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Survey on Various Change Detection Techniques for Hyper Spectral Images

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Abstract— The "hyper" in hyper spectral means "over" as in "too many" and refers to the large number of measured wavelength bands. Hyperspectral images are called spectrally over determined, which means that they give ample spectral information to identify and distinguish spectrally unique materials. Hyper spectral imagery provides the potential for more accurate and detailed information extraction than possible with any other type of remotely sensed data. The main objective of this research paper is to study various techniques used in Change Detection for hyper spectral Images.

Keywords— Hyperspectal images, Remote Sensing,PCA, CVD, Image differencing, ICA

I. INTRODUCTION

Remote sensing change detection has played an important role in many applications. Most of the traditional change detection methods deal with single-band or multispectral remote sensing images. Hyperspectral remote sensing images provide detailed information on spectral changes so as to present promising change detection performance. The challenge is how to take the advantage of the spectral information at such a high dimension. Accurate change detection of the earth's surface features is extremely important for monitoring environmental changes and resource management. Remote sensing technology provides a large-scale view of landscape over a long period of time and has been demonstrated to be an efficient method for change detection . Change detection by remote sensing has been widely used in many applications such as land-use/land-cover monitoring, urban development , ecosystem monitoring , and disaster monitoring . Traditional change detection methods have been intensively studied. However, almost all of them are based on single-band or multispectral remote sensing images . Recently, hyper spectral Images have attracted increasing attention due to the wealth of information contained and the wide range of potential applications [1]. Hyper spectral sensors measure radiance by a large number of bands covering a wide spectral range. Although multitemporal multispectral images can show spectral changes in several bands, the spectral information Offered by multispectral data is not so elaborate. Hyper spectral imagery offers more abundant and more detailed information on spectral changes in multitemporal scenes than multispectral images, which can improve the change detection performance. Conventional change detection methods generally depend on a difference value in each individual band, such as image differencing or the image ratio. The physical meaning of the continuous spectral signatures is ignored. Comparatively, the foremost advantage of hyper spectral data is that the high-dimensional spectral information can indicate the fine spectral signatures and the physical characteristics of different materials . For hyper spectral data, the presence of real change is represented by the change of a spectral signature from one material to another material. Therefore, its more reasonable to directly measure the difference in the spectral signatures of different materials when solving a hyperspectral change detection problem. Several kinds of methods have been proposed for hyperspectral change detection. In post-classification methods , classification maps of multitemporal hyperspectral images are compared to obtain the change detection result. Post-classification provides "from-to" change results and has been widely used; however, its accuracy is limited because pixels misclassified in one dataset will result in errors on the "from-to" change detection map,its no matter whether or not the corresponding pixels in the other dataset are correctly classified. Image transformation techniques, and principal component analysis(PCA) , originating from multispectral methods, transform hyper spectral data into another feature space to label the changed areas. Although these methods can make use of hyper-band information, they generally do not consider the continuous spectral signatures from hyper spectral data. The third kind of hyper spectral change detection method is anomaly change detection. Anomaly detection algorithms consider anomaly changes as outliers in a difference image . Anomaly detection focuses on distinguishing unusual targets from a typical background, and this assumption confines its application in general change monitoring. Based on the above analysis of the current hyper spectral change detection methods, it is clear that we need to explore change detection algorithms by focusing on two main points. To explore the high-dimensional spectral information and the continuous spectrum, the algorithm should directly measure the difference in the signatures to define the detailed changes in the different materials. At same time, considering the practical application, the algorithm should be simple and easy to apply[1].

1.1 Difference of Hyper spectral images from multispectral images:

Hyper spectral systems differ from multispectral sensors because they collect information in many contiguous narrow bands (5 to 10 nm) while hyperspectral images generally contain dozens to hundreds of bands. Multispectral systems not cover the spectrum contiguously and their bands are generally wide (70 to 400 nm). These systems usually have a dozen or fewer bands. In a hyperspectral image, a single pixel will contain information about reflectance across the entire spectral range of the sensor producing what is called a spectral signature. The spectrum obtained from one image pixel will resemble a spectrum of the same material obtained through laboratory spectroscopy permitting detailed identification of materials[11].

1.2 Applications of Hyper spectral Image analysis:

Hyper spectral imagery has been used to detect and map a wide variety of materials having characteristic reflectance spectra. For example, hyper spectral images have been used by geologists for mineral mapping and to detect soil properties including moisture, organic content, and salinity. Vegetation scientists have successfully used hyper spectral imagery to identify vegetation species , study plant canopy chemistry, and detect vegetation stress [11]. Military personnel have used hyper spectral imagery to detect military vehicles under partial vegetation canopy, and many military target detection objectives such as:

- Atmospheric Correction
- Spectral Libraries
- Target Identification
- Spectral Angle Mapper (SAM)

1.3 Techniques used in Change Detection for hyper spectral Images:

Many kinds of methods have been proposed for hyperspectral change detection:

- Principal component Analysis (PCA)
- Change Vector Analysis (CVA)
- Image Differencing
- Image Rationing

II. RELATED STUDY

Chen W. et. al (2013) In this paper, two types of additional information, i.e., spatial information in the neighbourhood of the corresponding pixel in Time 1, and the spectral information of undesired land-cover types, are used to construct the background subspace for special applications. The subspace distance is calculated to determine whether the target is anomalous with respect to the background subspace. The anomalous pixels are considered as changes so that it can take advantage of the high-dimensional information and the spectral signatures in hyperspectral images, and, at the same time, is very easy to apply[1].

M. Ilsever C.U et. al (2012) In this paper they present an techniques for detection of hyperspectral images. They used the pixel-based change detection methods such as Image differencing ,Automated thresholding ,Image rationing , Change vector analysis (CVA) . The basic premise in using remote sensing data for change detection is that changes in land cover must result in changes in radiance values and changes in radiance due to land cover change must be large with respect to radiance changes caused by other factors[2].

Turgay.C et. al (2009) The proposed paper presents a novel technique for unsupervised change detection in multitemporal satellite images using principal component analysis (PCA) and k-means clustering. The difference image is partitioned into $h \times h$ nonoverlapping blocks. The change detection is achieved by partitioning the feature vector space into two clusters using k-means clustering with $k = 2$ and then assigning each pixel to the one of the two clusters by using the minimum Euclidean distance between the pixel's feature vector and mean feature vector of clusters. The proposed algorithm is simple in computation yet effective in identifying meaningful changes which makes it suitable[3].

Yakoub Bazi, F.M.D et. al (2010) In this paper, the unsupervised change-detection problem in remote sensing images is formulated as a segmentation issue where the discrimination between changed and unchanged classes in the difference image is achieved by defining a proper energy functional. In order to increase the robustness of the method to noise and to the choice of the initial contour, a multi resolution implementation, which performs an analysis of the difference image at different resolution levels, is proposed. The experimental results obtained on three different multitemporal remote sensing images acquired by low- as well as high-spatial-resolution optical remote sensing sensors suggest a clear superiority of the proposed approach compared with state-of-the-art change-detection methods[4].

Jin Chen, X. C et. al (2011) In this research Postclassification comparison (PCC) and change vector analysis (CVA) have been widely used for land use/cover change detection using remotely sensed data. However, PCC suffers from error cumulation stemmed from an individual image classification error, while a strict requirement of radiometric consistency in remotely sensed data is a bottleneck of CVA. This paper proposes a new method named CVA in posterior probability space (CVAPS), which analyzes the posterior probability by using CVA[5].

Selim Hemissi, B.S et. al (2013) *explained that* Multitemporal hyper spectral images are gaining an ever-increasing importance revealed by the ambition of the remote sensing community to develop new generation of sensors. Therefore, multitemporal images classification and change detection issues are greatly relevant in several research topics. In this paper, we propose a novel approach for modeling the temporal variation of the reflectance response as a function of time period and wavelength; summarizing the spectral signature of hyperspectral pixels as a 3-D mesh. This approach is adopted for hyperspectral time series analysis leading to the main following contribution: an advanced form of the temporal spectral signature defining the reflectance at each pixel as a congregation of the spatial/spectral/temporal dimensions. Afterward, by formulating the temporal data set in an adequate multidimensional feature space of contextual data, an innovative processing scheme exploiting the theoretical backgrounds of 3-D surface reconstruction and matching is adopted for data interpretation[6]

Zhengguang.S.W et. al (2012) In this paper, A novel strategy based on a relevance vector machine (RVM) coupled with principal component analysis (PCA) is proposed for failure detection, isolation, and recovery (FDIR) of a multifunctional self-validating sensor. The working principle and the online updating algorithm of the RVM predictor are emphasized to identify and recover faults. The proposed predictor can effectively isolate multiple simultaneous faults of multifunctional sensors and accomplish failure recovery with high accuracy and good timeliness. Further, it also possesses a good ability of tracking fault-free signals with sudden changes. Failure detection is carried out by using PCA-based squared prediction error statistics. The PCA-RVM method can distinguish the normal signals with sudden changes from faulty signals. The performance of the strategy is compared with other different predictors, and it is evaluated in a real multifunctional self-validating sensor experimental system[7].

Diego F.P et. al (2011) In this paper, author address this challenging issue and propose a novel technique (formulated in terms of a compound decision problem) capable of identifying specific “targeted” land-cover transitions by exploiting the ground truth available only for the classes of interest at the two dates, while providing accuracies comparable to those of traditional fully supervised change-detection methods. The proposed technique relies on a partially supervised approach that jointly exploits the expectation-maximization algorithm and an iterative labelling strategy based on Markov random fields accounting for spatial and temporal correlation between the two images. Moreover, the proposed method is applicable to images acquired by different sensors (or to different sets of features) at the two investigated times. Experimental results on different multitemporal and multisensory data sets confirmed the effectiveness and the reliability of the proposed technique[8]

Ashish.G.S et.al (2013) proposed that the Experiments are carried out on three-multispectral and multitemporal remote sensing images. Results of the proposed change detection scheme are compared with those of the manual-trial-and-error technique, automatic change detection scheme based on GMRF model and iterated conditional mode algorithm, a context sensitive change detection scheme based on HTNN, the GMRF model, and a graph-cut algorithm. A comparison points out that the proposed method provides more accurate change detection maps than other methods[9]

Lorenzo .B.D ,et. al (2000) One of the main problems related to unsupervised change detection methods based on the “difference image” lies in the lack of efficient automatic techniques for discriminating between changed and unchanged pixels in the difference image. Such discrimination is usually performed by using empirical strategies or manual trial-and-error procedures, which affect both the accuracy and the reliability of the change-detection process. To overcome such drawbacks, in this paper, they propose two automatic techniques (based on the Bayes theory) for the analysis of the difference image. One allows an automatic selection of the decision threshold that minimizes the overall change detection error probability under the assumption that pixels in the difference image are independent of one another. The other analyzes the difference image by considering the spatial-contextual information included in the neighbourhood of each pixel[10].

Juan Gu*a, Xin Lia , Chunlin Huanga, Yiu Yu Hob(2007) based on Independent Component Analysis (ICA), is proposed. The environmental changes can be detected in reduced second and higher-order dependencies in multi-temporal remote sensing images by ICA algorithm. This can remove the correlation among multi-temporal images without any prior knowledge about change areas. Different kinds of land cover changes are obtained in these independent source images. The experimental results in synthetic and real multi-temporal multi-spectral images show the effectiveness of this change detection approach.

Table1 Comparison of various tehnique:

Technique	Based on	Advantages	Disadvantages
Segment Based Approach	Segment Based Classification	Less Complexity	-
Change Detection Of Object	Global Information System Functionality	-	Require Some Prior Knowledge Of Elements
PCA Technique	Pixel Using Threshold Level	-	Large Complexity
Hyper Spectral Remote Sensing	Subspace Based Change Detection	Effectively Deal With Signature Difference	-

III. CONCLUSIONS

ICA method is a suitable tool for improving change information extraction in multitemporal remote sensing images. We have attempted to survey the recent state of the art in image change detection without emphasizing a particular application area. The performance of a change detection algorithm can be evaluated visually and quantitatively based on application need.

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