A New Approach for Multi Index Automatic Change Detection in HR Remotely Sensed Imagery

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***Abstract*— In recent years the technology is growing rapidly and the development of the country very fast and also due to this the infrastructures are increasing. Hence the changes could be noted by using new generation of Earth observation sensors with high spatial resolution or high resolution (HR) which provide detailed information for change detection. The widely used methods for high-resolution image change detection rely on textural/structural features. In order to get the high resolution images for viewing the areas in this project we use multi index automatic change detection method is proposed for the high-resolution imagery. The advantages are as follows: 1) The information (images) sent by the satellite would be in very low size, low pixels so in order to improve the viewing ability we use high-dimensional but low-level features (e.g., textural and structural features) i.e. multi index representation method. The multi index representation refers to the enhanced vegetation index, the water index, and the recently developed morphological building index. I am going use this technique for implementing in military places, which has a very large application. Moreover, the traditional methods based on the state-of- the-art textural/morphological features were also implemented for the purpose of comparison, which further validates the advantages of my project.**

***Key words*— Building detection, change detection, high resolution, morphological.**

I.INTRODUCTION

DETECTION of land cover/use changes is one of the most Fundamental and useful tasks for various applications suchas urban expansion, urban planning, damage assessment, Convenient to obtain remotely sensed imagery over certain deforestation, and urban landscape monitoring. With the rapid development of Earth observation techniques, it becomes area at different times. Thus, land cover/use changes can be effectively detected and analyzed by processing the multi temporal remote sensing images.

In order to timely process the big remote sensing data and rapidly transfer the data into information and knowledge, it is necessary to develop automatic techniques for image change detection. A few studies have recently addressed the automatic change detection methods, including studies on multilevel change vector analysis, morphological filters with change vector analysis, multi temporal morphological attribute Profiles; pulse coupled neural networks, and hierarchical spectral change analysis. The basic idea of the proposed method is to represent complicated high-resolution scenes by a set of low dimensional semantic indexes that are used to replace traditional high-dimensional but low-level features (e.g., textural features and morphological profiles). Specifically, urban primitives, e.g., buildings, vegetation, and water, are automatically extracted by the morphological building index (MBI), the enhanced vegetation index (EVI), and the normalized difference water index (NDWI), respectively.

Change detection using high spatial resolution remote sensing images has received increasing interest since detailed ground change information is now available. However, a large intra class variance and a small interclass variance can lead to inaccuracy for the traditional spectral based and pixel based image processing framework when high spatial resolution imagery is used for change detection. In order to deal with this problem and improve the accuracy of change detection from high resolution data, researchers have proposed to take spatial features into consideration for change detection.

The notable characteristics of the multi index method include the following aspects.1) The complicated urban scenes can be automatically and effectively represented by a set of low dimensional information indexes.2) The local histograms of these indexes are able to describe the frequency and spatial arrangement of the urban primitives. Consequently, the multi temporal multi index representations can be used to detect the structural changes of the urban scenes.The proposed change detection method is described by the following steps.

1. Calculation of Information Indexes
2. Automatic Change Detection
   a) Block based
   b) cell based
3. Types of Change

II. MULTIINDEX URBAN REPRESENTATION

In this paper, three urban primitive indexes, i.e., MBI, EVI, and NDWI, are used to represent a typical urban scene. Please note that these three indexes provide information not only for buildings, vegetation, and water but also for nonbuildings, nonvegetation, and nonwater features, which actually enhances the discrimination ability of distinguishing different urban structures.

A. MBI

MBI is an effective method for automatic building detection. It is able to represent spectral–spatial properties of buildings (e.g., brightness, size, contrast, directionality, and shape) by a set of morphological operators. It should be noted that buildings are spectrally similar with the bright soil, and hence, the original MBI algorithm is improved in this study by introducing a post processing step, aiming to reduce false alarms from the urban bright soil. The modified MBI algorithm is described as follows.

Step 1—Calculation of Brightness: The brightness is the maximum value of the visible bands for each pixel, which is used to represent the structures with high reflectance (e.g., candidate buildings). The visible bands are considered since they have the most significant contributions to the spectral reflectance of buildings.

Step 2—Top-Hat Morphological Profiles: Considering the fact that buildings and their spatially adjacent shadows lead to high local contrast, MBI is defined using differential morphological profiles (DMPs) of the white top-hat by reconstruction, i.e., DMPWTH, as follows:

$$\mathrm{DMPWTH} = \{\mathrm{DMPWTH}(s, \mathrm{dir}) : s\mathrm{min} \leq s \leq s\mathrm{max}, \mathrm{dir} \in D\} \quad (1)$$

$$\mathrm{DMPWTH}(s, \mathrm{dir}) = |\mathrm{WTH}(s+\Delta s, \mathrm{dir}) - \mathrm{WTH}(s, \mathrm{dir})| \quad (2)$$

Where WTH(s, dir) represents the white top-hat of the brightness image obtained in step 1 by using a linear structural element (SE), with s and dir being the scale and the direction, respectively. $s$min and $s$max indicate the range of the spatial size of buildings, and Δs is the interval of the profiles. D is the set of directions for the linear SE.

Step 3: MBI is calculated by

$$MBI = \frac{\sum_{s,dir} DMP_{WTH}(s,dir)}{N_{D\times} N_S} \quad (3)$$

where ND and NS denote the number of directions and scales for the morphological profiles, respectively. Buildings correspond to the areas with high MBI values, due to their large local contrast in various directions and scales.

Step 4—Postprocessing: As aforementioned, in order to refine the result of the building detection, a post processing step is proposed to suppress the false alarms of bright soil from the original MBI. Spectral information plays a key role for identification of soil. It should be noted that bright soil in an urban scene often has a yellow tone, corresponding to the urban construction sites.

Therefore, based on the WorldView-2 images used in this study, a yellow soil index (YSI) can be defined using the normalized difference of yellow (Y) and blue (B) channels, i.e.,

$$YSI = \frac{Y-B}{Y+B} \quad (4)$$

B. EVI

The vegetation information is automatically extracted by the EVI. It was developed by enhancing the vegetation signals through the difference between near-infrared (NIR) and red (R) bands and, at the same time, reducing the aerosol effects using blue (B) band. EVI is defined as

$$EVI = 2.5\frac{NIR-R}{NIR+6R-7.5B+1} \quad (5)$$

C. NDWI

The NDWI is adopted to detect the water bodies. It high lights the water areas by maximizing the reflectance in green(G) band and minimizing the low reflectance in near infrared (NIR) band, i.e.,

$$NDWI=\frac{G-NIR}{G+NIR} \quad (6)$$

The water information is further refined by imposing an area based threshold on the NDWI such that small noise and errors (e.g., shadows) can be removed.

III. CHANGE DETECTION

Based on the previous discussions, it can be stated that Multiple information indexes have the potential for achieving automatic change detection from urban areas. Two examples for the multi index automatic change detection are shown in Fig. 3, from which it is clearly seen that the structural changes in high resolution images can be effectively indicated by the information indexes. Consequently, the multi temporal multi index representations can be used to detect the structural changes of the urban scenes. The proposed change detection method is described by the following steps.

Step 1—Calculation of Information Indexes: Information on buildings, vegetation, and water is obtained at the pixel level based on the MBI, the EVI, and the NDWI, respectively;and the corresponding post processing is then used to suppress the noise in the initial result, i.e., removing bright soil from buildings and shadow from water bodies.

Step 2—Automatic Change Detection: The image is first divided into a series of blocks with the size of N × N (pixels) for each one, which is viewed as the basic unit for the change detection. This strategy is called “hot spot” detection, which is a commonly used approach for change detection from high-resolution images.

A) Block-based strategy: In this case, the scene is represented by the frequencies of the primitives in the multi index histogram of the block. For the block histograms at times T1 and T2, a weighted distance is used to determine whether changes occur in this area, i.e.,

$$\mathrm{WDist} = \sum_{i=1}^{\mathrm{Dim}}(\mathrm{Dist}(i) \times W(i)) \tag{7}$$

$$\mathrm{Dist}(i)=|H_1(i)\text{-}H_2(i)| \tag{8}$$

$$W(i) = \frac{\mathrm{Dist}(i)}{\sum_{J=1}^{\mathrm{Dim}}(\mathrm{Dist}(j)} \tag{9}$$

where W_{Dist} is the weighted distance between the histograms H_1 and H_2. Dim is the dimension of the histogram. $H_1(i)$ and $H_2(i)$ represent the frequency of the ith bin in the histograms H_1 and H_2, respectively. W(i) is expressed as the normalized distance between $H_1(i)$ and $H_2(i)$, in order to further enlarge the difference for the dissimilar bins.

B) Cell-based strategy: As shown in Fig. 4, spatial arrangement of the primitives can be considered by dividing each block into n × n cells. This way, a cell is viewed as a basic unit to calculate the frequencies of the information indexes. A block is then represented by n × n histograms, each one representing the frequencies of the multiindex features in each cell. Subsequently, the similarity measure between the bit temporal histograms is calculated, in order to determine whether changes occur in this block. In this case, the distance measure can be extended from , i.e.,

$$\mathrm{WDist}_{\mathrm{cell}} = \sum_{x=1}^{n\times n}(\sum_{i=1}^{\mathrm{Dim}} \mathrm{Dist}^x(i) \times W^x(i)) \tag{10}$$

$$\mathrm{Dist}^x(i)=|H_1^x(i)\text{- }H_{12}^x(i)| \tag{11}$$

$$W^x(i) = \frac{\mathrm{Dist}^x(i)}{\sum_{J=1}^{\mathrm{Dim}} \mathrm{Dist}^x(j)} \tag{12}$$

Step 3—Types of Change: It should be noted that most of the automatic change detection methods only indicate whether Changes take place in the block but cannot provide specific Information related to the types of changes. In this paper, however, based on the information indexes, it is possible to further provide the change information corresponding to each block, by investigating which information index is subject to significant changes in terms of both frequency and spatial arrangement in the block. This can be viewed as a by-product of the proposed change detection method.

IV. DATA SETS AND RESULTS

Fig.1: Image of the Bangalore region 13/Jan/2015.

Fig.1 is the raw image from the satellite of the area of the Bangalore city taken in 13 Jan 2015 with the co-ordinates lat-12.921242 and log-77.641255 is the position at the center of the image with 240 square km distance. It is of pixel size 140x390 feet taken on Jan 13, 2015 from Landsat – 7 satellite.

Fig.2: Image of the Bangalore region 8/Apr/2017

Fig.2 is the raw image from the satellite of the area of the Bangalore city taken in 8 Apr 2017 with the co-ordinates lat=12.921242 and log=77.641255 is the position at the center of the image with 240 square km distance. It is of pixel size 140x390 feet taken on Jan 13, 2015 from Landsat – 7 satellite.

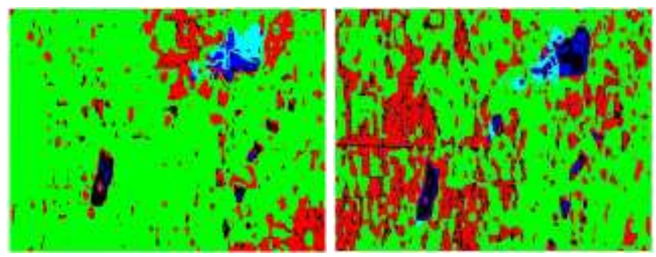

Fig.3: Multi index output 2015(left), 2017 (right)

Fig.3 is the multiuindex output for the change detected in the image. You can see that the part is the buildings, green is the vegetation and the blue is the water bodies. The black image is for soil part or the shadow part which is removed during the multiindex of the image. Fig.4 is the morphological output index of the two images which are used as the input the Fig. 6.10 shown explains about the various structures and different levels of basic things like vegetation, water levels and other empty land or the shadow.

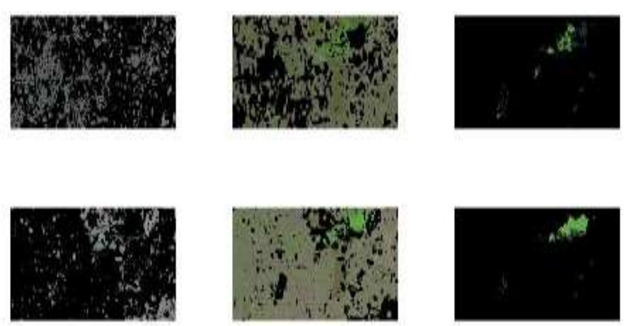

Fig.4: Final change detection of water, building and vegetation.

We can see there are different colors used to map different morphological units one such is the buildings water bodies and vegetation that is the green parts on the earth. I have used the Bangalore city to explore the change detection that has happened is the year 2015 and the year 2017.

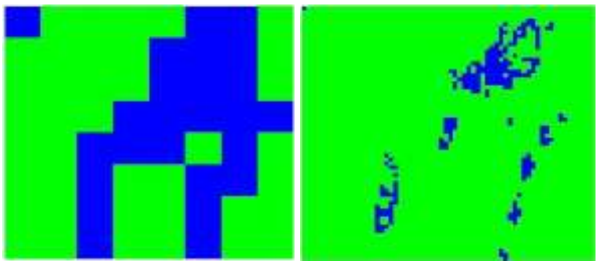

Fig.5: Change detection using block based (left) and cell based (right).

This change is noted down on the multi index image and the roc curve which gives the clear change detected in the two images this change detected can be plotted on the bar graph for easy understanding and to check the total change with reference to the pixel of the image using these pixels in different ratios we can easily calculate the accuracy of the change detected.

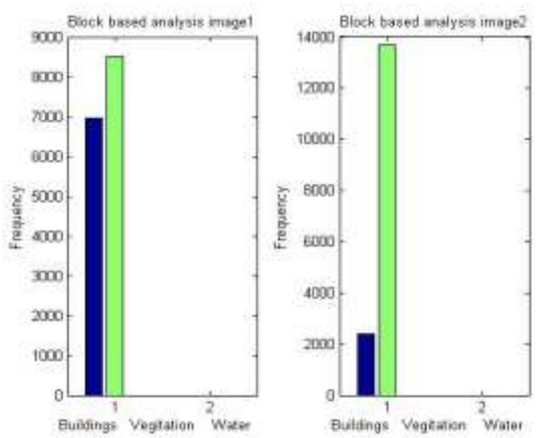

Fig. 6: Graphical Representation Of Block Based.

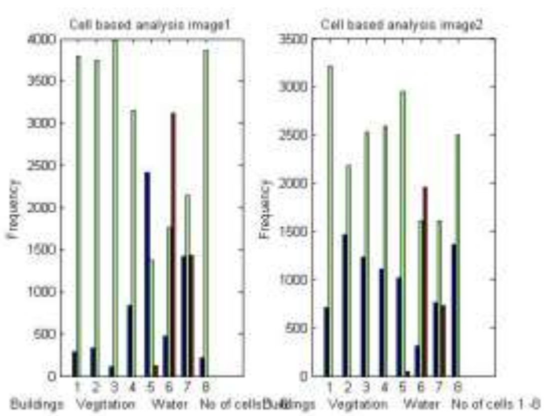

Fig. 7: Graphical Representation of Cell Based.

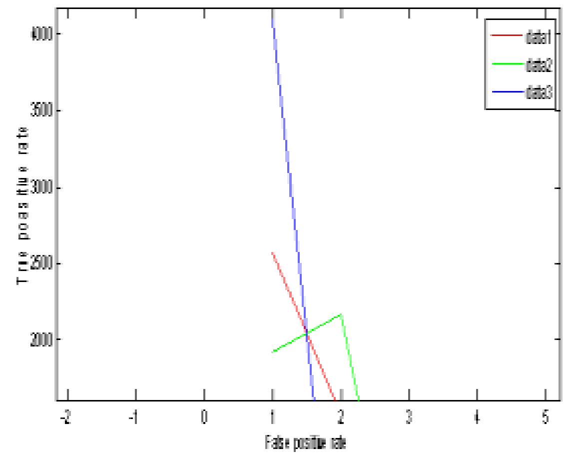

Fig.8: ROC Curve for Cell Based.

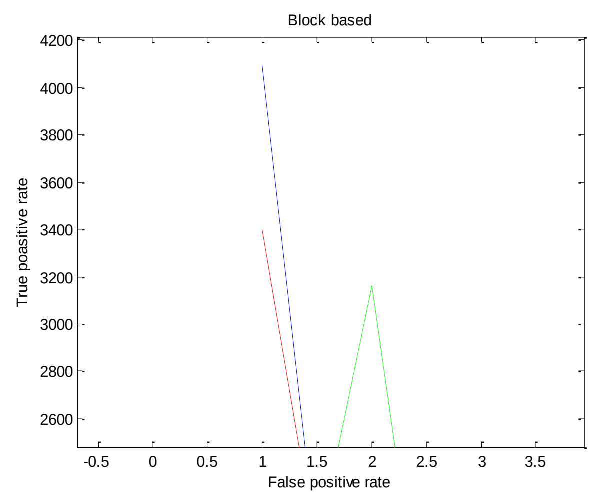

Fig.9: ROC Curve for Block Based.

V. COMPARISON

The greater part of existing change recognition techniques could be characterized into three groups, the conventional pixel based change detection the object based change identification and the hybrid change detection. Both PBCD and OBCD have drawbacks and hence we established HCD strategies. There is no ideal HCD technique started yet.

Breaking down the complementarities of PBCD and OBCD strategy, we propose another unsupervised algorithm level fusion scheme (UAFS-HCD) which is used in order to improve the accuracy of the pixel based techniques using spatial domain approach. This is done by following approaches.1) Getting the preliminary change with PBCD at first to estimate few parameters for OBCD.2) Determining the unaltered territory areas and to wipe out the territories without changes, which reduces the error amplification phenomenon of OBCD.3) Acquiring the final change mask by methods for OBCD technique.

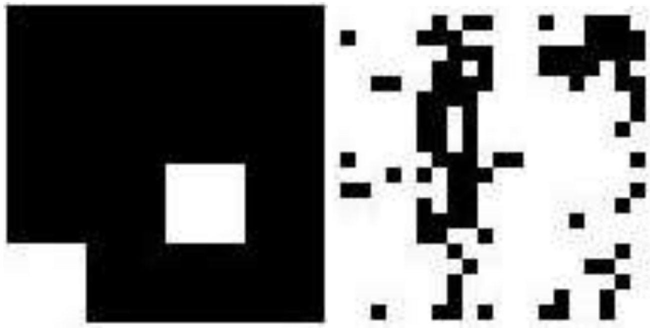

Fig.10: Block based CD(left), Cell based CD(right) imagery of existing system.

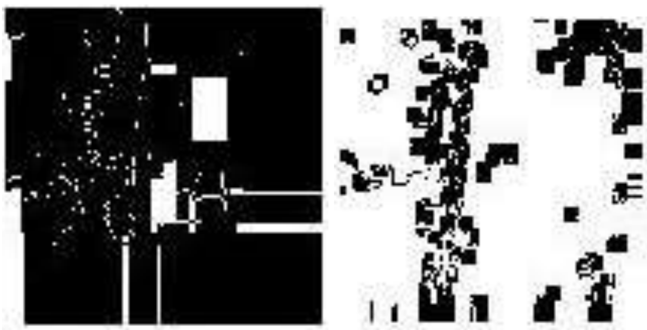

Fig.11: Block based CD(left), Cell based CD(right) imagery of proposed system.

VI. CONCLUSION

In this paper, an innovative change area procedure in light of the multi record picture depiction has been proposed for high assurance remote distinguishing imagery over urban scenes. The proposed technique is fit for fulfilling satisfactory change recognizable proof precision with a game plan of low dimensional; however semantic information records are saved in the database. Two specific systems are completed for the proposed procedure. The first is a block based approach where the frequencies of the information records are considered for change area. The other is the cell based one where each block is moreover scheduled into a movement of cells. Along these lines, the frequencies as well as the spatial course of action of the data files in the square can be misused. A near review was led between the proposed multi record strategy and the customary multi include technique for programmed change location. Likewise, the proposed multi list model can consequently show which class the adjustment in the territory is identified with. This is a repercussion of the proposed strategy. Rather, conventional programmed change location can just decide if changes happen in this district or not.

ACKNOWLEDGMENT

The authors are grateful to Dr. Mohan Manghnani, Chairman, New Horizon College of Engineering (NHCE) Bengaluru, for his encouragement for carrying out his work. They are thankful to Dr. Manjunatha, Principal, New Horizon College of Engineering (NHCE) Bengaluru, for his encouragement for this research work. They are also very grateful to Dr. Sanjay Jain, Professor and HOD, ECE Dept. New Horizon College of Engineering Bengaluru, for providing necessary backbone support to proceed on this endeavor. Finally, we are highly indebted to our parents for encouraging us to excel in our chose fields.

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