Automatic Change Detection Approach Based on Fusion of Multi-Temporal Images Over Urban Areas

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ABSTRACT

Urban areas are rapidly changing all over the world and therefore provoke the necessity to update urban maps frequently. Remote sensing has been used for many years to monitor these changes. With the availability of multi-sensor, multi-temporal, multi-resolution and multi-frequency image data from operational Earth observation satellites the fusion of digital image data has become a valuable tool in remote sensing image evaluation. Therefore, the goal of an image fusion algorithm is to integrate the redundant and complementary information obtained from the source images in order to form a new image which provides a better description of the scene for human or machine perception. In this paper, an attempt has been made to design an automatic change detection solution. The approach presented here takes advantage of fusion in two levels. That is, Feature-level fusion, which uses attributes (or features) extracted from the raw data as inputs and uses them into new features, or feature map and Decision-level fusion, that takes the decisions from each image as inputs and fuses them to obtain a global decision. The purpose of this paper is to reveal urban changes. Using multi-temporal Landsat MSS and Landsat TM images, changes in New Delhi city in India is detected.

Keywords - Automatic change detection, D-S evidence theory, fuzzy integral, fuzzy set theory, majority voting

I. INTRODUCTION

Many urban regions around the world are undergoing rapid, wide ranging changes in land use and land cover. As cities grow, the landscape is altered in dramatic ways. While some of these changes are caused by natural processes such as long-term changes of climate or short-term vegetation successions and geo-morphological processes, human activity increasingly modifies surface cover through direct actions such as deforestation, urbanization, or indirectly through man induced climate change. The growth patterns are usually visible in satellite imagery and because of this remote sensing has become an effective tool for assessing and monitoring land use packets in an effective and timely manner. Multi-sensor data often presents complementary information about the region surveyed, so image fusion provides an effective method to enable comparison and analysis of such data. The main objective of employing fusion is to produce a fused result that provides the most detailed and reliable information possible. Fusing multiple information sources together also produces a more efficient representation of the data. The main objective of employing fusion is to produce a fused result that provides the most detailed and reliable information possible. In the past few years, there has been a growing interest in the development of change detection techniques for the analysis of multi-temporal remote sensing imagery. This interest stems from the wide range of applications in which change detection methods can be used, like environmental monitoring, agricultural surveys, urban studies [2] and forest monitoring.

Map updating is an intensive task requiring timely and accurate information from multiple sources of data especially for detailed mapping of complex urban scenes. The primary method of updating land cover and land use maps has been, and in some case still is, through human interpretation. In this process, the full range of human interpretation capabilities can be employed, including the interpreter's own knowledge of the area. However, it is time consuming, subject to errors of omission and the abilities of the interpreter vary greatly. Also, there are limits to the ability of humans to absorb and process large volumes of information. Computer assisted methods offer approaches to detection and identification of land cover and land use change. Since each image has own geometrical distortion and problems of alignment of multi-temporal images, two images should be registered so that pixels with the same coordinates in the images may be associated with the same area on the ground.

There are two main approaches to the change detection problem: They are unsupervised approach and supervised approach. The unsupervised approach (no ground truth) produces a change detection map in which changed areas are separated from unchanged ones. Image differencing [5], Principal component analysis (PCA) [6], change vector analysis (CVA) [7] are all belongs to this approach. The supervised method (ground truth) generates a change detection map where changed areas are identified and the land-cover transition type can be identified. This includes techniques such as Post classification comparison (PCC) [3], support vector machine (SVM) [2] and artificial neural network (ANN) [4] and so on.

This paper is organized into four sections. Section II briefly describes the adopted algorithms for computing Spectral Change Difference (SCD) algorithm datasets and also the proposed fusion procedure for change detection. Section III presents the experiments and analyses the corresponding results. Finally, section IV concludes the paper with some remarks.

II. METHODOLOGY

The proposed approach relies on three steps: first is to apply Spectral Change Difference (SCD) algorithm to the input images which is acquired from the same area but at different times, second is based on fusion at feature-level. And finally fusion is performed at decision level.

1.1 Spectral Change Difference algorithm (SCD):

In spectral change difference algorithm, images of two dates are transformed into a new single-band or multi-band image, which contains the spectral changes. The resultant image must be further processed to assign the changes to specific land cover types. Since these methods are based on pixel-wise or scene-wise operations, they are sensitive to image registration and co-registration accuracy. Discrimination of change and no-change pixels is of the greatest importance in successful performance of these methods. A common method for discrimination is use of statistical threshold. In this method a careful decision is required to place threshold boundaries to separate the area of change from no-change. Spectral change difference algorithm is as follows:

1.1.1 Simple Differencing

In this method, two co-registered image dates are subtracted pixel by pixel in each band to produce a new change image between two dates. It is the most direct indicator of spectral change in reflectance. It is denoted by Y_{SD}:

$$Y_{SD}^{i} = \left| X_{T2}^{i} - X_{T1}^{i} \right|, \qquad i=1, 2,\ldots.N \qquad (1)$$

Where N is the band number and X_{T1}^{i} and X_{T2}^{i} represent the pixel reflectance spectra of i-th band at time T_1 and T_2, respectively.

1.1.2 Simple Ratioing

Two co-registered image dates are ratioed pixel by pixel in each band. The no-change area is characterized by ratio values close to 1. Depending on the nature of changes between two dates changed areas will have higher or lower values. It is denoted by Y_{SR}:

$$Y_{SR}^{i} = \left| \left(\frac{X_{T2}^{i}}{X_{T1}^{i}} \right) - 1 \right|, \qquad i=1, 2,\ldots.N \qquad (2)$$

It reflects the change information through the ratioing of two images. After the absolute value operation, the pixels with larger values correspond to higher possibilities of change, and those pixels with a value close to 0 are hints to no-change areas. Ratioing is immune to false positives caused by sun elevation angle, shadows and terrain, at least to some extent.

1.1.3 Absolute distance

The ability to determine absolute distance to an object is one of the most basic measurements of remote sensing. It is denoted by Y_{AD}:

$$Y_{AD} = \sum_{i=1}^{N} \left| X_{T2}^{i} - X_{T1}^{i} \right|, \quad i=1, 2,\ldots.N \qquad (3)$$

It integrates the change information on each band into a single band through simple addition.

1.1.4 Euclidean distance

It is also known as minimum distance. It is denoted by Y_{ED}:

$$Y_{ED} = \sqrt{\sum_{i=1}^{N} (X_{T2}^{i} - X_{T1}^{i})^2}, \qquad i=1, 2,\ldots.N \qquad (4)$$

It calculates the mean spectral reflectance in each band for each class. Distance of each image pixel to class means is calculated. Pixel is assigned to class for which minimum distance is smallest. In some cases a maximum distance may be provided (not in Multi-spectral image) Pixels exceeding maximum distance are placed in "other" category.

1.1.5 Chi Square transformation

Y is distributed as a Chi-square random variable with ρ degrees of freedom (ρ is the number of bands)It is denoted by Y_{CST}:

$$Y_{CST} = \sqrt{\sum_{i=1}^{N} \left(\frac{X_{T2}^{i} - X_{T1}^{i}}{\sigma_i^{diff}} \right)^2}, \qquad i=1, 2,\ldots.N \qquad (5)$$

Where σ_i^{diff} represents the standard deviation. Multiple bands are simultaneously considered to produce a single change image.

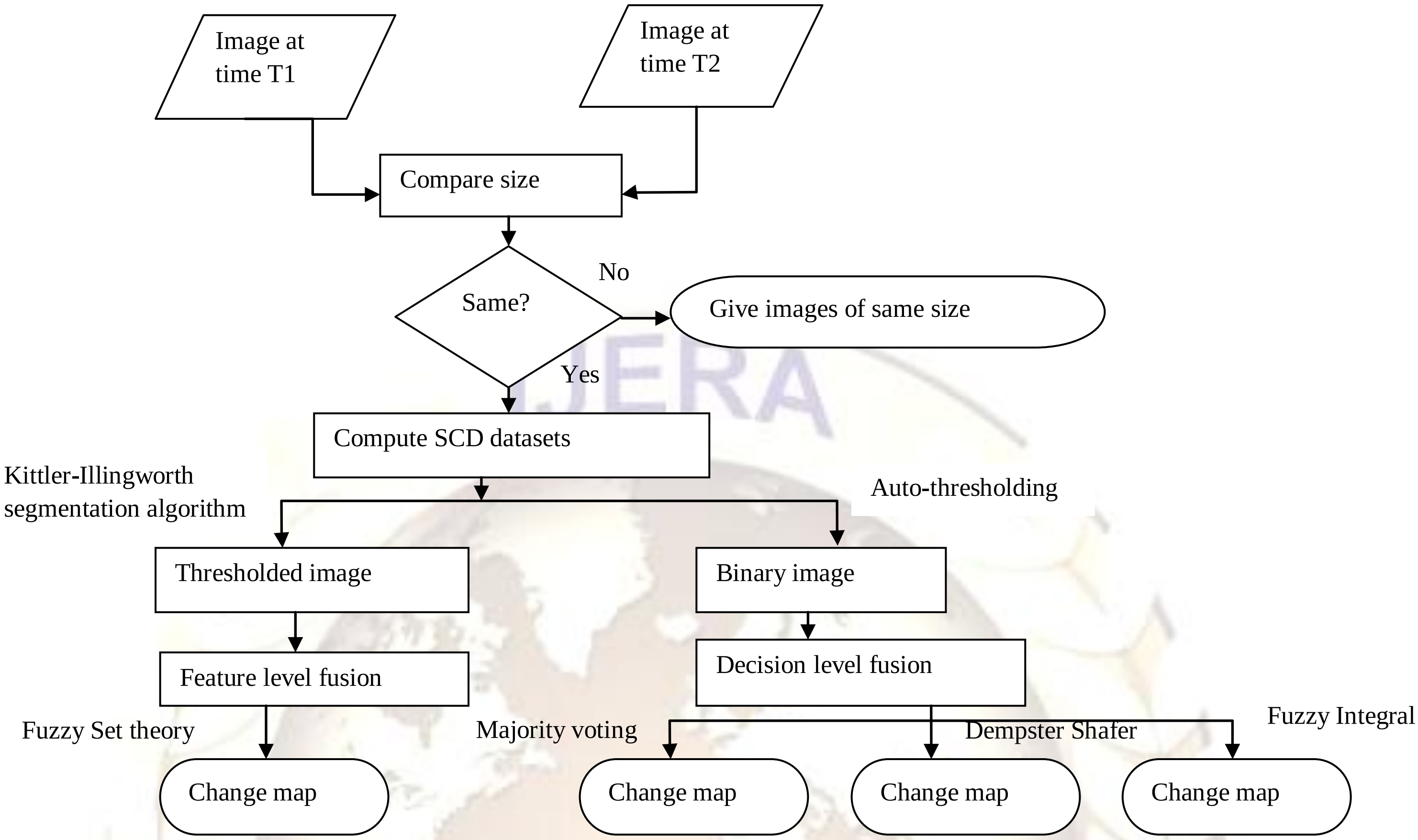


Fig.1. Flowchart of the fusion procedure aimed at fusing multiple spectral change difference (SCD) images

1.2 Feature level fusion:

Medium-level fusion, also called feature-level fusion, uses attributes (or features) extracted from the raw data as inputs and uses them into new features, or feature map. Several features which are extracted from the raw data are used for tracking. Feature-level fusion approaches for target tracking can be formulated using the powerful framework of graphical models. The goal of dissertation is to develop feature-level information fusion methods for target tracking in High Speed Networks.

In the feature-level fusion, each sensor observes an object, and a feature extraction is performed to yield a feature vector from each sensor. After using an association process to sort feature vectors into meaningful groups, these feature vectors are then fused and an identity declaration is made based on the joint feature vector. The fusion model which is used in feature level fusion is

1.2.1 Fuzzy Set theory(FS)

The use of fuzzy sets here is consistent with that of fuzzy classification methods that are increasingly used in remote sensing to allow pixels to retain some degree of membership in one or more land use classes [8].A fuzzy set is one for which the degree of membership for any element of the set may range from zero to one, and so is well suited to ambiguous or partial membership. Fuzzy set theory defines set membership as a possibility distribution. The general rule for this can expressed as:

$$f:[0,1]^n \rightarrow [0,1] \qquad (6)$$

Where *n* some number of possibilities. This basically states that we can take *n* possible events and use *f* to generate as single possible outcome.

1.3 Decision level fusion:

High-level fusion, also called decision-level fusion, takes the decisions from each sensor as inputs and fuses them to obtain a global decision. In the decision-level approach, each sensor performs independent processing to produce a declaration of identity, and then the declarations of identity from each sensor are subsequently combined via a fusion process. The fusion models in decision level fusion are

1.3.1 Majority voting(MV)

It is a basic and simple decision integration method [9], designed to combine the output results by multiple processors. The main idea of is to arrange the identified results according to some specific voting rules, for example, simple majority voting and weighted voting rules.

1.3.2 Dempster-Shafer(D-S) evidence theory

This method utilizes probability intervals and uncertainty intervals to determine the likelihood of hypotheses based on multiple evidence. In addition, it computes likelihood that any hypothesis is true. The concept of using a Dempster-Shafer approach is to fuse multi-sensor data. Dempster-Shafer evidence theory allows the representation of both imprecision and uncertainty and it is well suitable for remote sensing data fusion problems.

1.3.3 Fuzzy Integral(FI)

The Fuzzy Integral (FI) approach evaluates the performances of different processors by a fuzzy measurement. It is a meaningful formalism for combining classifier outputs that can capture interactions among the various sources of information. A popular fuzzy integral approach Sugeno Integral method is used.

However there are some detection and recognition problems from the above three methods (Spectral Change Difference algorithm, Feature and decision level fusion techniques).So Curvelet Transform is being used to overcome these drawbacks.

1.4 Curvelet Transform based image fusion:

Most natural images/signals exhibit line-like edges, i.e., discontinuities across curves (so-called line or curve singularities). The fusion of multi-temporal satellite images is a very useful technique in various applications of remote sensing. Since edges play a fundamental role in image representation, one effective means to enhance spatial resolution is to enhance the edges. The curvelet-based image fusion method [10] provides richer information in the spatial and spectral domains simultaneously. Curvelet Transform is a new multi-scale representation most suitable for objects with curves. It was developed by Candes and Donoho (1999).

Consider the images at two different dates. Curvelet Transform is applied to these two images. The exact reason for choosing the curvelet algorithm is because of its sparsity. Therefore the curvelet construction is now based on the consideration of polar coordinates in frequency domain and also to construct curvelet elements being locally supported near wedges. Curvelets are designed to handle curves using only a small number of coefficients. Hence it handles curve discontinuities well. The Curvelet Transform includes four stages:

1.4.1 Sub-band decomposition

It divides the image into resolution layers. Where each layer contains details of different frequencies: such as Low-pass filter and Band-pass (high-pass) filters.

1.4.2 Smooth partitioning

A grid of dyadic squares is defined. Here windowing function is applied

1.4.3 Renormalization

Renormalization is centering each dyadic square to the unit square [0,1]x[0,1] and each square is renormalized. The renormalized ridges has an aspect ratio of width≈length^2.For encoding these ridges efficiently, ridgelet transform is used.

1.4.4 Ridgelet analysis

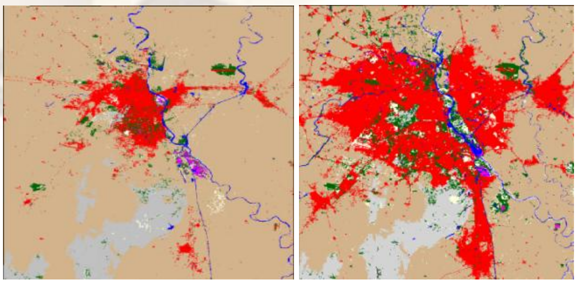
Each normalized square is analyzed in the ridgelet system.

III. EXPERIMENTS AND RESULTS

3.1 Experimental data

This section describes the study area, the urban changing event and the available remote-sensing images for testing and evaluating the proposed automated change detection algorithm.

India's mega-cities and its 4,000 cities and towns account for 60% of the gross domestic product. In 2001 the percentage of urban population is 28%. 35 cities have population more than a million, compared to 23 cities in 1991. By 2015 more than half of Indians are projected to be urban dwellers, 1/3 will be slum dwellers and squatters. In the national capital region 1/2 of households and 1/3 of population were migrants and a little less than 1/2 of migrants were from rural areas. The urban to urban stream of migration was found to be more important for larger cities like Delhi. To this aim, Landsat Multispectral Scanner (MSS) and Landsat Thematic Mapper (TM) images are used as experimental data source for urban expansion monitoring and land cover change detection task in the urban areas of New Delhi. In Fig. 2. The red color denotes the urban areas.



(a) (b)

Fig. 2. Remotely sensed images of New Delhi (a) May 8, 1974; (b) April 21, 1999

3.2 Results:

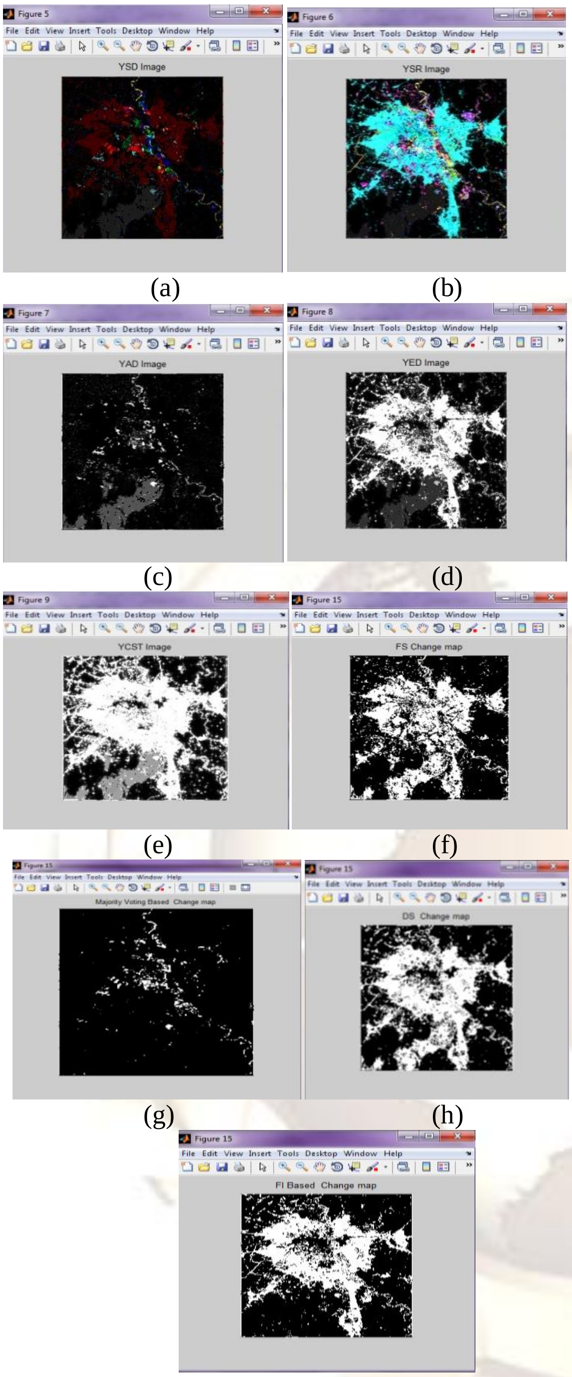


Fig. 3. Change detection results (a)Y_{SD}; (b) Y_{SR}; (c) Y_{AD};(e) Y_{ED};(f)Y_{CST};(h)FS feature level fusion;(i)MV decision level fusion;(j)DS decision level fusion;(k)FI decision level fusion.

The performance is evaluated in terms of overall accuracy, kappa statistic, omission and commission. Overall accuracy is the percentage of pixels correctly classified. Kappa statistic accounts for number of pixels correctly classified by chance and it is always lower than overall accuracy. The z-test is defined as:

$$z = \frac{k_2 - k_1}{\sqrt{\sigma_{k2}^2 - \sigma_{k1}^2}} \qquad (7)$$

Where K_1 and K_2 are two selected kappa coefficients σ^2_{k1} and σ^2_{k2} are variances. Omission is the pixels that are placed in another class which are omitted. Commission is the pixels placed in a class in which they do not belong.

TABLE I
Comparison of Fusion Scheme with Curvelet Based Fusion Scheme for Change Detection

Fusion level	Fusion method	Fusion scheme for change detection			
		Overall accuracy (%)	Kappa	Omission (%)	Commission (%)
SCD	Y_{SD}	78.5678	0.7213	18.4224	3.0098
	Y_{SR}	80.0882	0.4140	19.5654	0.34641
	Y_{AD}	78.2377	0.7289	18.1446	3.6176
	Y_{ED}	69.5033	0.8316	4.5752	25.9216
	Y_{CST}	78.2149	0.7210	18.1111	3.674
Feature level	FS	70.4118	0.8279	4.9306	24.6577
Decision level	MV	78.2639	0.7267	18.1364	3.5997
	DS	69.4583	0.8317	4.567	25.9747
	FI	81.3954	0.8242	4.1528	14.4518
Curvelet based fusion scheme for change detection					
SCD	Y_{SD}	78.5931	0.6640	18.6185	2.7884
	Y_{SR}	80.3007	0.0833	19.6895	0.0098039
	Y_{AD}	72.0605	0.4489	18.7304	9.2092
	Y_{ED}	81.6887	0.8180	3.5605	14.7508
	Y_{CST}	80.9534	0.8316	3.4788	15.5678
Feature level	FS	97.7263	0.7924	0.60703	1.6667
Decision level	MV	79.71	0.6325	18.6961	1.594
	DS	97.0842	0.8586	0.33007	2.5858
	FI	98.3317	0.8265	0.42484	1.2435

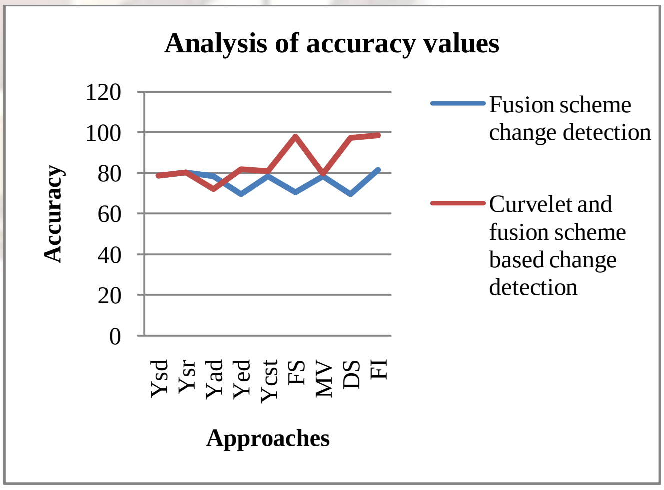


Fig. 4. Comparison graph of accuracy values for different approaches

IV. CONCLUSION

The change detection method based on fusion of multiple Spectral Change Difference (SCD) data set is feasible and more effective for urban expansion monitoring and land cover change detection over urban areas than the change information extracted by single SCD algorithms. From the experimental results in New Delhi study area, it is confirmed that the limitation and uncertainties caused by a single SCD image can be reduced using suitable fusion techniques. Fusion methods combine the various SCD images. Feature level fusion can effectively reduce omission errors and Decision level fusion is good at restraining commission errors, but both of them lead to an increase of the overall accuracy and the optimum fused image can be obtained using Curvelet Transform.

In future, the challenging problem such as computational cost of curvelet transform can be overcome by exploring the suitable thresholding function that incorporate and exploit the special characteristics of the curvelet transform.

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