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A hypothesis independent subpixel target detector for hyperspectral Images

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ABSTRACT

In previous work, the statistical characteristics of the background or the noise under H_0 hypothesis are similar as that under H_1 hypothesis. Accordingly, the parameters under both hypotheses are estimated by the maximum likelihood method and finally a generalized likelihood ratio test based detector is developed, such as the matched subspace detector. Unfortunately, this kind of statistical similarity for both hypotheses may be changing, which is directly related to the unknown beforehand target fill factor. A hypothesis independent method is proposed to solve this problem, which uses different approaches to estimate the parameters for different hypotheses. Experiments on simulated data and real hyperspectral image demonstrate the ability of this proposed detector for subpixel target detection.

1. Introduction

As we know that, any target detection application seeks to identify a relatively small number of objects with fixed shape or spectrum in a scene. However, hyperspectral target detection is much different from other target detection methods [1], as hyperspectral image (HSI) conveys abundant spectral information [2–4]. Furthermore, due to the low spatial resolution of the sensor, targets are likely to be embedded in a single pixel, and subpixel targets detection becomes a research focus [5,6].

The subspace model is usually employed for the subpixel target detection [7–10]. The matched subspace detector (MSD) is a typical subpixel targets detector. MSD employs the linear mixture model (LMM) to model the background or target pixel which corresponds to the H_0 or H_1 hypothesis, and uses the maximum likelihood method (MLE) to estimate the unknown parameters for two hypotheses [11–13]. This work assumes that the background power under H_0 hypothesis remains the same as that under H_1 hypothesis. However, in practice, it is usually the case that the background power will change with the appearance of target, and the background variance is directly related to the target fill factor which is the percentage of the pixel area occupied by the target [14]. Based on this point, a hypothesis independent method named HMSD is presented in this paper which is based on the matched subspace detector, and where the noise power is estimated using different methods. As the number of target pixel in the HSI is much limited, it is convenient to use the target-free data to calculate the noise variance under the null hypothesis. The noise under the alternative hypothesis is unknown and can be estimated using the MLE method. The detailed information about the method is discussed in the following.

2. HMSD

The test pixel in the hyperspectral image is modeled in terms of the target subspace and background subspace

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respectively. The competing hypotheses for a mixed pixel are:

$$\mathbf{x} = \mathbf{B}\mathbf{a}_{b0} + \sigma_0\mathbf{n}, \quad \text{Under } H_0$$
$$\mathbf{x} = \mathbf{S}\mathbf{a}_t + \mathbf{B}\mathbf{a}_{b1} + \sigma_1\mathbf{n}, \quad \text{Under } H_1 \tag{1}$$

The notations are listed in Table 1. The background subspace can be defined by the first Q eigenvectors of the image covariance matrix corresponding to the larger eigenvalues.

If we estimate the noise variance σ_0^2 with the target-free data and estimate the remaining unknown parameters ($\mathbf{a}_{b0}$, $\mathbf{a}_{b1}$, $\mathbf{a}_t$, σ_1^2) using the MLE technique, thus a new detection statistic can be developed by the generalized likelihood ratio test (GLRT) approach. To do this, we calculate the likelihood equations for the null and alternative hypothesis as

$$L(\mathbf{x}|H_0) = (2\pi\sigma_0{}^2)^{-L/2} \times \exp\left\{-\frac{1}{2\sigma_0{}^2}(\mathbf{x}-\mathbf{B}\mathbf{a}_{b0})^T(\mathbf{x}-\mathbf{B}\mathbf{a}_{b0})\right\}$$
$$L(\mathbf{x}|H_1) = (2\pi\sigma_1{}^2)^{-L/2} \times \exp\left\{-\frac{1}{2\sigma_1{}^2}(\mathbf{x}-\mathbf{S}\mathbf{a}_t-\mathbf{B}\mathbf{a}_{b1})^T \times (\mathbf{x}-\mathbf{S}\mathbf{a}_t-\mathbf{B}\mathbf{a}_{b1})\right\} \tag{2}$$

Taking the derivative of the logarithm of (2) with respect to each of the unknown parameters and setting them equal to zero allows us to arrive at the MLE-based abundance estimation

$$\widehat{\mathbf{a}}_{b0} = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T\mathbf{x}$$
$$\widehat{\mathbf{a}}_{b1} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{x}$$
$$\widehat{\mathbf{a}}_t = (\mathbf{C}^T\mathbf{C})^{-1}\mathbf{C}^T\mathbf{x} \tag{3}$$

And the noise variance estimation for the alternative hypothesis is

$$\widehat{\sigma}_1^2 = \frac{1}{L-J}||\mathbf{P}_E^\perp\mathbf{x}||^2 = \frac{1}{L-J}||\mathbf{x}_E^\perp||^2 \tag{4}$$

where $\mathbf{A} = \mathbf{P}_S^\perp\mathbf{B}$, $\mathbf{C} = \mathbf{P}_B^\perp\mathbf{S}$, and $\mathbf{E} = [\mathbf{B}, \mathbf{P}_B^\perp\mathbf{S}]$. $\mathbf{P}_E = \mathbf{E}(\mathbf{E}^T\mathbf{E})^{-1}\mathbf{E}^T$, $\mathbf{P}_E^\perp = \mathbf{I} - \mathbf{P}_E$, and $\mathbf{x}_E^\perp = \mathbf{P}_E^\perp\mathbf{x}$. $\mathbf{P}_S$ and $\mathbf{P}_B$ are the orthogonal projection matrices onto the target and background subspaces, and $\mathbf{P}_E$ is the orthogonal projection matrix onto the concatenation of the background and target subspaces with background subspace effect eliminated in target subspace. Then, the GLR is given by

$$\frac{p(\mathbf{x}; \widehat{\mathbf{a}}, \widehat{\sigma}_1{}^2|H_1)}{p(\mathbf{x}; |H_0)} = \frac{\left\{2e^{(L-J)/L}\pi(L-J)^{-1}||\mathbf{x}_E^\perp||^2\right\}^{-L/2}}{(2\pi\sigma_0{}^2)^{-L/2}e^{\left\{\frac{||\mathbf{x}_B^\perp||^2}{2\sigma_0{}^2}\right\}}} \tag{5}$$

Using some algebra, the GLRT-based detector named HMSD is given by the following statistical test

$$D_{HMSD}(\mathbf{x}) = \frac{||\mathbf{x}_B^\perp||^2}{L\sigma_0{}^2} - \ln\frac{||\mathbf{x}_E^\perp||^2}{(L-J)\sigma_0{}^2} - \frac{L-J}{L} \tag{6}$$

where J=P+Q, $||\mathbf{x}_B^\perp||^2 = ||\mathbf{x}_t||^2 + ||\mathbf{x}_E^\perp||^2$, and $\mathbf{x}_t = \mathbf{P}_C\mathbf{x}$. We can rewrite the proposed detector in the following form

$$D_{HMSD}(\mathbf{x}) = \frac{||\mathbf{x}_t||^2}{L\sigma_0{}^2} + \frac{||\mathbf{x}_E^\perp||^2}{L\sigma_0{}^2} - \ln\frac{||\mathbf{x}_E^\perp||^2}{(L-J)\sigma_0{}^2} - \frac{L-J}{L} \tag{7}$$

We can see from (7) that the detection quality depends on the relation between the target contribution (the first term) and the background power change contribution (the second and third terms). We can adjust the background power change sensitivity of detector with respect to the target presence sensitivity using a factor m. Varying the factor m we can adapt the background power change to the detection performance. We can introduce the factor of signal detection sensitivity m and rewrite the proposed detector in the following form

$$D_{HMSD}(\mathbf{x}) = \frac{||\mathbf{x}_t||^2}{L\sigma_0{}^2} + m\left\{\frac{||\mathbf{x}_E^\perp||^2}{L\sigma_0{}^2} - \ln\frac{||\mathbf{x}_E^\perp||^2}{(L-J)\sigma_0{}^2}\right\} - \frac{L-J}{L} \tag{8}$$

For simplicity, we actually rewrite it in the following form:

$$D_{HMSD}(\mathbf{x}) = \frac{\text{m}||\mathbf{x}_t||^2}{L\sigma_0{}^2} + \frac{||\mathbf{x}_E^\perp||^2}{L\sigma_0{}^2} - \ln\frac{||\mathbf{x}_E^\perp||^2}{(L-J)\sigma_0{}^2} \tag{9}$$

In this paper, the noise variance under the null hypothesis was estimated by a local median filter method. A noise matrix is first estimated by subtracting the target-free image matrix with median filter from the original target-free image matrix, which is similar as that in Maximum Noise Fraction (MNF) method [15,16]. Then, the noise variance can be calculated from this noise matrix. However, in practice, the target-free image cannot obtain, in view of the limited number of targets, it can be replaced with the whole image. According to the aforementioned descriptions, the HMSD algorithm for hyperspectral target detection can be expressed as Table 2.

Table 1
Notations in HMSD model.

notation	Meaning	Size
$\mathbf{x}$	pixel spectrum vector	L × 1
$\mathbf{S}$	target subspace	L × P
$\mathbf{B}$	background subspace	L × Q
$\mathbf{a}_{b0}$, $\mathbf{a}_{b1}$	background abundance for two hypotheses	L × 1
$\mathbf{a}_t$	target abundance	L × 1
$\mathbf{n}$	multivariate normal noise	L × 1
σ_0^2, σ_1^2	variance for two hypotheses	

Table 2
The HMSD algorithm.

Input: a hyperspectral image, target prior spectra, and parameters *m and* Q;
Processing: Obtain the median filtered image, and then obtain the noise image; Calculate the noise variance σ_0^2; Calculate the image covariance matrix, and obtain the first Q eigenvectors corresponding to the larger eigenvalues as **B**; Compute the detection statistics via (9) **Output:** maps of the detection statistics of each pixel.