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Spectral-spatial target detection based on data field modeling for hyperspectral data

Da LIU, Jianxun LI *

School of Electronic, Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

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Abstract Target detection is always an important application in hyperspectral image processing field. In this paper, a spectral-spatial target detection algorithm for hyperspectral data is proposed. The spatial feature and spectral feature were unified based on the data filed theory and extracted by weighted manifold embedding. The novelties of the proposed method lie in two aspects. One is the way in which the spatial features and spectral features were fused as a new feature based on the data field theory, and the other is that local information was introduced to describe the decision boundary and explore the discriminative features for target detection. The extracted features based on data field modeling and manifold embedding techniques were considered for a target detection task. Three standard hyperspectral datasets were considered in the analysis. The effectiveness of the proposed target detection algorithm based on data field theory was proved by the higher detection rates with lower False Alarm Rates (FARs) with respect to those achieved by conventional hyperspectral target detectors.

1. Introduction

With the development of imaging techniques, hyperspectral imaging instrument has already became a very important data source in many applications, including medical and health application,[1] Earth monitoring,[2] agriculture monitoring applications,[3] and military target detection.[4,5]

Usually, HyperSpectral Imagery (HSI) processing focuses on the analysis and recognition of spectral data collected by sensors. As is well known, the spectral data are widely used for ground truth classification and target detection. Several classic target detection algorithms for multispectral and hyperspectral data have been proposed, such as: (A) the detector based on the probability density model, including the Adaptive Coherence Estimator (ACE)[6] and constrained energy minimization (CEM) method.[7] ACE detector is essentially a generalized likelihood ratio test (GLRT) detector with a cone decision boundary. CEM obeys the criterion that target samples should have as intensive responses as possible while background samples should have as weak responses as possible; (B) the target detection approaches based on the geometric models, such as Orthogonal Subspace Projection (OSP) approach,[7]

* Corresponding author.
E-mail address: lijx@sjtu.edu.cn (J. LI).
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and Adaptive Subspace Detector (ASD).[8] OSP projects the spectral data onto an orthogonal subspace and restrains background samples by using a linear subspace model. ASD is a GLRT detector based on the linear mixture model, which achieves the target detection by estimating the abundance of the endmembers; (C) spectral matching detector, such as Spectral Angle Mapper (SAM) technique,[9] adaptive matched filter (AMF)[10] and the Kernel-Based Regularized-Angle Spectral Matching (KAR-SM)[11] algorithm. SAM identifies unknown spectral signatures by the similarity measurement to a prior known spectrum, which is another important kind of HSI target detection method. AMF is a further advance of the traditional spectral matched filter, and employs the estimated background clutter covariance matrix to describe the local statistics information. KAR-SM improves the spectral matching performance by introducing the kernel technique and regularized spectral angle. Moreover, some feature extraction techniques are employed for HSI target detection, typically the manifold embedding based approaches. The manifold embedding method is a nonlinear Dimensionality Reduction (DR) technology, which focuses on exploring the manifold embedded in the high-dimensional space by keeping some local properties. In Ref. 12,13, two frameworks that unify different DR approaches, including their linearization, were proposed based on the manifold embedding idea. Typical manifold embedding target detection approaches including Manifold Embedding (ME)[13] detector, Unsupervised transfer learning based target detection (UTLD)[14] which is also named as Transfer Manifold Embedding (TME) in Ref. 15, and Sparse Transfer Manifold Embedding (STME) technique.[15] TME detector preserves the discriminative information from training data to testing data which are not in the same feature space and with different data distributions by using a transfer regularization term. STME utilizes discriminative manifold embedding to extract spectral features and avoids the possible overfitting in small sample size learning by introducing sparse and transfer constraints.

From the aspect of imaging mechanism, there should be a relationship between the spectral information and spatial information, because spatial neighbors always affect the measured signal by secondary illumination in HSI. The adjacency effects caused by surface reflection and atmospheric scattering have been shown in Ref. 16. Several spectral-spatial classification methods[17–19] for HSI have been proposed. The spectral features and spatial features are actually extracted and processed independently in these methods. A drawback of these approaches is that the spectral features and spatial features are measured in different scales. Hence, the spectral and spatial features are usually simply stacked. Moreover, the spatial information extraction always relies on rich prior image information and image segment, which are difficult to be achieved in target detection application. A Data Field based Support Vector Detector (DFSVD)[20] was proposed to achieve the spectral-spatial target detection for HSIs. Based on the data field modeling, the spectral information and spatial information are fused as data field potential. Then, a hyper-sphere with higher potential for target detection is determined by using the support vectors. However, the spatial k-NNs in DFSVD are simply regarded as unit charges, which may make the spatial information lost. Besides, the charge characteristic of the spatial k-NNs is mutually set according to target types, which may also bring errors to target detection results. Another data field based method for HSI classification was proposed in Ref. 21. The classification method in Ref. 21 fused the spectral and spatial features based on a linear fusion model. It should be noted that the weight coefficient can be effectively learned and describe the inner connection between spectral and spatial features due to the rich label information.

In this paper, a spectral-spatial hyperspectral target detection method on the basis of data field theory is proposed. The spectral information and spatial information are unified as radiation features in the data field modeling in both the spectral space and image spatial space. Then, local information is introduced to the discriminative manifold embedding in order to explore the discriminative information for target detection which lies in the decision boundary and emphasize the samples located in the boundary margins. Hence, the two data fields are fused and the most discriminative features that contain both spectral and spatial information are extracted. The performance of the presented target detection algorithm is demonstrated by three widely used HSI test datasets. Different from the data field based classification method in Ref. 21 which trained a weight coefficient, the target detection algorithm in this paper aims to train an optimal transfer matrix, which can be seen as a structure feature of the target samples in the data field modeling.

This paper is organized as follows: Section 2 presents the proposed data field modeling approach in HSI. Section 3 proposes the feature extraction method inspired by manifold learning idea with the data field modeling. In Section 4, the experimental results on three HSI test datasets are analyzed and illustrated. Furthermore, the determining method and the influence of the key parameters on the algorithm performance are discussed in this section. The contributions of this study are presented and conclusions are drawn in Section 5.

2. Data field modeling

In this paper, we first unify the spatial information and spectral information by the introduction of data fields. In order to apply the field theory in physics to mathematical modeling, data field was proposed and used for simulating the physical field. In a data field, data always interacted with each other. Due to the data interaction, according to the data field idea, the property of a data point in data fields is jointly determined by itself and the data interacted with it. For the purpose to describe the data interaction in data fields, data can be considered as radiation sources and the radiation effects between the data can be seen as the descriptions of the data interactions. In this study, data field theory is employed for the data modeling in HSIs. Thus, the identification for a test pixel is not merely dependent on its own reflectance spectra signatures, but also the relationships with other pixels in the HSI.

By prior knowledge, a training sample set can be obtained which consists of two parts: a positive training set denoted by $\{\boldsymbol{x}_i\}_{i=1,2,\ldots,N_i}$ and a negative training set denoted by $\{\boldsymbol{x}_l\}_{l=1,2,\ldots,N_l}$. In the paper, positive samples are represented by subscript i and negative samples are denoted by l. Further, $N = N_i + N_l$ denotes the size of the training set, where N_i and N_l denote the positive sample number and the negative sample number, respectively. In this paper, for the purpose of data field modeling in HSI, several rules are proposed as follows: