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A target detection method for hyperspectral image based on mixture noise model

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ABSTRACT

Subpixel hyperspectral detection is a kind of method which tries to locate targets in a hyperspectral image when the spectrum of the targets is given. Due to its subpixel nature, targets are often smaller than one pixel, which increases the difficulty of detection. Many algorithms have been proposed to tackle this problem, most of which model the noise in all spatial points of hyperspectral image by multivariate normal distribution. However, this model alone may not be an appropriate description of the noise distribution in hyperspectral image. After carefully studying the distribution of hyperspectral image, it is concluded that the gradient of noise also obeys normal distribution. In this paper two detectors are proposed: *mixture gradient structured detector* (MGSD) and *mixture gradient unstructured detector* (MGUD). These detectors are based on a new model which takes advantage of the distribution of the gradient of the noise. This makes the detectors more accordant with the practical situation. To evaluate the performance of the proposed detectors, three different data sets, including one synthesized data set and two real-world data sets, are used in the experiments. Results show that the proposed detectors have better performance than current subpixel detectors.

1. Introduction

With the development of remote sensing and pattern recognition [1–4,41,42], target detection has aroused more and more concerns [5–7] in hyperspectral image. Hyperspectral target detection [8–10] is the process of locating certain ground material in a hyperspectral image, when spectral signature of the material is known in advance. Hyperspectral target detection has been widely used for both military and civilian purposes [11,12]. For instance, it can be used to monitor water quality, forest fire danger, land-utilized condition and enemy military dispositions, which makes it an important research area.

In hyperspectral imaging system, the spectrum can be divided into many more narrow and contiguous bands with a wide range of wavelengths. Owning to the high wavelength resolution, a hyperspectral image can be regarded as a set of images. Each image covers a narrow wavelength range. This makes hyperspectral image a three-dimensional data cube with two spatial dimensions and a spectral dimension. Different bands of a pixel can form a continuous spectrum, and each ground material often has its unique spectral signatures, which makes it possible to identify targets. On the other hand, the spatial resolution of hyperspectral images is limited [43–45]. Sometimes a pixel may consist of more than one material, and target is mixed with background, which is called subpixel target. Subpixel target is difficult to detect, because the spectral spectrum of the mixed pixel is often different from the target spectrum.

A number of algorithms [46–49] have been proposed to solve the subpixel detection problem. One kind of algorithm tried to find an optimal projection vector so that background signatures are suppressed while target signatures are maintained after the projection. In this case, targets and background can be separated. Representatives of this kind of algorithm are *orthogonal subspace projection* (OSP) [13], *kernel orthogonal subspace projection* (KOSP) [14], *constrained energy minimization* (CEM) [15], *target-constrained interference-minimized filter* (TCIMF) [16], kernel-based TCIMF (KTCIMF) [17], etc. In these algorithms, the noise is assumed to be a zero-mean multivariate normal distribution [50,51].

Another kind of algorithm is based on hypothesis testing [18–21]. In these algorithms, firstly a couple of hypotheses including null hypothesis and alternative hypothesis are formulated. Then a detector is designed to judge whether the pixel in the image belongs to the null hypothesis or the alternative hypothesis. Depending on the model used to describe background signature,

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hypothesis testing based algorithms can be divided into two classes: structured detector and unstructured detector. One example of structured detector is *adaptive matched subspace detector* (AMSD) [22]. The AMSD used linear mixing model to represent background. In this case, each pixel can be represented as the product of background endmembers and their corresponding abundance. Although AMSD can correctly find targets from the image in most cases, it has some drawbacks. For AMSD, endmembers are the eigenvectors of the data correlation matrix, and the sum-to-one and nonnegative constraint are not satisfied, which will result in the loss of physical meaning. *Adaptive cosine/coherent estimate* (ACE) [20] is another example of statistical hypothesis testing based algorithms. Compared with AMSD, ACE assumed that background signature consists of only noise which obeys multivariate normal distribution. This makes ACE a very fast algorithm since it does not extract endmembers from background. However, recent study has shown that multivariate normal distribution cannot correctly model the background in hyperspectral imaging [23].

To overcome the shortage of hypothesis testing based algorithms, two hybrid detectors for subpixel targets, including *hybrid structured detector* (HSD) and *hybrid unstructured detector* (HUD), have been proposed [24] in recent years. These algorithms use both physics and statistics to model the background, and targets are then detected using statistical hypothesis. By doing so, physical meaning is brought into the original background model, and experiments also show that hybrid detectors perform better than typical hypothesis testing based algorithms.

In subpixel detection, one of the key factors that alter the target observations is the estimation of the noise statistics [25,22,26]. All the aforementioned algorithms model the noise as a set of *independent and identically distributed* (i.i.d.) noise random variables for all spatial points, each of which follows a multivariate normal distribution or multivariate Gaussian distribution. However, this model is weak [27] because it does not capture an important property of image noise, which is that image noise exhibits spatial randomness. Recent study [27] has shown an interesting observation that normal distribution alone may not be an appropriate description of the noise in images, the gradient of noise should also obey normal distribution. This observation can be easily explained that the i.i.d. property makes the gradient of noise random variables also follow multivariate Gaussian distributions with different standard deviations.[1]

To further validate this observation, a simulation experiment is performed on hyperspectral image. In Fig. 1(a), 10 dB Gaussian noise is added to the original hyperspectral image, and distributions of noise and gradient of noise are shown in Fig. 1(b). From Fig. 1 it can be concluded that the gradient of the noise within a pixel among different bands also follows Gaussian distribution. The distribution of noise in the hyperspectral image needs to be exploited in order to better detect targets from backgrounds. However, to our knowledge in current target-detection algorithms, the distribution of the gradient of noise has never been studied.

In this paper, a stronger model of noise is proposed to regard the distribution of noise and its gradient. Based on the new model, we then follow the work of hybrid detectors, and propose two new hybrid detectors, *mixture gradient structured detector* (MGSD) and *mixture gradient unstructured detector* (MGUD), which make full use of the gradient distribution of the noise.

The rest of the paper is organized as follows. Section 2 introduces *fully constrained least squares* (FCLS), HSD and HUD which are related to the proposed algorithm. Section 3 describes the two proposed detectors MGSD and MGUD. Performance comparisons of different algorithms are given in Section 4, and finally conclusion is given in Section 5.

[1] If n_1 and n_2 are normally distributed and independent, then their difference $n_1 - n_2$ is also distributed normally.

2. Related work

This section introduces *linear mixture model* (LMM), *fully constrained least squares* (FCLS), and reviews the HSD and HUD detection algorithms, which are related to the proposed algorithm. Both LMM and FCLS are important parts of HSD and HUD. HSD is a structured detector which takes advantage of both FCLS and AMSD, while HUD is an unstructured detector which is based on FCLS and ACE.

2.1. Linear mixture model (LMM)

In order to tackle the subpixel detection problem, a model is needed to describe the inner structure of pixels. The most commonly used model is *linear mixture model* (LMM) [28,29,52,53]. This model assumes that each pixel is a linear combination of different elements (called endmember), and each element has its own weights (called abundance). The model can be represented as

$$x = E\alpha + n, \tag{1}$$

where x is a $l \times 1$ vector that represents the spectrum of the current pixel. l is the number of bands. E is a $l \times p$ matrix, where the ith column represents the spectrum of the ith endmember, and the jth row represents the spectrum of the jth band. $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_p]^T$ is a $p \times 1$ vector representing the abundance of different endmembers. To enhance the physical meaning of LMM, two constraints are added to the model:

$$\sum_{i=1}^{p} \alpha_i = 1$$

$$\alpha_i > 0. \tag{2}$$

The former is called *abundance sum-to-one constraint* (ASC) and the latter is called *abundance nonnegative constraint* (ANC). By using those two constraints, the true abundance can be extracted from mixed pixels. The estimated abundance is helpful for analyzing the distribution of different materials in the scene.

2.2. Fully constrained least squares (FCLS)

FCLS is an algorithm which is used to estimate the abundance of endmembers in the image. The algorithm begins with ANC, and tries to minimize the least squares error while guaranteeing that the abundance is nonnegative. This can be expressed as:

$$\min_{\alpha} (x - E\alpha)^T (x - E\alpha), \quad \alpha_i \geq 0 \ \ \forall\, i. \tag{3}$$

Eq. (3) is a constrained optimization problem, which can be solved by using Lagrange multipliers:

$$\hat{\alpha} = (E^T E)^{-1} E^T x - (E^T E)^{-1} \lambda, \tag{4}$$

where

$$\lambda = E^T (x - E\hat{\alpha}). \tag{5}$$

To solve Eqs. (4) and (5), an active set based algorithm is adopted to ensure that the solution meets the Karush–Kuhn–Tucker conditions. The iterating step begins with an unconstrained least squares estimation of α. Then two index sets, including passive set P and active set R, are built. Indices (Lagrange multipliers) corresponding to the positive abundance values are put in P, while the remaining indices corresponding to the negative and zero