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RESEARCH PAPER

Semi-supervised change detection approach combining sparse fusion and constrained k means for multi-temporal remote sensing images

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Abstract Change detection is the measure of the thematic change information that can guide to more tangible insights into an underlying process involving land cover, land usage and environmental changes. This paper deals with a semi-supervised change detection approach combining sparse fusion and constrained k means clustering on multi-temporal remote sensing images taken at different timings $T1$ and $T2$. Initially a remote sensing fusion method with sparse representation over learned dictionaries is applied to the difference images. The dictionaries are learned from the difference images adaptively. The fused image is calculated by combining the sparse coefficients and the dictionary. Finally the fused image is subjected to constrained k means (CKM) clustering combining few known labelled patterns and unlabelled patterns which have been collected from experts. The enhanced (CKM) approach (ECKM) is compared with k means, adaptive k means (AKM) and fuzzy c means (FCM). Experimental results were carried out on multi-temporal remote sensing images. Results obtained using PCC and $F1$ measure confirms the effectiveness of the proposed approach. It is also noticed that the ECKM provides better results with less misclassification of errors as compared to k means, adaptive k means and fuzzy c means.

1. Introduction

Detection of changes in land cover/land use (Rawat and Kumar, 2015) and changes due to natural hazards is a challenging task to deal with. Semi-supervised change detection techniques are widely used in remote sensing and play an important role in many application domains. They include environmental monitoring (Shalaby and Tateishi, 2007; Ghosh et al., 2015), assessment of land cover dynamics (Rawat et al., 2013), forest monitoring (Kennedy et al., 2007), urban studies (Peijun et al., 2010; Hazarika et al., 2015), etc. The most widely used change detection technique contains three steps, pre-processing, comparison and analysis. In pre-processing, the multispectral images are normalised using band ratio algorithms (Song et al., 2001). The multispectral images are registered, geometric or radiometric corrected,

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atmospheric corrected (Hadjimitsis et al., 2010) for further usage in subsequent steps. Comparison of images is done using absolute differencing or change vector analysis for comparing the images taken at different timings. Finally at the analysis phase the changed pixels are differentiated from the unchanged pixels to identify the change (El Bastawesy et al., 2014; El Hattab, 2014).

Based on the literature (Subudhi et al., 2014; Hussain et al., 2013) of sorting out the changed pixels from the unchanged one two approaches are commonly used, supervised and unsupervised. Supervised approach needs to reference map information for setting parameters whereas an unsupervised approach does not. Since a supervised approach (Volpi et al., 2013) provides higher change detection accuracies compared to unsupervised, a reference map is difficult to obtain for certain remote sensing applications. Hence a semi-supervised approach (Lal et al., 2015a; Roy et al., 2012) is proposed with a combination of sparse fusion (Lal et al., 2015b).

The use of semi-supervised and unsupervised approaches has been well documented in the literature (Bovolo et al., 2008). Among them the most widely used is the novel approach using an ensemble of semi-supervised classifiers proposed by Roy et al. (2014) for change detection in remotely sensed images. The approach uses a multiple classifier system in a semi-supervised (learning) framework instead of using a single weak classifier. Iterative learning of base classifiers is continued using the selected unlabelled patterns along with a few labelled patterns. Ensemble agreement is utilised for choosing the unlabelled patterns for the next training step. Finally, each of the unlabelled patterns is assigned to a specific class by fusing the outcome of base classifiers using some combination rule. A novel spatio-contextual fuzzy clustering algorithm was proposed by Subudhi et al. (2014) for unsupervised change detection from multispectral and multi-temporal remote sensing images. The proposed technique uses fuzzy Gibbs Markov Random Field (GMRF) to model the spatial grey level attributes of the multispectral difference image. The change detection problem is solved using the maximum a posteriori probability (MAP) estimation principle. The MAP estimator of the fuzzy GMRF modelled difference image is found to be exponential in nature. Mishra et al. (2012) have used two fuzzy clustering algorithms, namely fuzzy c-means (FCM) and Gustafson–Kessel clustering (GKC) along with local information for unsupervised change detection in multi-temporal remote sensing images. Ghosh et al. (2011) proposed a context-sensitive technique for unsupervised change detection in multi-temporal remote sensing images. The technique is based on a fuzzy clustering approach and takes care of spatial correlation between neighbouring pixels of the difference image produced by comparing two images acquired on the same geographical area at different times.

In this paper a change detection technique for multi-temporal remote sensing images is proposed with four fundamental steps: pre-processing, comparison, fusion and analysis. After comparison the difference images are fused for further analysis in the proposed approach. Based on the literature, (Gong et al., 2012; Lal and Anouncia, 2015) fusion also plays an important role in change detection for remotely sensed images. An improved AIHS (IAIHS) method was proposed for pan sharpening and multi-spectral images by Leung et al. (2014). Through the IAIHS method, the amount of spatial details injected into each band of the multispectral (MS) image is appropriately determined by a weighting matrix, which is defined on the basis of the edges of the panchromatic and MS images and the proportions between the MS bands. An innovative object-oriented change detection approach based on multi-scale fusion was proposed by Wang et al. (2013). This approach introduced the classical colour texture segmentation algorithm J-segmentation (JSEG) to change detection and achieved the multi-scale feature extraction and comparison of objects based on the sequence of J-images produced in JSEG. A novel spatial and spectral fusion model (SASFM) that uses sparse matrix factorization to fuse remote sensing imagery with different spatial and spectral properties has been proposed by Huang et al. (2014).

On the basis of the above mentioned analysis, in the literature no method is available that simultaneously takes advantage of both fusion and semi-supervised clustering approaches for change detection. The main objective of this work is to present robust techniques taking the advantages of sparse fusion and constrained k means clustering for multi-temporal remote sensing images. In this paper we propose a combination of sparse fusion and semi-supervised clustering approach detecting changes for multi-temporal and multi-spectral remote sensing images. In greater detail, the proposed method uses ADM and CVA for generating the difference images obtained from two co-registered and radiometrically corrected multispectral band images acquired over the same geographical area at two different instants of time $T1$ and $T2$. The difference images are fused using sparse representation coefficients and the fused image is clustered as changed (C) and unchanged (UC) pixels by applying CKM. In order to assess the effectiveness of the ECKM, we considered multi-temporal data sets corresponding to the geographical areas of Dead Sea in Israel, and compared the results produced by the proposed approach with unsupervised clustering approaches.

The organisation of this paper is as follows. Section 2 presents an overview of the materials and methods and describes the proposed scheme in detail. In Section 3, experimental results and discussion are described. Performance evaluation of results for change detection are analysed in Section 4. Finally, Section 4 draws the conclusions of this work.

2. Materials and methods

2.1. Study area

The Dead Sea is located in the Middle East, between Jordan and Israel. It is one of the saltiest lakes in the world. Its shores are located 400 m below the sea level. The Dead Sea is 50 km long and 15 km wide at its widest point and lies between 31.544893 N latitude and 35.484123 E longitude. Its main tributary is the Jordan River which lies in the Jordan Rift Valley. The Dead Sea is fed mainly by the Jordan River, which enters the lake from the north. Due to the large-scale projects done by Israel and Jordan to divert water from the Jordan River for the purpose of irrigation and other water needs, the surface of the Dead Sea has been dropping dangerously for at least the past 50 years. If the shrinkage continues, it is likely that the Dead Sea might disappear completely by 2050. The images of Dead Sea in the year 1984 and 2014 has been acquired by the Landsat 5 and 8 satellites both in October having a time window of acquisition (before/after) of thirty