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Hyperspectral anomalous change detection based on joint sparse representation

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ABSTRACT

Anomalous change detection aims at finding small but unusual changes from the unchanged or generally changed background in multi-temporal hyperspectral remote sensing images. It is important to model the spectral variations of background so as to highlight the anomalous changes. In this paper, we proposed a hyperspectral anomalous change detection method based on joint sparse representation. A background dictionary is constructed by the randomly selected pixels in the stacked multi-temporal images. The local neighborhood pixels surrounding the test pixel are presented by joint sparse representation with the background dictionary. Thus, the change tendencies in the local background are modeled by the active dictionary bases. The difference of separate reconstruction coefficients of the test pixel with the active bases will reflect the probability to be anomalously changed. Three detectors, which are coefficient difference, Mahalanobis distance of coefficient difference and multi-temporal residual analysis, are proposed to measure the change intensity. Two experiments with the datasets of "Viareggio 2013 Trial" and one Hyperion indicate that the proposed method obtains better performances than the comparative methods.

1. Introduction

Change detection is identifying the landscape changes by detecting the spectral difference in multi-temporal remote sensing images covering the same study area at different times (Singh, 1989). It is one of the major applications of remotely sensed data, since the information of land-cover changes at short intervals in consistent periods is extremely important for monitoring the society development, ecosystem changes, and understanding their interactions (Coppin et al., 2004). Change detection has played an important role in land-use/land-cover change monitoring, urban development study, and disaster evaluation (Conchedda et al., 2008; Dou et al., 2014; Gil-Yepes et al., 2016; Lu et al., 2011; Song et al., 2014; Wang et al., 2017).

There are numerous researches about change detection methods, which can be categorized into the following types (Hussain et al., 2013): (1) direct comparison, makes a direct comparison for multi-spectral band values, including image differencing (Mas, 1999), image ratio (Foran, 1987), regression (Ridd and Liu, 1998), and change vector analysis (CVA) (Bovolo and Bruzzone 2007; Li et al., 2016; Zhuang et al., 2016); (b) transformation, extracts transformed features from the original spectral values, including principal component analysis (PCA) (Celik, 2009), multivariate alteration detection (MAD) (Nielsen, 2007; Nielsen et al., 1998), and slow feature analysis (SFA) (Wu et al., 2017); (c) classification-based method, detects the "from-to" change types by classification, including post-classification (Wu et al., 2017; Xian et al., 2009), multi-date classification (Huang et al., 2010); (d) GIS-integrated method, interprets landscape changes by combining GIS data (Sofina and Ehlers 2016); (e) Advanced method, takes advantage of machine learning methods and other advanced theories in change detection, such as genetic algorithm (Celik, 2010), and deep learning (Gong et al., 2016; Zhang et al., 2016).

With the development of hyperspectral imaging technology, it is feasible to obtain multi-temporal hyperspectral remote sensing images covering the interested areas. Due to its ability to provide more abundant and detailed spectral information, multi-temporal hyperspectral imagery brings great potential in deep interpretation and monitoring of landscape variations. One of the two main topics in hyperspectral change detection is separating various change types in accordance to the high-dimensional spectral features, including spectral unmixing method (Ertürk et al., 2017; Liu et al., 2016; Sicong et al., 2015; Wu and Du 2017), spectral change vector analysis (Liu et al., 2015a, 2015b), and blind source separation.

The other main topic is hyperspectral anomalous change detection, that aims at finding small but unusual changes from the unchanged or

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generally changed background (Theiler, 2008; Theiler et al., 2010; Theiler and Wohlberg, 2012). Compared with the general changes, the interesting and meaningful anomalous changes are mostly small, and may be easily ignored from the notice of human analysts. The motivation of anomalous change detection is to narrow down the interested changed areas, and highlight the pixels with the 'anomalous' changes to remind the analyst to examine (Theiler and Wohlberg, 2012).

Eismann et al. (2008) proposed a basic diagram for anomalous change detection, where the predictor plays an important role in modeling the spectral variations within the background. Chronochrome (CC) is an effective method that predict the spectral changes by least squares linear regression (Du et al., 2007; Eismann et al., 2008; Schaum and Stocker, 1998; Theiler and Wohlberg, 2012). Another widely used method is covariance equalization (CE), that assumes the multi-temporal images should have the same statistical distribution after whitening (Eismann et al., 2008; Mayer et al., 2003). Meola et al. (2011) utilized physical model to simulate the spectral values, which is too complex to employ (Meola et al., 2012). In summary, it can be seen that the key for anomalous change detection is to model the general tendency of background spectral variation, and find the anomalies from this tendency. However, due to the complexity of landscape changes, it is hard to find a single statistical model to estimate the spectral variation.

In recent years, sparse representation has been proved to be a powerful tool in the interpretation of hyperspectral images (Zhang et al., 2017). The basic idea is that most spectral features in the hyperspectral image can be represented by only a few coefficients in an over-complete dictionary, with quite small losses (Li et al., 2015). It has the ability to model the spectral signals without assuming and estimating the specific statistical distribution, which might be very useful in modeling the change tendency.

Therefore, in this paper, we proposed a hyperspectral anomalous change detection method based on joint sparse representation. The multi-temporal hyperspectral images are firstly stacked to be a higher dimensional dataset. Then, for every test pixel, a surrounding dual window is used to select local neighborhood pixels. The stacked spectral features of these local neighborhood pixels, which indicate their spectral variations, are assumed to belong to a limited subspace, and can be sparsely represented by the highly redundant dictionary constructed from the background. Thus, the active dictionary bases represent the change tendencies in this local background. If the test pixel is anomalously changed, its separate reconstruction coefficients in multi-temporal images to the active bases will be quite different, since its spectral change cannot be represented by the tendency; otherwise, both of its spectral features in two multi-temporal images will belong to the subspaces spanned by the active bases. Therefore, we proposed three detectors based on the separate reconstruction coefficients of the test pixels for anomalous change detection. The proposed method is named as "Joint Sparse Representation based Anomalous Change Detection (JSRACD)".

The rest of this paper is organized as follows. Section 2 details the methodology of the proposed JSRACD. The experimental results and analysis are shown in Section 3. Finally, the conclusion is drawn in Section 4.

2. Methodology

2.1. Sparse representation

In the model of sparse representation, a signal is assumed to be approximately represented by a sparse linear combination of elements from an over-complete dictionary. Sparse representation has been successfully applied in numerous research areas of hyperspectral image interpretation, such as classification (Chen et al., 2011), unmixing (Feng et al., 2017) and target detection (Li et al., 2015; Zhang et al., 2017). In a hyperspectral image, $\boldsymbol{x} \in \mathbb{R}^B$ denotes a spectral feature vector, where B is the number of spectral bands. Given an over-complete dictionary $\mathbf{H} \in \mathbb{R}^{B\times D}$ with $B \ll D$, the spectral feature $\boldsymbol{x}$ can be approximately represented by a sparse coefficient vector $\boldsymbol{\xi}$ multiplying the dictionary $\mathbf{H}$, where only a few entries in the coefficient vector $\boldsymbol{\xi}$ are non-zero. The sparse vector $\boldsymbol{\xi}$ can be recovered by solving

$$\boldsymbol{\xi} = \operatorname{argmin} \|\mathbf{H}\boldsymbol{\xi} - \boldsymbol{x}\|_2 \quad \text{subject to} \quad \|\boldsymbol{\xi}\|_0 < K_0 \tag{1}$$

where $\|\cdot\|_0$ means the ℓ_0-norm, which indicates the number of non-zero entries in the vector. K_0 is the given upper bound on the sparsity level (Zhang et al., 2015).

In hyperspectral images, considering the spatial correlation, the local neighborhood pixels in a small area usually consist of few kinds of materials, and share a common sparsity pattern corresponding to an over-complete dictionary (Li et al., 2015). It means that the spectral feature vectors in a small local region can be approximately presented by a sparse linear combination of a few elements in an over-complete dictionary, while these elements are weighted with different coefficients for each pixel (Chen et al., 2011). This kind of problem can be solved by joint sparse representation (JSR), which have attracted lots of interests in remote sensing researches (Chen et al., 2011; Lu et al., 2017; Xu et al., 2016).

Give a spectral matrix for local neighborhood pixels $\mathbf{S} = [\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_N] \in \mathbb{R}^{B\times N}$, where N indicates the number of pixels, it can be sparsely represented with an over-complete dictionary as

$$\mathbf{S} = [\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_N] = [\mathbf{H}\boldsymbol{\xi}_1 + \boldsymbol{\varepsilon}_2, \mathbf{H}\boldsymbol{\xi}_2 + \boldsymbol{\varepsilon}_2, \cdots, \mathbf{H}\boldsymbol{\xi}_N + \boldsymbol{\varepsilon}_N] = \mathbf{H}\Psi + \Sigma \tag{2}$$

where Ψ is the matrix of sparse representation coefficients for all pixels, and Σ is the residual matrix. In joint sparse representation, Ψ shows the common sparsity pattern, which means only a few row in this matrix are non-zero. The active dictionary bases in $\mathbf{H}$ show the common materials in this local neighborhood. The optimization model can be expressed as

$$\Psi = \operatorname{argmin} \|\mathbf{H}\Psi - \mathbf{S}\|_F \quad \text{subject to} \quad \|\Psi\|_{row,0} < K_0 \tag{3}$$

where $\|\cdot\|_{row,0}$ denotes the number of non-zero rows in the matrix. We can call this matrix Ψ as a row-sparse matrix. For the optimization of joint sparse representation, we utilize simultaneous orthogonal matching pursuit (SOMP) algorithm, and please refer to (Mairal et al., 2009, 2010).

2.2. Joint sparse representation for multi-temporal images

Although there are many proposed works taking advantage sparsity in hyperspectral image interpretation, they mainly focus on anomaly detection or classification in a single hyperspectral image (Qu et al., 2018). In this paper, we proposed a method aiming at finding anomalous changes from background, dealing with multi-temporal images. The formal mathematical description of anomalous change detection can be presented as (4):

$$\mathscr{A}(i, j) = Anomaly(\boldsymbol{x}_{i,j}, \boldsymbol{y}_{i,j} | \boldsymbol{S}_X, \boldsymbol{S}_Y) \tag{4}$$

where $\mathscr{A}(i, j)$ is the anomalous change intensity, $Anomaly(\cdot)$ is the indicator for anomaly, $\boldsymbol{x}_{i,j}$ and $\boldsymbol{y}_{i,j}$ are the spectral features of the corresponding pixels (i, j), $\boldsymbol{S}_X$ and $\boldsymbol{S}_Y$ indicate the feature matrices of the background in multi-temporal images. This formal mathematical description illustrates that anomalous change detection aims at finding the anomalies of the spectral feature changes under the condition of the spectral variance of background. It will include the modelling of background spectral variance, the representation of spectral features of the detected pixels, and the anomalous change measurement.

Based on joint sparse representation, we propose a new anomalous change detection algorithm – JSRACD. The basic idea of the proposed JSRACD is shown in Fig. 1. The change tendencies in the local window are extracted by the active dictionary bases with joint sparse representation. The test pixel can be separately represented by the active bases. If the test pixel is not anomalously changed from the local