Background of Hyperspectral Change Detection

Subjects: Remote Sensing

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Hyperspectral image change detection (HSI-CD) is an interesting task in the Earth’s remote sensing community. HSI-CD methods are feeble at detecting subtle changes from bitemporal HSIs, because the decision boundary is partially stretched by strong changes so that subtle changes are ignored.

change detection (CD) hyperspectral image (HSI) simple linear iterative clustering (SLIC)

1. Introduction

Change detection (CD) is a sensing task that analyzes the bitemporal or multitemporal images for the identification of the changed scene over time. Recently, lots of satellite missions carrying hyperspectral sensors have been launched consecutively, which means hyperspectral images (HSIs) have become an important data source for Earth observation. The abundant spectral information can boost target detection [1][2][3], anomaly detection [4][5][6], and classification [7][8][9]. Binary hyperspectral image CD (HSI-CD) is a special task in which the final change map (change map) reflects the change or not at the pixel level, i.e., zeros denote unchanged regions, and ones indicate changed regions. Such tasks can be applied to disaster assessment [10][11], agriculture and forestry monitoring [12][13], urban expansion research [14][15] and so on. The HSI-CD task consists of three steps: data preprocessing, change identification, and change map output and evaluation. Among them, change identification is the most important and challenging step. The changes can be divided into strong and subtle changes according to the change intensity [16]. Strong changes are associated with bitemporal HSIs that have significantly different spectral features. In contrast, subtle changes just have small differences in spectral features between the bitemporal HSIs. For example, during the transition of land cover from bare land to crop, different water contents or different growth rates of the crops indicate different changes, where the lower water content or slower growth rate corresponds to subtle changes. Furthermore, subtle changes may be induced by mixed pixels that are usually present in the edge areas of the HSIs, because the spatial resolution of HSIs is limited. The changes of partial endmembers in the mixed pixels belong to subtle changes. However, the detection of subtle changes is challenging. Since HSIs can provide intensive sampling of spectral features over a wide spectral range, it is possible to accurately monitor changes at fine spectral scales. That is, HSIs have the advantage of being able to characterize subtle changes.

To exploit changes, kinds of methods have been proposed, including supervised and unsupervised methods. The former ones are limited by the availability of ground truths. Contrarily, the later ones do not require any a priori information and have aroused wide attention. Furthermore, the accurate detection of subtle changes without a priori data and with a lower false alarm rate is an interesting and meaningful task for HSI-CD. Therefore, it was focused on unsupervised methods. Unsupervised binary CD methods that are applicable for HSI-CD can be generally classified into four types: (a) image algorithm-based methods [17], (b) image transform-based methods [18], (c) HSI-CD specified methods [19], and (d) deep learning-based methods [20].

2. Image Algorithm-Based Methods

The image algorithm-based methods assume that changes lead to significant differences in gray pixel levels and thus directly perform algebraic operations on bitemporal HSIs to determine pixel changes. The simple and commonly used arithmetical operations are image subtraction [21], image regression [22], and image rationing [23]. One typical algorithm is the change vector analysis (CVA) [24], which uses spectral vector subtraction to analyze the differences in the spectral bands. Recently, some modified CVA algorithms have also been proposed [25][26]. Structural similarity (SSIM) is also introduced into the image similarity measurement based on structural information degradation [27] and then used for the HSI-CD in [28]. These methods directly detect pixel pairs independently, which makes them sensitive to noise and misalignment errors.

3. Image Transform-Based Methods

Image transformation-based methods transform images into a specific feature space to emphasize changed pixels and suppress unchanged ones. Principal component analysis (PCA) [29] is a common algorithm for dimensionality reduction. Nielsen et al. [30] proposed a multivariate alteration detection (MAD) method based on typical correlation analysis, which used linear transformations of bitemporal HSIs to maximize changes. MAD has been successfully applied to vegetation monitoring in HSIs [31]. Iterative reweighted MAD (IR-MAD) [32] is an expanded version of MAD in iterative form. In addition, the slow feature analysis (SFA) method extracts slowly changing features from a time series [33][34]. It can be used for HSI-CD by suppressing unchanged features and highlighting the changed features [35]. Iterative SFA (ISFA) [36] assigns high weights to invariant pixels during iteration so that they can play a greater role in feature extraction.

4. HSI-CD Specified Methods

Recently, many CD methods have been proposed specifically for HSI-CD. Chen et al. [37] proposed an HSI-CD model based on spectrally and spatially regularized low-rank and sparse decomposition. It improved the already established low-rank and sparse decomposition to implement HSI-CD. Wu et al. [38] proposed an HSI anomalous CD method based on joint-sparse representation. In this method, the background dictionary is constructed by randomly selecting background pixels from the image. Then, it uses the constructed background dictionary to capture changes. In addition, spectral unmixing is also widely used in the implementation of HSI-CD [39][40][41][42][43]. These methods use spectral unmixing to determine whether the pixel changes directly or indirectly.

The tensor decomposition reconstruction detector (TDRD) HSI-CD method [44] implements a Tucker decomposition and reconstruction strategy for bitemporal HSIs to form new HSIs with increased separability. A novel patch tensor-based CD method (PTCD) [45] considers the non-overlapping local similarity property to make full use of the spatial structure information of bitemporal HSIs. In [46], MaxtreeCD is first proposed to exploit multiple morphological attributes to fully explore the spatial information, then a spectral angle weighted-based local absolute distance (SALA) is designed to determine the spectral change. It is found that MaxtreeCD can detect the complete changes and have good detection performance.

5. Deep Learning-Based Methods

Deep learning has swept across the field of remote sensing image interpretation due to the significant advantages in deep feature representation and nonlinear problem modeling [47][48][49][50]. For unsupervised HSI-CD, the pseudo-labels generated with unsupervised model-driven methods are usually used for training an artificial neural net (ANN). Li et al. [51] proposed a noise modeling-based unsupervised HSI-CD framework, in which the noise model is used to purify pseudo-labels for the end-to-end training process. Song et al. [52] proposed an HSI-CD architecture based on a recurrent 3D fully convolutional network, in which the pseudo-labels were generated by principal component analysis (PCA) and spectral correlation angle (SCA). Wang et al. [53] proposed a general end-to-end 2-D CNN (GETNET) HSI-CD framework, in which mixed-affinity matrices were formed, and features were extracted for classification. The pseudo-labels of the GETNET were produced by CVA. Du et al. [54] proposed a DSFA framework that extracted unchanged paired pixels from the CVA as training samples. The two trained ANNs were used to transform the bitemporal images separately. The invariant pairwise pixels were suppressed, and the changed pairwise pixels were highlighted using SFA constraint. Li et al. [28] proposed an improved pseudo-label generation mechanism that utilized CVA and SSIM to jointly guide the pseudo-label generation, which can be called the self-generated credible labels method (SGCL). The simple ANN with a single convolution layer can obtain accurate CD results. However, the generalization of the method needs to be improved because it cannot achieve desirable results on complex datasets with various changes, and the quality of the pseudo-label depends on both CVA and SSIM. Sun et al. [55] designed a new population confidence-based sample selection method to extract better quality and diverse pseudo-labels. However, the method is time-consuming. The image difference (ID) algorithm and spectral unmixing (SU) manner were also used to generate pseudo-training data [56], and the performance of this method is heavily dependent on the quality of spectral unmixing. In addition, some methods do not rely on pseudo-labels to achieve unsupervised HSI-CD [57][58][59] but exploit the characteristics of HSIs and the power of neural networks.

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