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Performance analysis of change detection techniques for land use land cover

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ABSTRACT

Remotely sensed satellite images have become essential to observe the spatial and temporal changes occurring due to either natural phenomenon or man-induced changes on the earth's surface. Real time monitoring of this data provides useful information related to changes in extent of urbanization, environmental changes, water bodies, and forest. Through the use of remote sensing technology and geographic information system tools, it has become easier to monitor changes from past to present. In the present scenario, choosing a suitable change detection method plays a pivotal role in any remote sensing project. Previously, digital change detection was a tedious task. With the advent of machine learning techniques, it has become comparatively easier to detect changes in the digital images. The study gives a brief account of the main techniques of change detection related to land use land cover information. An effort is made to compare widely used change detection methods used to identify changes and discuss the need for development of enhanced change detection methods.

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1. INTRODUCTION

The satellites and unmanned aerial vehicles are fast becoming a huge data source. This has paved the way for use of remote sensing images to detect changes on the earth's surface. Change pertaining to the surface of earth have become important for monitoring the local, regional and global resources and environment. Change detection (CD) has been defined in [1] as "the process of identifying differences in the state of an object or phenomena by observing it at different times". In other words, change detection is the process of finding regions that have undergone spatial or spectral modifications and the reasons behind it. A change map is constituted from the images captured at different period of time.

Change detection techniques provide valuable information of the possible transformations a given scene has suffered over time. Change detection is complicated by the fact that change can occur in the temporal and/or spectral domains [2]. Changes can be due to: a biological action in nature, biological action, and human activity. As human and natural forces continue to alter the landscape, various public and private agencies are finding it increasingly important to develop monitoring methods to assess these changes. Change detection can be used to measure five different types of change [3]: change in the identity of a feature over time, change of a feature's shape over time, change of a feature's location over time, change in a feature's size over time, and change in the identify of a feature over time. Gong *et al.* [4] have characterized change detection approaches into two broad groups: bi-temporal CD which measures changes based on a ‘two-epoch’ timescale and temporal CD that analyses the changes based on a ‘continuous’ timescale.

2. NEED AND IMPORTANCE OF CHANGE DETECTION

Availability of satellite images has given rise to the use of these images in monitoring the changes occurring on the surface of the earth. Timely and accurate analysis of the detected changes play an important role in understanding natural phenomenon and changes occurring due to these. It is also used to understand the impact of anthropogenic activities on the environment. The foremost aim of change detection method is to identify significant changes occurring at the same location over a period of time. These changes are captured in a series of images by a satellite. Popular satellite data for remote sensing applications are Landsat multispectral scanner (MSS), thematic mapper (TM), SPOT, and MODIS. Major steps involved in the change detection process are [5]: image pre-processing, selection of suitable techniques, and accuracy assessment. Figure 1 shows the framework of change detection [6]. The change detection has got its various applications few of them are as follows: deforestation, crop monitoring, moisture content of soil, urban planning, and water quality.

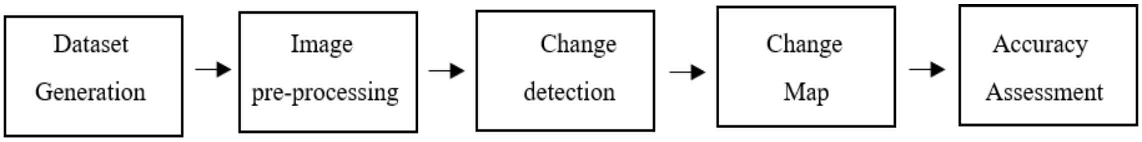

Figure 1. Change detection framework

3. REVIEW OF CHANGE DETECTION TECHNIQUES

The Earth’s surface marks the presence of different types of landscapes. The selection of proper change detection tool is important to analyze changes in these land forms. Image pre-processing plays a major role in the outcome change detection process. Depending on the application, there are many approaches for change detection of satellite images [7]. Figure 2 shows the different change detection methods. A comparative analysis of four of the most commonly used change detection methods namely: i) transformation-based CD, ii) classification-based CD, iii) artificial neural network (ANN) based CD, and iv) advanced models of CD is presented in this study.

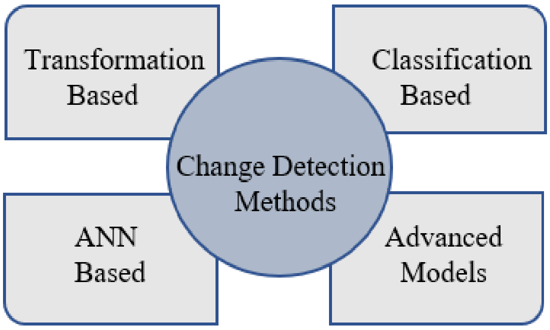

Figure 2. Change detection methods

3.1. Transformation based CD

Change detection using pixel transformation for detecting the measure of change in the images has been extensively studied in the literature. As mentioned in Table 1, these methods are: principal component analysis (PCA) [8]–[10], a variant of PCA called Tasselled Cap or Kauth-Thomas (KT) transformation [11], [12], Gramm-Schmidt transformation and Chi-Square Transform [13]. Table 1 gives details regarding the different transformation-based methods and the application areas in which these methods were used. Out of all the methods mentioned in the literature, PCA is the most frequently used approach for detecting change or no-change information.

Principal component analysis is a transformation-based change detection technique. It is a dimensionality reduction method in which principal components are computed by performing a change of basis. The data in the direction of maximum variance is retained. The reduced features are uncorrelated with each other. PCA based land use change detection technique was used in [8] to identify land use changes in the Hangzhou City from 2000 to 2003. PCA was used to enhance the change information in the Landsat images. A hybrid classifier gave improved accuracy. Based on principal component analysis [9] proposed a framework for detecting changes in multidimensional data streams. Their method reduces computational costs by using a density estimator. The efforts required to minimize threshold setting is reduced through the use of Page-Hinkley test. Chakraborty [14] used MODIS Terra images to detect change in forest areas of the Barak Basin of north-eastern India that covers the states of Assam, Manipur, Mizoram, Nagaland and Tripura. PCA was applied on enhanced vegetation index (EVI) composite images of 2000 to 2006. The forest change map was used to identify hotspots or areas of high disturbance. Robust PCA (RPCA) via principal component pursuit (PCP) was used in [15] for change detection in ultrawideband very high-frequency synthetic aperture radar (SAR) images of CARABAS-II data set. RPCA refers to the problem of PCA when the data may be corrupted by outliers [16]. The main drawback of this approach is, it is difficult to label the changed area in an image.

Table 1. Detailed survey of transformation-based change detection method

Author	Specific method	Dataset	Application area
Fung and Ledrew [8]	PCA	Landsat	Land cover change detection
Gong [9]	PCA	Landsat	Land cover change detection
Deng *et al.* [10]	PCA	Spot-5 Landsat	City expansion
Solano-Correa *et al.* [11]	Tasseled Cap Transformation	Landsat	Land cover change detection
Thakkar *et al*. [12]	Tasseled Cap Transformation	Landsat	Land cover change detection
Vazquez-Jimenez *et al.* [13]	Chi-square	Quickbird	Land cover change detection
Chakraborty [14]	PCA	MODIS	Forest change detection
Schwartz *et al.* [15]	RPCA	CARABAS-II	Land cover change detection

3.2. Classification based CD

This approach is entirely dependent on the choice of data for change analysis. The methods are divided into pre-classification and post-classification. The pre-classification approach is mostly used for change and no-change, rate of change, and image enhancement, while the post-classification is mostly used for "from-to" change analysis and comparison of individually classified images. Table 2 presents a detail study of different classification-based methods along with the application area in which they were used. From the study, it was found that post-classification method was the most used in classification-based change detection. The pre-classification approach is used in [17] for image enhancement, change and no-change, and change rate, while the post-classification is mostly used for "from-to" change analysis and comparison of individually classified images. Afify [18] has compared image differencing, post-classification, principal component analysis, and image rationing techniques to monitor and assess the extent of land cover changes in the city of Burg El-Arab, Egypt. Among these four techniques, the post classification change detection technique provided the highest accuracy followed by the image rationing (IR) and image differencing (ID) techniques while the PCA technique gave the least accuracy. Urban land cover change of Hurghada in Egypt was evaluated by [19]. Of the five change detection techniques applied, post-classification method was found to be the most suitable and accurate method. Hossen *et al.* [20] used unsupervised iso-data clustering, Mahalanobis distance, maximum likelihood supervised classification, normalized difference water index, and minimum distance supervised classification to evaluate and predict future changes in Manzala Lake, Egypt. Maximum likelihood classifier (MLC) achieved highest overall accuracy of 93.33% in comparison to other techniques. To predict future changes, linear regression was used. Supervised classification technique maximum likelihood algorithm was used to determine changes in the Kupti watershed of Darwha block, Maharashtra, India over the period of 15 years from 2000 to 2016 [21]. Classes demarcated on the basis of supervised classification: agriculture, forest cover, wasteland, habitation, and waterbody. Historical data from Corona dataset was mapped with Landsat data and changes in the forest areas of Virginia-Maryland, United States and Mato Grosso-Tocantins-Pará, Brazil were studied by [22]. Corona images were used to detect changes in the year 1960 and Landsat images were used for the period 1980 to 2000. Forest changes were mapped using the support vector machine (SVM) algorithm [23].

SVM was used by [24] to analyze built-up and non-built-up changes in Landsat images of Harare Metropolitan Province, Zimbabwe. Halmy *et al.* [25] mapped the land use/land cover (LULC) distribution of the north-western desert of Egypt to study land use/land cover changes of the desert landscape for 1988, 1999, and 2011. A random forest approach was used to produce the LULC maps with more than 90%

accuracy. From their study they found that depending upon the land use, the study area was subjected to different types of modifications. Markov-CA was used to project changes in 2023 by extrapolating current trends.

Pre-classification and post-classification change detection techniques were used in [26] on Tanguar Haor, Bangladesh images to analyze changes from 1980 to 2010 in. In pre-classification approach: change vector analysis, normalized difference vegetation index, and normalized difference water index (NDWI) analysis were implemented to assess the change scenario. Maximum likelihood classification technique was used to categorize land cover into shallow water, deepwater, vegetation, and settlement. ENVI thematic change workflow tool was used as a post classification tool. Combination of these techniques helped to understand the direction, dynamics, state, and magnitude of change.

Bitemporal change detection to determine the urban growth of Madurai, India with wavelet-based post classification change detection technique on two MSS land cover images of 1996 and 2004 was explored in [27]. Texture feature vector was given as input to a fuzzy c-means classifier to identify the urban growth of the city. The accuracy of the change map was assessed using error matrix analysis which showed the superiority of this method as compared to change vector analysis, image differencing, and PCA. Vignesh *et al.* [28] grouped images into clusters and used them as training sets for an unsupervised classification algorithm ensemble minimization learning algorithm (EML) for land cover classification. This algorithm can classify different vegetation types. A disadvantage is it requires some improvement in classification accuracy.

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Table 2. Detailed survey of classification-based change detection method

Author	Specific Method	Dataset	Application area
Afify [18]	Post classification	Landsat	Urban change detection
Kamh *et al.* [19]	Post classification	Landsat	Urban growth
Hossen *et al.* [20]	MLC, Linear regression	Landsat	Future land cover prediction
Patangray *et al.* [21]	maximum likelihood algorithm	Landsat-4 Google Image Landsat-8	Analyzing changes in the watershed area
Song *et al.* [22]	SVM	Corona Landsat-5 Landsat-7	Forest cover change analysis
Huang *et al.* [23]	SVM	Landsat	Forest cover change analysis
Kamusoko *et al.* [24]	SVM	Landsat	Urban growth
Halmy *et al.* [25]	Random forest	Landsat	Desertification
Haque and Basak [26]	Pre-classification Post-classification	Landsat	Landscape change over decades
Raja *et al.* [27]	Wavelet-based post classification	Landsat	Urban expansion
Vignesh *et al.* [28]	Ensemble Minimization Learning algorithm	Landsat	Rural and urban change detection

3.3. Artificial neural networks-based CD

The use of artificial intelligence for satellite image processing has increased in recent years. One of the earlier mentions of the use of artificial neural networks (ANN) for multi-temporal change analysis is found in [29]. Bi-temporal comparison of two images of Wilmington, North Carolina were acquired of Landsat TM. A backpropagation training algorithm with four layers was used to detect land changes. Final classes were: forest, agriculture or bare or urban, cypress or wet deciduous or marsh, and water. The ANN model had an overall accuracy of 95.6% for four class classification schemes whereas the maximum likelihood classifier gave an accuracy of 86.5%. In [30] ANN was used to perform vegetation change detection on two images of 2003 and 2004. The results were compared with the post-classification method. It was observed that combining NDVI differencing method with visual interpretation gives better results. Fkirin [31] used two datasets and trained the neural network to detect changes using an improvement factor. Not just change detection, but changes in classes like vegetation to water, and desert to vegetation were also detected.

3.4. Advanced models of CD

In recent times, convolution neural networks and recurrent neural networks have been employed in the study of change detection. A detailed study of the use of artificial neural networks and advanced neural models for change analysis is presented in Table 3. Morgan *et al.* [32] used the U-net convolutional neural network (CNN) classification algorithm. Results of change in bi-temporal high-resolution images were compared with random trees and support vector machine algorithms. Comparisons showed that U-Net classifier had an overall accuracy of 92.4% as opposed to SVM with 81.6% and RT with 75.7%.

Ahangarha *et al.* [33] trained the U-net CNN model for generating change maps of Hong Kong city images from the Onera satellite change detection (OSCD) dataset. This dataset consists of images captured using the Sentinel-2 satellite. Overall accuracy was 95% and value of Kappa was close to one. The use of a deep belief network for image differencing was studied in [34]. An increase in the difference between changed area and a decrease in the not changed area was achieved by tuning the deep belief algorithm through a modified backpropagation algorithm. Change detection results are generated through clustering analysis of difference images. In [35] CNN was used for semantic segmentation. Their model was able to locate places of change in given input images. Zhang and Lu [36] have proposed spectral-spatial joint learning network (SSJLN) that contains three parts: spectral-spatial joint representation, feature fusion, and discrimination learning. They evaluated the performance of their proposed method on four datasets. Other extensions of CNN are also studied. Mou *et al.* [37] has used a combination of convolutional neural network and recurrent neural network, Karandikar [38] have proposed a pixel-based method that uses differencing and LSTM as feature fusion, and [39] implemented convolutional neural network under an object-based image analysis framework. Pomente *et al.* [40] pretrained the data with sufficient labeled samples in other domain data and used it in the deep feature learning phase of multilevel convolutional neural network. Zhu *et al.* [41] used SegNet, Venugopal [42] used deep lab dilated convolutional neural network (DL-DCNN), Varghese [43] used ChangeNet, while in [44] Hopfield neural network was used. In most cases, freely available Landsat [45] data is used. [46] discusses the pros and cons of using artificial intelligence in remote sensing. Recent studies show the use of advanced models of deep neural networks can improve accuracy of change detection [47]–[50]. Use of CNN and RNN has changed the way digital remotely sensed images are processed

Table 3. Detailed survey of artificial neural network and advanced models of change detection method

Author	Specific Method	Dataset	Application Area
Dai and Khorram [29]	ANN	Landsat	Land change analysis
Zang *et al.* [30]	ANN	Landsat	Vegetation change detection
Morgan *et al.* [32]	U-Net	NAIP	Coastal marsh change detection
Ahangarha *et al.* [33]	U-Net CNN	Onera Satellite CD	Environmental change detection
Chu *et al.* [34]	Deep Belief Networks	--	Land change analysis
Jong and Bosman [35]	CNN	Vaihingen Dataset	Land change analysis
Liu *et al.* [39]	CNN	Opendata	Land change analysis
Zhu *et al.* [41]	SegNet	--	Land change analysis
Varghese *et al.* [43]	ChangeNet	VL-CMU-CD Tsunami GSV	Visual change detection
Ghosh *et al.* [44]	Hopfield type neural network SOM based neural network	Landsat-5 Landsat-7	Urban change analysis

4. CONCLUSION

New algorithms and methods are developed to overcome the drawbacks of the existing algorithms. For case of remotely sensed data, there are many aspects which govern the outcome of any change detection algorithm. Some common factors identified from the literature are difficulty in image acquisition, noise, pre-processing of images, size of images, and computational complexity. Complexity of image pre-processing increases if data is captured from different sources. Due to the varying nature of the data collected, there is no single technique which is applicable on all types of satellite images. Careful consideration of application area is required while selecting a change detection method. Another important factor is the source of satellite data.

The paper has discussed majorly used methods of change detection found in literature. In transformation-based methods, principal component analysis was found to be the most popular. A main disadvantage of this method is the difficulty of interpreting and labelling change data on the transformed images. In classification-based methods, post classification and maximum likelihood classifier are the commonly used techniques. Although classification-based change detection methods are the common choice for detecting changes, it is tedious and time consuming to select training samples. This affects the classification accuracy and as a result change detection is unsatisfactory. From the past few years, many researchers have applied artificial intelligence techniques in change detection. However, there is still no efficient way to design and train the neural network and it is still an enduring issue in the field of remote sensing. In view of all this, we conclude that a hybrid changes detection framework comprising of individual change detection technique improves the overall accuracy

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