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A targeted change-detection procedure by combining change vector analysis and post-classification approach

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ABSTRACT

In remote sensing, conventional supervised change-detection methods usually require effective training data for multiple change types. This paper introduces a more flexible and efficient procedure that seeks to identify only the changes that users are interested in, here after referred to as "targeted change detection". Based on a one-class classifier "Support Vector Domain Description (SVDD)", a novel algorithm named "Three-layer SVDD Fusion (TLSF)" is developed specially for targeted change detection. The proposed algorithm combines one-class classification generated from change vector maps, as well as before- and after-change images in order to get a more reliable detecting result. In addition, this paper introduces a detailed workflow for implementing this algorithm. This workflow has been applied to two case studies with different practical monitoring objectives: urban expansion and forest fire assessment. The experiment results of these two case studies show that the overall accuracy of our proposed algorithm is superior (Kappa statistics are 86.3% and 87.8% for Case 1 and 2, respectively), compared to applying SVDD to change vector analysis and post-classification comparison.

1. Introduction

Satellite-based approaches have emerged as an effective way to detect and classify different types of changes occurring in land surface (Rogan and Chen, 2004; Hussain et al., 2013; Sinha and Kumar, 2013; Benedek et al., 2015). A variety of change-detection techniques based on remote-sensing technology has been developed (Lu et al., 2004; Blaschke, 2010; Chen et al., 2013; Hussain et al., 2013). Some methods, including image differencing (Metternicht, 1999; Sinha and Kumar, 2013) and clustering-based method (Bruzzone and Prieto, 2000), are relatively easy to implement because no training data is needed (Chen et al., 2012), but they only provide limited binary change ("change" vs "no change") information (Hussain et al., 2013). Other supervised methods, such as the post-classification approach (Yuan et al., 2005; Silván-Cárdenas and Wang, 2014), supervised change vector analysis (Bovolo et al., 2008; He et al., 2011) and direct classification (Bruzzone et al., 2004; Nemmour and Chibani, 2006), can identify detailed change type as "from-to" information by using given training samples, and thus are more preferable when ground truth information is available (Bruzzone et al., 2004).

Despite the potential advantages, users are often confronted with the difficulty of gathering high-quality ground-truth data for training when supervised methods are applied (Fernandez-Prieto and Marconcini, 2011). An effective training set for change detection should meet the following criteria: (1) contain samples representing all land-cover classes (Muñoz-Marí et al., 2007); (2) sample both before-and after-changes images (Kennedy et al., 2009); (3) represent most intra-class variance. Acquisition of such exhaustive training data is often labor intensive and practically uneconomical.

Moreover, our environmental system is constantly changing; nothing stays the same from moment to moment, causing a serious uncertainty issue when we try to identify real land-cover changes. The complexity of spectral differences between bi-temporal images might be caused by land-cover transition, which is what people are usually interested in, but might also come from interference factors such as changes in atmospheric conditions, sun angle, seasonal variation (Chen et al., 2013), or even fluctuation in the measurement tools. Discriminating the desirable changes in traditional supervised change detection depends on the assumption that real land cover change holds higher changing magnitude

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(Johnson and Kasischke, 1998). This assumption would be violated when the interference factors misleadingly yield similar large and inherently-patterned numerical differences between bi-temporal images. As a consequence, a great number of erroneous and misleading interpretations can exist when full-class detection results are produced by the traditional supervised approach.

The motivation of this paper originates from the fact that nowadays more and more application-oriented land monitoring tasks have a very clear and specific objective such as measuring urban expansion, monitoring deforestation or mapping disaster region. Provided that we narrow our focus on only change types that are of interest to users, the constraint of preparing exhaustive ground-truth data can be relaxed as few change categories are required to be characterized, while the issue of irrelevant changes can be minimized since most of them can be grouped into a broad type "background class" without the necessity to explore the details. Such an advantageous procedure that aims to discriminate one or several specific land change types has been termed as "targeted change detection" by Fernandez-Prieto and Marconcini (2011), who proposed a novel technique based on the Expectation Maximization algorithm and Markov Random Fields to tackle the problem. Unfortunately, they investigated the problem more from a computation perspective, and the iterative global optimization of Markov Random Fields used in their method is inapplicable to those large remotely sensed dataset.

Ideally, targeted change detection methods would outperform conventional supervised ones in most cases, due to their ability to fulfil change identification while gaining flexibility: even in the extreme case of full category detection, targeted detection still can reach the goal by applying a one-by-one strategy. However, in reality, the difficulty of classification based on an extremely incomplete training set makes the targeted change detection a major methodological challenge. Unlike traditional supervised techniques, which compare a measurement (probability, distance, similarity, etc.) for each class to decide pixels' label, the measurements for most classes are unknown in the scene of targeted change detection, which hinders a reliable discrimination of our target from the background.

In order to overcome the problem, an algorithm called "Three-layer SVDD Fusion (TLSF)" is proposed in this paper. The SVDD here, referred to "Support Vector Domain Description", is introduced as a novel classifier for solving one-class classification in Section 3.1. In remote-sensing community, the SVDD approach has been reported to be capable of generalizing effective description of targeted classes on a single imagery (Muñoz-Marí et al., 2007; Sanchez-Hernandez et al., 2007; Sakla et al., 2011). Inheriting all the related merits of Support Vector Machine (SVM) (Banerjee et al., 2006; Mountrakis et al., 2011; Shao and Lunetta, 2012; Löw et al., 2013), SVDD is appealing in light of (1) the non-parametric assumption on the data distribution; (2) fewer samples needed; (3) good generation without overfitting. It is, therefore, selected as the primary means for targeted classification in our procedure.

To further increase the reliability of the final map, our method improves the "comparison" step in change detection by combining two complementary approaches, namely post-classification approaches and change vector analysis. Post-classification approach compares two thematic maps obtained by individually classifying before- and after-change images (Hussain et al., 2013). The limitation of this method is that the results are heavily contaminated by compounded errors caused by combining two inconsistent classification procedures due to a lack of consideration of their temporal correlation (Bruzzone et al., 2004; Tewkesbury et al., 2015). Conversely, change vectors analysis only exploits temporal correlation of every pixel pair by subtracting their feature vectors. Because a baseline reference vector is ignored, change vector analysis is limited by its inefficiency in distinguishing two ambiguous feature pairs which are numerically different, but retain similar difference values (Tewkesbury et al., 2015). Previous efforts in supervised change detection for combining temporal correlation and single-date classification such as direct classification (Bruzzone et al., 2004; Nemmour and Chibani, 2006) suffered from a large number of change types that are needed to be labeled (Tewkesbury et al., 2015). However, this concern does not exist any longer in the target change detection since only targeted types need to be trained.

The remainder of the paper is organized as follows: Section 3 presents a detailed description of TLSF algorithm; Section 4 discusses how to implement TLSF and make it workable based on two benchmarking cases; Section 5 describes the testing results of our proposed procedure compared with other possible solutions in two case studies; and Section 6 concludes the study.

2. Study area, satellite data and preprocessing

Two case studies have been considered. The first study area is an urban region, the northern suburb of the City of Kingston, located in Eastern Ontario, Canada. In the last twenty years, north Kingston has experienced a certain level of urbanization: natural conifer forests in the suburban area were cleared and converted to urban land use, making it a good example for studying urban expansion. To test our method, we used a pair of 4 m resolution IKONOS images of this area collected on April 25, 2000 and May 5, 2014, respectively, as shown in Fig. 1(a). The IKONOS images were ordered from the DigitalGlobe with the central latitude and longitude of about 44.254 and −76.565 degrees, respectively. The imagery from 2014 has minor cloud cover, so we first applied a mask (Sawaya et al., 2003) to mask out the cloud region (see Blue region in Fig. 1(a)). The IKONOS image pairs were co-registered with an RMSE of 0.5 pixels in the ENVI software. For radiometric normalization, an automatic procedure based on T-point thresholding algorithm was employed based on the previous research (Ye and Chen, 2015).

The second study area is an interior forest of the south-central Black Hills in western South Dakota, United States. On 24 August 2000, a human-caused Jasper fire burned this forest. Two 30 m resolution Landsat 7 ETM+ images, as shown in Fig. 1(b), collected before and after the fire at the path of 33 and Row 30 were used. Both images were collected from USGS achieve with the geometric correction. Bands 3, 4 and 7 were selected as feature bands since previous research has indicated that this band group was effective in investigating burned forest (Koutsias and Karteris, 2000). The characteristics of these two pairs of images are summarized in Table 1.

3. Three-layer SVDD Fusion (TLSF) algorithm

3.1. Support Vector Domain Description (SVDD)

The procedure of Support Vector Domain Description (SVDD) can be summarized as follows: starting with a training set belonging to the targeted class denoted as $\{x_i \in \mathbb{R}^N,\ i = 1, \ldots, n\}$ (N is the dimension number of original feature space), SVDD exploits a minimum enclosed hypersphere with the radius R and center a that contains all training objects (see Fig. 2). Considering that the training set may contain outliers due to sampling errors, a set of slack variables $\xi_i > 0$ are introduced. The objective function is (Tax and Duin, 1999, 2004):

$$\min_{R,a}\left\{R^2 + C\sum_i \xi_i\right\} \tag{1}$$