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Unsupervised transfer learning for target detection from hyperspectral images

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A B S T R A C T

Target detection has been of great interest in hyperspectral image analysis. Feature extraction from target samples and counterpart backgrounds consist the key to the problem. Traditional target detection methods depend on comparatively fixed feature for all the pixels under observation. For example, RX employs the same distance measurement for all the pixels. However, the best separation results usually come from certain targets and backgrounds. Theoretically, they are the purest targets and backgrounds pixels, or the constructive endmembers in the subspace model. So using those most representative pixels' feature to train a concentrated subspace is expected to enhance the separability between targets and backgrounds. Meanwhile, applying the discriminative information from these training data to the large testing data which are not in the same feature space and with different data distributions is a challenge. Here, the idea of transfer learning from interactive annotation technique in video is employed. Based on the transfer learning frame, several points are taken into consideration and the proposed method is named as an unsupervised transfer learning based target detection (UTLD) method. Firstly, the extreme target and background pixels are generated from robust outlier detection, providing the input for target samples and background samples in transfer learning. Secondly, pixels are calculated from the root points in a segmentation method with the purpose to preserve the most distribution feature of the backgrounds after reduced dimension. Thirdly, sparse constraint is imposed into the transfer learning procedure. With this constraint, a simpler and more concentrated subspace with clear physical meaning can be constructed. Extensive experiments reveal the performance is comparable to the state-of-art target detection methods.

1. Introduction

Automatic target detection from remote sensing images has been of great interest for years [1–3]. It is of particular importance in many domains, especially to military application. Spectral imaging reveals ground objects with fine resolution so as to explore the minor spectral difference between those visually undistinguished ones. Thus much attention has been paid to automatic target detection for hyperspectral images (HSI) [4–10].

The foremost key to targets detection from the HSI is the targets' features. Spectral features are most widely used feature in state-of-art target detection methods [4], where it is assumed that targets present a diagnostic difference from other background objects by means of spectral. Several kinds of methods are developed on this basis, such as linear mixture model based method and subspace based method. Linear mixture models construct the mixture composition of each pixel by endmembers, promising for detecting sub-pixel targets [5]. Subspace based methods present good performance on suppressing the pixels lying on background subspace and outburst those target signals [5,6]. The above two kinds of methods both employ physical model, requiring prior information about targets. Still other kind depends on the statistic model, with no prior knowledge about target, and it is called the unsupervised one (including anomaly detection). [7,8].

In these conventional methods, targets pixels and background pixels are manually chosen and then used to construct subspace based detector, where the target pixels and the background pixels are assumed to be separable. However, the number of the training pixels are usually limited and the correspondingly constructed subspace may over-fit the training pixels so as not to accurately detect the rest target pixels [1]. Can we find some way to preserve the discriminative information and avoid the over-fitting simultaneously? Transfer learning has shown its good performance to learn a subspace from limited samples [11,12], so it is thus introduced in target detection from hyperspectral images in this

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paper. Focusing on exploiting the training samples' discriminative information and learning a proper subspace from both training targets/background samples and those unlabeled samples, we have make several contributions for hyperspectral target detection in the paper:

1) A multivariate outlier analysis is used to automatically choose certain target pixels and background pixels as positive training and negative training samples, respectively. Meanwhile, existing target detection methods mainly depend on manually selecting pixels as training samples.
2) A segmentation method is employed to get the most representative and informative unlabeled samples. In this way, the wealthy continuous spatial feature in hyperspectral images can be fully considered. Existing methods usually randomly select the unlabeled samples or the all the samples in the image are used to learn a detector, like the constrained energy minimization [2] and adaptive matched subspace filter [5].
3) With the training labeled samples (including positive and negative samples) and unlabeled samples, a transfer learning based subspace construction method is formulated. Where a pairwise discriminative analysis is used to enhance the target-background pixels' separability. Existing target detection methods for hyperspectral images mainly depend on the labeled samples to construct subspace,.

The remainder of this paper is organized as follows. Section 2 presents unsupervised coarse target recognition by multivariate outlier detection method. Section 3 details the segmentation to get representative root pixels. The coarse target and background samples and unlabeled background root pixels are merged in sparse transfer learning for dimension reduction in Section 4. Section 5 discusses the extensive experiments by target detection to the dataset with reduced dimension. Section 6 concludes the paper.

2. Unsupervised target and background feature extraction

In this section, a multi-variable outlier analysis is employed to obtain the positive and negative samples [13], which are necessary for the transfer learning. Here, positive samples actually refer to the training targets pixels in the image dataset, and negative samples refer to the training non-target/background pixels from the image dataset.

The main idea behind the multi-variable outlier analysis is to iteratively figure out the mean and covariance matrix of the background pixels from image dataset to construct an optimal Mahalanobis distance based detector and finally extract the probable outliers.

Step 1: Randomly select one third of the pixels in the image dataset as the initial basic subset. Each pixel is virtually a vector containing b' components according to the b' bands.

Step 2: Compute the mean vector and the covariance matrix using the initial basic subset as follows:

$$\overline{\mathbf{x}} = \frac{1}{M}\sum_{i=1}^{M}\mathbf{x}_i \tag{1}$$

$$\mathbf{C} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1b'} \\ \cdots & & & \\ \sigma_{b'1} & \sigma_{b'2} & \cdots & \sigma_{b'b'} \end{bmatrix} \tag{2}$$

where $\sigma_{ij} = 1/M\sum_k(\mathbf{x}_{ik}-\mathbf{m}_i)(\mathbf{x}_{jk}-\mathbf{m}_j)$, $k=1,\ldots,M$, M is the number of pixels in the subset, $\boldsymbol{m}_i$ and $\boldsymbol{m}_j$ are the means of the ith band and the jth band, respectively. $\boldsymbol{x}_{ik}$ is the value in the ith band of the kth pixel.

Step 3: Compute the Mahalanobis distance of each pixel vector in the image using the mean vector and the covariance matrix constructed above:

$$d_i = \sqrt{(\mathbf{x}_i-\overline{\mathbf{x}})^T\mathbf{C}^{-1}(\mathbf{x}_i-\overline{\mathbf{x}})}, i = 1,\ldots M \tag{3}$$

Step 4: Set the threshold η, and the pixels in the image with a distance under the threshold η would be set as the new basic subset. Reed and Yu have shown that RX statistics under the null hypothesis have a Chi-square distribution [14]. A Mahalanobis-based detector usually has a Chi-square distribution with p degrees of freedom [13]. The threshold is defined as the square root of $1-\alpha$ percentile of the Chi-square distribution with p degrees of freedom. p equals the band number b' Since the basic subset contains only part of the pixels in the hyperspectral imagery, the square root is multiplied by the inflation factor, which is the same factor as in [15]:

$$\eta = \chi_{p,\alpha}c_{Npr} \tag{4}$$

where $\chi_{p,\alpha}$ is the square root of $1-\alpha$ percentile of the Chi-square distribution with p degrees of freedom, and $c_{Npr}=c_{Np}+c_{hr}$ is the inflation factor.

$$c_{hr} = \max\{0,(h-r)/(h+r)\} \tag{5}$$

$$h = (n+p+1)/2 \tag{6}$$

$$c_{Np} = 1+\frac{p+1}{n-p}+\frac{1}{n-h-p} \tag{7}$$

where r is the size of the current basic subset, n is the total number of the pixels in the image.

Step 5: Iterate Step 2 to Step 4 until the basic subset no longer changes.

Step 6: Nominate the pixels excluded by the final basic subset as outliers. The finial basic subset constitutes the background pixels.

The above procedure is the basic idea of BACON. It has been proved that BACON includes those pixels with a distance smaller than η to the basic subset in each iteration, but the number of iterations is usually small [15]. Besides, it searches for the most reasonable mean vector and the covariance matrix to detect the anomaly pixels by updating the basic subsets in the iterations. The final mean tends to drift toward the real center of non-outlying background pixels [7].

The following is the way we propose to choose positive and negative samples from BACON results. The outliers excluded from the dataset may contain the spectral anomalies, mainly the noisy pixels or the rare ones of no interest. In order to eliminate the spectral anomaly pixels, all the excluded pixels are further investigated. Half of the pixels with larger norms in them are discarded. The remaining pixels are used as positive samples. As to the background pixels, they are clustered into several groups by k-means [16]. The number of the groups is equal to three times of the number of positive samples. In each group, the pixel with the largest average distance from all the positive samples is chosen. All the chosen background pixels comprise the final negative samples. With the positive and negative samples, pair-wise discriminative information can be constructed, which will be detailed in Section 4.

3. Construction of unlabeled pixels

In this section, a segmentation and a subsequent manifold analysis are carried out to obtain the unlabeled samples, which are necessary for transfer learning. The purpose is to fully exploit the spatial feature and the manifold feature in hyperspectral images to get the proper unlabeled samples for transfer learning.