between the target and background. Therefore, this new algorithm is referred to as the clever eye algorithm (CE). Based on the Sherman–Morrison formula and the gradient ascent method, CE could derive the optimal target detection result in terms of energy. Experiments with both synthetic and real hyperspectral data have verified the effectiveness of our method.

1. Introduction

The detection and identification of ground materials of interest within a scene acquired from airborne and spaceborne platforms using hyperspectral sensors is of great interest and importance in remote sensing applications. Usually, the technique of target detection can be conducted spatially (Cheng et al., 2013; Han et al., 2015; Liu et al., 2014) and/or spectrally (Manolakis and Shaw, 2002; Manolakis et al., 2001a; Chang et al., 2001). Limited by the spatial resolution of the remote sensing image, target detection methods utilizing spatial characteristics, such as shape and texture, sometimes fail to provide a good performance. However, algorithms based on spectral information, using statistical or physical approaches, have been widely studied and developed due to their mathematically or physically tractable properties and have good performance in many practical situations.

Hyperspectral target detection algorithms based on spectral information can be categorized into four classes: the first is the spectral matching method, which usually includes the minimum distance method (Keshava, 2004), cross correlogram spectral matching (van der Meero and Bakker, 1997), and spectral angle mapping (Kruse et al., 1993). The second is based on the spectral absorption characteristics of a target and the most representative algorithms are the spectral feature fitting method (Clark et al., 1990) and all the spectral indices (such as the normalized difference vegetation index, NDVI (Myneni et al., 1995)). The third category is based on a technique of spectral unmixing, such as the orthogonal subspace projection method (Harsanyi, 1993; Du et al., 2003; Arora et al., 2013) or the least-squares method. The abundance map of the target endmember can be regarded as the corresponding detection result.

The last category of target detection technique is based on the statistical characteristics of an image, which is usually designed using the generalized likelihood ratio test approach (Manolakis et al., 2000, 2009a,b). Different types of statistical models used for the target and background will lead to different target detection

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http://dx.doi.org/10.1016/j.isprsjprs.2015.10.014
0924-2716/

algorithms, such as the Kelly detector (Kelly, 1986, 1987; Kelly and Forsythe, 1989), the matched subspace detector(Scharf and Friedlander, 1994), the matched filter (MF) detector (Manolakis et al., 2000; Chen and Reed, 1987; Manolakis and Shaw, 2002), and the adaptive subspace detector, which is also known as the adaptive cosine estimator (Kraut and Scharf, 1999; Kraut et al., 2001).

Among the above detectors, the MF detector is the most commonly used technique in the field of communication and signal processing applications. It has been widely applied and further developed in target detection for remote sensing imagery (Manolakis et al., 2009a, 2009b; DiPietro et al., 2010; Manolakis et al., 2001b; Funk et al., 2001; Minet et al., 2011). MF requires the mean vector and the covariance matrix of the target and background distribution. The MF detector is at optimum performance in the Neyman–Pearson sense when the target and background classes follow multivariate normal distributions with the same covariance matrix, which is an unlikely assumption for real-world images. Moreover, the target of interest usually has a low probability distribution, so there is often no sufficient training data to estimate the mean vector and covariance matrix for the target. As a result, if we use a target spectrum from the spectral library or image, then the algorithm will result in the adaptive MF (Manolakis and Shaw, 2002), which is the commonly used detector for low-probability targets. Mixture tuned MF (Boardman, 1998; Boardman and Kruse, 2011) which combines the statistical method of the MF with the deterministic method of the linear mixing model, has been widely applied in the field of hyperspectral target detection (Mitchell and Glenn, 2009; Dópido et al., 2011).

Harsanyi (1993) developed the constrained energy minimization (CEM) algorithm based on signal processing theory, which has been widely applied in hyperspectral target detection (Sohaib et al., 2012; Chang and Ji, 2006; Arora et al., 2013; Harsanyi and Chang, 1994; Farrand and Harsanyi, 1997; Geng et al., 2013; Chang et al., 2000; Gabr et al., 2010; Du and Nekovei, 2009; Du et al., 2007; Chang and Wang, 2006). CEM performs a matched filtering of hyperspectral images, which linearly constrains a desired target signature while minimizing the total energy of the output of the background. It only requires the knowledge of target spectra to be provided as a user endmember. Unlike MF, CEM has no requirement on the distribution of data, but it uses the autocorrelation matrix to form the detector, so it can still be categorized into a statistical approach.

It is noteworthy that the CEM detector has a quite similar form to the MF detector, except that the MF detector needs the data to be centralized first. However, they have different target detection results, which are caused by the change in the position of the data origin. That is to say, the selection of the data origin will have a direct impact on the performance of the detectors. However, the zero and mean vector positions are two special points, and there are thousands of other points in the feature space. So for a given data set, it is necessary to establish which point is the best one to move the data cloud to. It is a very important issue in target detection area, which has not received enough attention yet so far.

In this paper, we present a new algorithm to find the best data origin for target detection from the perspective of output energy. Let us imagine the process of target detection as looking at the data cloud by a "clever eye" in the feature space. The clever eye can automatically adjust its position and viewing direction according to target and background distribution. Searching the best data origin is equivalent to the process whereby the clever eye searches the optimal position and direction for observing the biggest difference between target and background. Thus we name the proposed method as the *clever eye algorithm* (*CE*).

2. Method

2.1. Constrained energy minimization

CEM is originally derived from the linearly constrained minimized variance adoptive beam-forming in the field of digital signal processing. It uses a finite impulse response (FIR) filter to constrain the desired signature by a specific gain while minimizing the filter output energy (Harsanyi, 1993; Farrand and Harsanyi, 1997).

Assume that we are given a finite set of observations $S = \{\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_N\}$, where $\mathbf{r}_i = (r_{i1}, r_{i2}, \cdots, r_{iL})^T$ for $1 \leqslant i \leqslant N$ is a sample pixel vector, N is the total number of pixels, and L is the number of bands. Suppose that the desired signature $\mathbf{d}$ is also known. The objective of CEM is to design an FIR linear filter $\mathbf{w} = (w_1, w_2, \cdots, w_L)^T$ to minimize the filter output power subject to the constraint, $\mathbf{d}^T\mathbf{w} = \sum_{l=1}^{L} d_l w_l = 1$. Then the problem yields (Harsanyi, 1993)

$$\begin{cases} \min\limits_{\mathbf{w}} \frac{1}{N}\left(\sum\limits_{i=1}^{N} y_i^2\right) = \min\limits_{\mathbf{w}} \mathbf{w}^T\mathbf{R}\mathbf{w} \\ \mathbf{d}^T\mathbf{w} = 1 \end{cases}, \tag{1}$$

where $y_i = \mathbf{w}^T\mathbf{r}_i$, and $\mathbf{R} = (1/N)\left(\sum_{i=1}^{N}\mathbf{r}_i\mathbf{r}_i^T\right)$ turn out to be the sample autocorrelation matrix. The solution to (1) is called the CEM operator with weight vector $\mathbf{w}_{CEM}$ given by (Harsanyi, 1993)

$$\mathbf{w}_{CEM} = \frac{\mathbf{R}^{-1}\mathbf{d}}{\mathbf{d}^T\mathbf{R}^{-1}\mathbf{d}}. \tag{2}$$

2.2. Matched filter

MF has been widely used in communications, signal processing and pattern recognition applications. It is usually derived by maximizing the cost function, which measures the distance between the means of two normal distributions in units of the common variance. The MF detector has a similar form to the CEM, but the main difference is that it requires data centralization first. The expression of an MF detector can be written as (Manolakis and Shaw, 2002)

$$\mathbf{w}_{MF} = \frac{\mathbf{K}^{-1}(\mathbf{d}-\mathbf{m})}{(\mathbf{d}-\mathbf{m})^T\mathbf{K}^{-1}(\mathbf{d}-\mathbf{m})}, \tag{3}$$

where $\mathbf{m} = (1/N)\sum_{i=1}^{N}\mathbf{r}_i$ is the mean vector and $\mathbf{K} = (1/N)\left[\sum_{i=1}^{N}(\mathbf{r}_i-\mathbf{m})(\mathbf{r}_i-\mathbf{m})^T\right]$ is the covariance matrix.

Comparing the two forms of CEM and MF detectors (refer to (2) and (3)), we can find that the centralization process in MF is to move the data origin from the zero point to the mean vector in the feature space. Therefore, if we take the CEM detection result as an observation when moving the data to the zero point, the MF result can be regarded as the other observation when moving the data to the mean vector point. From this point of view, the difference in the detection results of CEM and MF is merely caused by the change of data origin. This phenomenon is very interesting, and inspires us to obtain a better detection result through searching for a better data origin. However, do best origins exist for specific data sets? If so, how much are they and where are they? To answer these questions, we give a detailed discussion in the following.

2.3. Clever eye algorithm

In this section, we propose a new method to search the best data origin, and develop a new detector for target detection. To