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Probability estimation of change maps using spectral similarity

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Abstract: Change detection, which is a process of identifying changes occurred in a geographical area over the time, plays a key role in many applications including assessing natural disasters, monitoring crops, and managing water resources. In the past decades, many change detection techniques have been proposed. Hence, evaluating and analyzing of probability of changes and interpreting them, is essential task which leads to better management of natural resources and preventing disasters. For this purpose, we adopted an approach to estimate probability of occurring detected changes. Based on this approach, change pixels will be categorized and labeled as probabilities (as a percentage). In this paper, the proposed framework consists of the following four steps. Firstly, this research produces binary change maps from methods have been proposed in the literature. Then unmixing process adopted and in next step spectral similarity of pixels is calculated in abundances map (of endmembers) domain. A measurement of spectral similarity identifies the finer spectral differences between the two-hyperspectral images. Finally, masking spectral similarity values by binary change map resulting change probability map. The experimental results show that the method has a good result, and can be widely used in hyperspectral change detection applications.

Keywords: change detection; probability; hyperspectral; spectral similarity.

1. Introduction

Change detection (CD) is a fundamental and challenging subject of research, including remote sensing (RS), monitoring and surveillance, civil engineering, mechanical engineering, medical diagnosis, and etc [1, 2]. In RS applications, CD is defined as the process of detecting the variations of materials in a given scene, due to time or as a result of a significant event (such as a natural hazard) and natural metamorphoses, by analyzing co-registrated multi-temporal images of the same geographical area acquired at different times [3]. The remote sensing CD has a wide range of practical application in many fields, such as disaster assessment, urban sprawl, land cover monitoring, environmental monitoring, ecosystem monitoring [3, 4]. The main principle for utilizing RS data for CD is that changes in the object of interest will alter the spectral behavior (reflectance value) that is separable from changes caused by factors such as atmospheric conditions, illumination and viewing angles, soil moistures, and etc [1, 5].

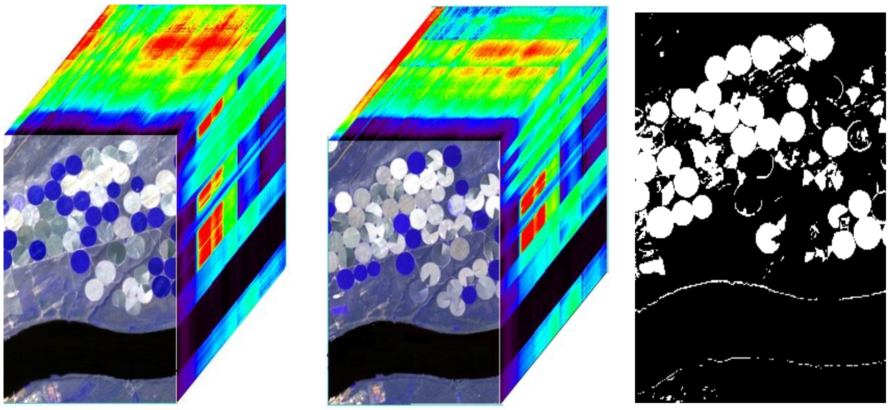
The Earth's surface undergoes significant changes over time due to influences originating from the increasing urbanization and human population [1, 6]. In addition, the demand for natural resources have been increased which leads to side effects in land cover and land use [1]. Hence, an analysis of the changes by the RS tool is necessary for the better management of natural resources, and preventing disasters [6]. In addition, for the planning purposes, estimating probability/intensity of changes is necessary.

In the past decades for discriminating *change/no-change* pixels many binary CD techniques have been proposed [6]. Evaluating and analyzing of probability/intensity of occurred changes and interpreting them, is essential task which leads to better monitoring of study area. The purpose of this paper is producing probability/intensity map of changes. For this purpose, we adopted an approach to estimate probability/intensity of detected changes. Based on this approach, change maps's probability/intensity is produced and pixels categorized based on percentage of probabilities.

2. Experiments

2.1. Study Area and Data Set

In this work, we utilized a widely used real-world hyperspectral images (HSIs) to evaluate the performance of the proposed method. This data set is a reference and benchmark data set that has been used previously in many hyperspectral CD approaches [6]. This data set can be found online in http://rslab.ut.ac.ir. Figure 1 shows the case study area that covers a range of 307×241 of an irrigated agricultural field in the city of Hermiston in Umatilla County, Oregon, USA. The data were acquired on May 1, 2004, and May 8, 2007. The main changes between the acquisition dates relate to land cover changes of agricultural fields.



(a) (b) (c)

Figure 1. The (a) and (b) false color composite of the original hyperspectral images acquired in 2004 and 2007 of the USA data set respectively, and (c) binary change map ground truth.

Due to environmental and equipment conditions, data pre-processing plays a crucial role in RS before the beginning of the main process. The pre-processing are made in two steps: (1) geometric preprocessing and (2) spectral preprocessing (including remove no-data bands, destriping, noise reduction, smile–frown detection, radiometric calibration, and atmospheric correction) [7].

2.2. Adopted Methodology

The focus of this research is producing probability/ intensity of occurred changes. To this end, distinguishing *change/no-change* pixels is crucial. In the past decades, many binary CD algorithms have been proposed. After discriminating *change/no-change* pixels, *change* pixels will be categorized as a percentage of probabilities based on proposed approach. According to the flowchart in Figure 1, the proposed framework consists of the following four steps after pre-processing. In first step, binary change map is produced and *change/no-change* pixels are discriminated. In second step, unmixing process is utilized. In order to produce a probability/intensity map of changes between two multi-temporal images, some similarity metrics are used in third step for measuring spectral similarity of pixels in abundances (of endmembers) space. A measurement of spectral similarity identifies the finer spectral differences between the two HSIs. Finally, in fourth step spectral similarity values are masked by binary change map (BCM) leads to probability/intensity map.

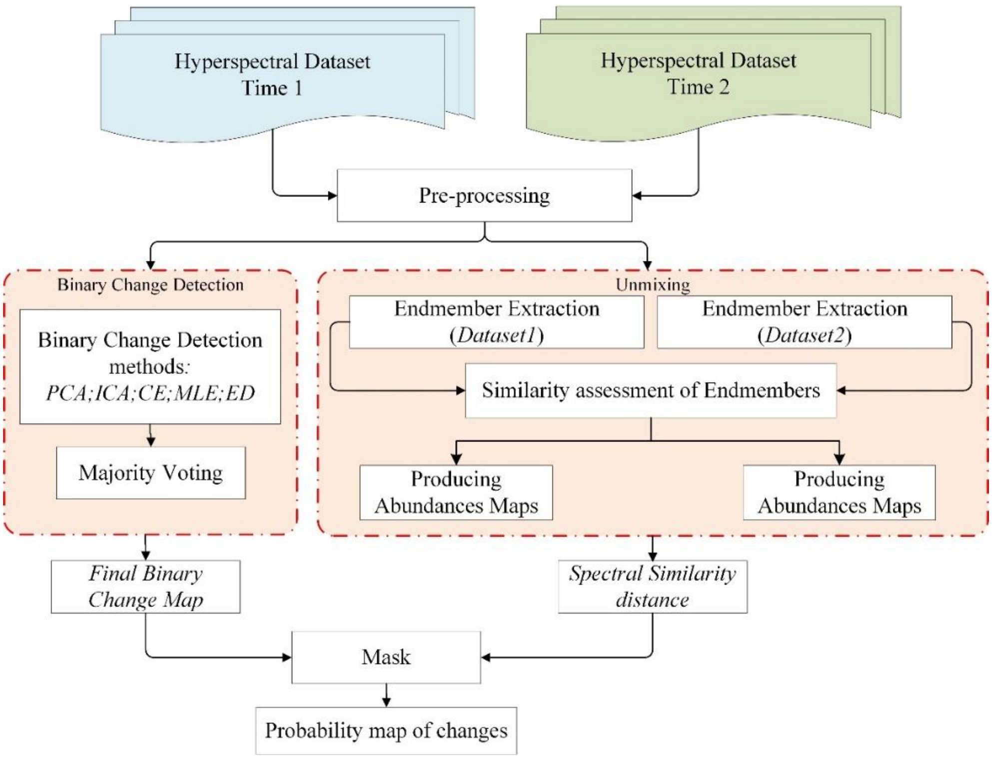


Figure 2. The flowchart of the proposed approach to produce probability map of changes.

2.2.1. Step 1

To distinguish *change/no-change* pixels, we used five binary CD methods, which have been proposed in the literature. The most representative *change/no-change* methods are image math and transformations such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), Cross Equalization (CE), Maximum Likelihood Estimator (MLE) and Euclidian Distance (ED) [6]. Figure 3 shows the visual analysis of aforementioned binary CD methods. The final BCM obtained using majority voting concept (of implemented methods) to achieve a change map with high accuracy.

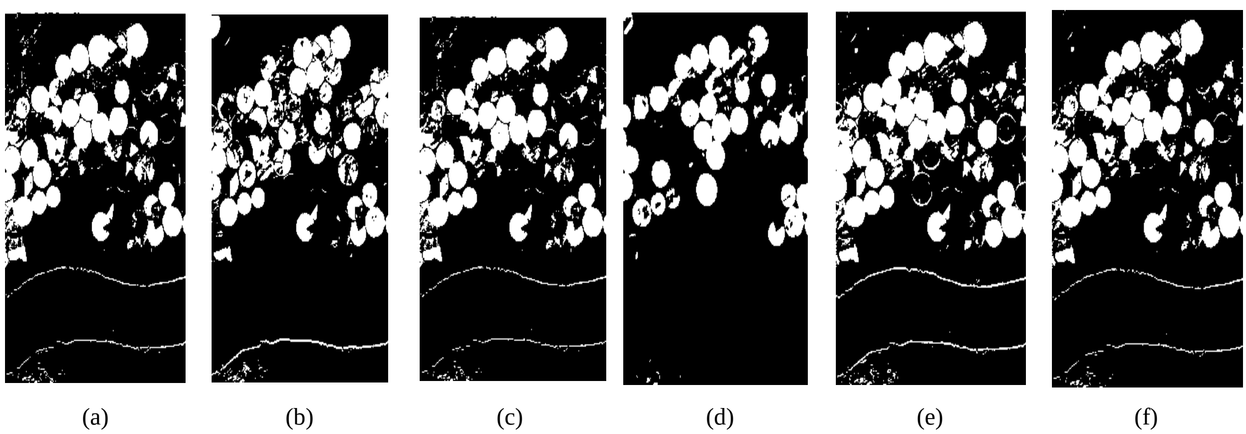


Figure 3. Result of the performance of binary change detection methods in USA dataset. (a) PCA, (b) ICA, (c) CE, (d) MLE, (e) ED, and (f) Final BCM.

Numerical evaluation of implemented methods and final BCM presented in Table 1. The accuracy of the CD methods is measured through Overall Accuracy (OA), Kappa (κ), False Positive Rate (FPR) and Matthews Correlation Coefficient (MCC) indices.

Table 1. Numerical analysis of binary change detection methods.

Method	OA (%)	κ	FPR	MCC
PCA	96.20	0.8835	0.0583	0.8845
ICA	88.68	0.6504	0.2425	0.6516
CE	96.54	0.8909	0.0672	0.8912
MLE	87.83	0.5874	0.3856	0.5900
ED	96.15	0.8852	0	0.8911
Final BCM	97.00	0.9055	0.0527	0.9059

2.2.2. Step 2

Endmember extraction is a vital step in spectral unmixing of HSIs. Endmembers refer to the pure materials spectra in HSIs, and endmember extraction is a process of finding the spectra of all the endmembers [7]. In this research, the endmembers are extracted using the simplex identification via split augmented Lagrangian (SISAL) method [8]. In continues similarity assessment of endmembers based on spectral angle mapper (SAM) algorithm adopted (Equation (1)). Finally, using fully constrained least squares (FCLS) method proposed in [9] estimates the fraction of abundances.

2.2.3. Step 3

The objective of this step is to make an analysis of four similarity metrics to produce change probability/intensity map. The selection of the metrics has been conducted considering its aim and good performance of detecting spectral differences. According the above, the selected metrics are SAM [10], Pearson Correlation Coefficient (PCC) [11], Bray-Curtis dissimilarity (BCD) [12] and Jeffries-Matusita Distance (JMD) [13].

The SAM was proposed in [10] to measure the similarity between two spectral feature vectors. In [14], the angle between each multi-temporal image and a reference vector measured by means of SAM metric was proposed as a solution for CD in specific land covers. In this paper, the spectral similarity based on SAM obtained by considering each spectrum as a vector in abundances space. This algorithm can be calculated as Equation (1) [14-16].

$$\mathbf{S_{\alpha}} = \mathbf{cos^{-1}}\left(\frac{\sum_{i=1}^{n} x_i y_i}{|\sum_{i=1}^{n} x_i^2|^{\frac{1}{2}} |\sum_{i=1}^{n} y_i^2|^{\frac{1}{2}}}\right), \tag{1}$$

where x is spectral signature vector of a pixel (in abundances space) in time1, y is spectral signature vector of a pixel (in abundances space) in time2 and n is the number of abundances maps (endmembers). Spectral angle goes from 0 when signatures are identical to 90 when signatures are completely different.

The PCC is one of the most popular measures for calculating the dependency between two spectral vectors [11]. The PCC between spectral random vectors is defined as Equation (2) [11]. This measure is widely used in RS applications. A correlation of -1.0 shows a perfect negative correlation, while a correlation of 1.0 shows a perfect positive correlation. A correlation of 0.0 shows no relationship between the movements of the two variables.

$$\mathbf{P_{xy}} = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) - (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}, \tag{2}$$

The BCD metric is one of the well-known dissimilarity metric of quantifying the difference between samples that has the value between 0.0 (when signatures are completely different) and 1.0 (when signatures are identical) [12]. The normalized formula for calculating the BCD between two samples is given as Equation (3) [12].

$$\mathbf{S}(\mathbf{x},\mathbf{y}) = \frac{\sum_{i=1}^{n}|x_i+y_i|}{\sum_{i=1}^{n}(x_i-y_i)}, \tag{3}$$

The JMD is a widely used statistical separability criterion. It is a parametric criterion, for which the values range between 0.0 (when signatures are identical) and 2.0 (when signatures are completely different). The JMD is calculated as Equation (4) [13].

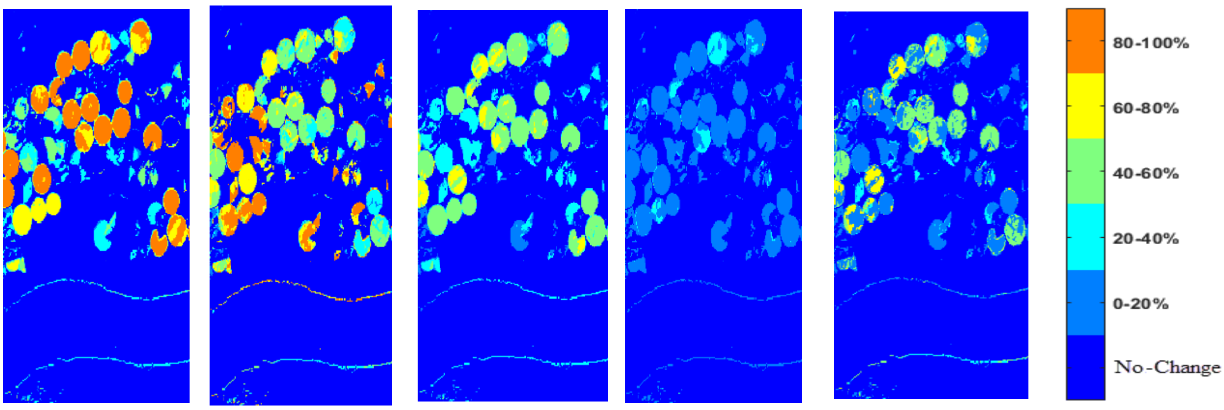
$$\mathbf{J}_{\mathbf{xy}} = \mathbf{2}(\mathbf{1}-\mathbf{e}^{-\mathbf{B}}),$$
$$\mathbf{B} = \frac{\mathbf{1}}{\mathbf{8}}(\mathbf{x}-\mathbf{y})^{\mathbf{T}}\left(\frac{\sum\mathbf{x}+\sum\mathbf{y}}{\mathbf{2}}\right)^{-\mathbf{1}}(\mathbf{x}-\mathbf{y})+\frac{\mathbf{1}}{\mathbf{2}}\ln\left(\frac{\left|\frac{\sum\mathbf{x}+\sum\mathbf{y}}{\mathbf{2}}\right|}{|\sum\mathbf{x}|^{\frac{1}{2}}\left||\sum\mathbf{y}|^{\frac{1}{2}}\right|}\right), \tag{4}$$

2.2.4. Step 4

In final step the results of step 3 masked by BCM produced in step 1. The results of this subsection presented in next section. For achieving final probability/intensity map, we utilized majority voting concept.

3. Results and Discussion

As shown in Figure 4, probability/intensity map of changes produced by using spectral similarity metrics.



(a) (b) (c) (d) (e) (f)

Figure 4. Result of probability estimation of change map's using spectral similarity metrics. (a) SAM, (b) PCC, (c) BCD, (d) JMD, (e) final probability map of changes, and (f) Legend.

By utilizing majority voting, the probability/intensity map of changes is produced more confidently. The probability estimation can be widely used in hyperspectral CD applications. Probability/intensity analysis was applied to analyze changed pixels. According to Figure 4(f) changes' probability is on a scale from 0% to 100%. Figure 4(e) shows that, probability of the most of changed pixels is in the range of 40-60%.

4. Conclusions

CD plays a key role in many applications including assessing natural disasters, monitoring crops, and managing water resources. In this study, an approach for analyzing detected changes is proposed. Utilizing the nature of occurred changes along with the probability/intensity of changes is a strategy that can be taken for better management of study area.

Abbreviations

The following abbreviations are used in this manuscript:

RS: Remote Sensing
HSI: Hyperspectral Image
CD: Change Detection
BCM: Binary Change Map
SAM: Spectral Angle Mapper
PCC: Pearson Correlation Coefficient
BCD: Bray-Curtis Dissimilarity
JMD: Jeffries-Matusita Distance

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