Automatic Building Change Detection and Open Space Area Extraction in urban areas

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Abstract

Automatic change detection and open space area extraction in urban environment is one of the crucial components towards the efficient updating of Geographic Information System (GIS), government decision-making, urban land management and planning. Original Morphological Building Index (MBI) can extract interest building features for multi-temporal high-resolution satellite image but this approach wrongly classified as buildings. In this paper, jointly approach of modified MBI, Normalized Different Vegetation Index (NDVI) and Entropy is developed for identifying low quality satellite images over different years. Then, matching-based change rule is applied to obtain changes area of urban region. The proposed method is insensitive to the geometrical differences of buildings caused by different imaging conditions and is able to significantly reduce false alarms and also achieves much improved detection accuracy and overall performance. The effectiveness of the method is validated by comparing with MBI-based Change Vector Analysis (CVA) and Multivariate alteration detection (MAD) transformation.

Keyword: feature extraction, modified MBI, change detection, matching-based change rule

1. Introduction

Nowadays, Urban sprawl is a worldwide challenge. It is necessary to detect the land-cover/use changes occurring with urban sprawl and make plans for suitable development. Change detection is one of the main applications of remote sensing in [1]. Although urban land cover changes can be monitored by traditional ground survey procedures, now remote sensing sensors provide a cost-effective source of information for detecting important spatial patterns of land cover change over a large geographic area in a recurrent way.

The variety of change detection techniques has been researched extensively from a theoretical and practical aspect during the last decades. Bovolo [2] incorporated object-based image analysis into change vector analysis (CVA), by which the spatial features are combined with the spectral information for multi-temporal image analysis. Dalla Mura *et al.* [3] proposed to jointly use morphological filtering and the CVA algorithm for high-resolution image change detection in order to filter out commission errors caused by the geometrical differences in the multi-temporal images.

Building may be surrounded by dense vegetation; they may have the same color as trees or trees may have colors other than green. Awrangjeb *et al.* [4] applies NDVI only and therefore cannot distinguish between a green building and a green tree. As a result, it fails to detect green buildings. Moreover, image quality may vary for the same scene even if images are captured by the same sensor, but at different dates and times. As a mathematical function, entropy is used to measure the level of disorder within a certain sample of values. In remote sensing terms, entropy represents mutual information between image A and B. While comparing entropies of two images taken with sufficient time gap, it will become changes in entropy represent the areas where changes have occurred.

In this paper, jointly approach of modified MBI, NDVI and entropy is proposed. Building structures are automatically indicated by MBI [5] and join technique of NDVI and entropy is improved for green color buildings to remove green tree or non-green trees. The proposed system carried on change detection process using matching based change rule described in [6]. According to the experimental result, the proposed jointly building extraction method of modified MBI, NDVI and entropy is effective and efficient for both high and low quality satellite imagery. The paper is organized as follow, Section 2 and 3 present the overview of the proposed system and system methodology. In section 4, the experimental result is described. Finally the conclusion is given in section 5.

2. Overview of the System

The overview of proposed urban change detection system is surmised in figure 1. Firstly, the two year satellite images are grabbed into the system. These input images are classified into Red, Green and Blue using color segmentation and apply hue color histogram matching in order to calculate these input two images are same or different. If second images are not mostly change, the system shows there is no increasing building in these years. Otherwise, the system goes on building extraction process among them modified MBI is used to automatically extract features index of building without using unsupervised learning. This method is effective for indication of buildings and will benefits to process low resolution images. And then NDVI and entropy is employed to classify green building and tree. These three methods can fully indicate building features and can extract open space area easily. Finally, change detection process is applied by using matching-based change rule and changed building area is displayed.

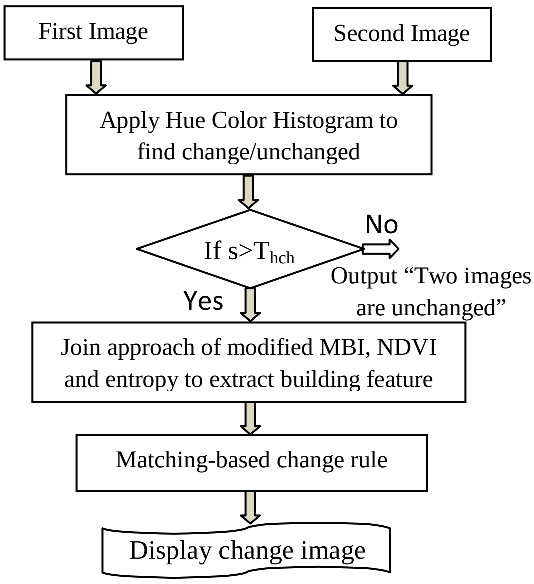


Figure 1: Overview of the proposed system

3. System Methodology

3.1 Morphological Building Index (MBI)

Mathematical morphology is an effective tool for extracting image components that are useful in the representation and description of region features. Opening and closing are two commonly used operators, used to remove bright (opening) or dark (closing) details. Morphological operators are applied to an image with a set of a known shape, called a structural element (SE) described in [7]. Some key properties of the morphological transformation that are applied to the building extraction are summarized as follows.

- Reconstruction: The reconstruction filter is an important class of morphological filters that have been proven to be very useful for image processing.
- Granulometry: It describes the sizes and scales of objects in an image. Granulometrices have been introduced in remote sensing image classification of urban areas. The multiscale morphological features are built based on the operators with increasing size of SE. Most of the existing morphological approaches referred to the disk-shaped SE.
- Directionality: However, the disk SE does not consider the directional information, which is essential for discrimination between spectrally similar objects such as buildings and roads since buildings are isotropic but roads are relatively anisotropic.

The modified MBI is defined by describing the characteristic of building feature especially color of building roof and image intensity value. The system runs on low resolution satellite images so their resolution and brightness of intensity values are very low. In order to achieve this problem, modified MBI is proposed as the following steps:

Step 1: Enhancement of Image

The input low resolution registered image is transformed to high contrast image by applying with only red intensity value and stored as the brightness value which is computed by Eq. 1.

$$s = T(f_R(x,y)) \qquad (1)$$

where $f_R(x,y)$ is a red color-space image, s is the result of enhanced red band image. [5] Presented the maximum of multispectral bands for each pixels but it lessen brightness of input low resolution image to extract brightness value because it is only suitable in multispectral band of high resolution satellite image. Now our method gives for both high and low resolution of various satellite images as Google Earth.

Step 2: Construction of MBI

The spectral-structural characteristics of buildings (e.g., contrast, size and directionality) are represented using the Differential Morphological Profile (DMP).The construction of MBI contains three steps.

(i) *White top-hat by Reconstruction* can be computed by Eq. 2.

$$W\_TH(d,s) = s - \gamma_b^{re}(d,s) \qquad (2)$$

where γ_b^{re} represents the opening-by-reconstruction of the brightness image, and s and d indicate length and direction of a linear SE, respectively.

(ii) *Morphological Profiles (MP)* of the white top-hat is defined as Eq. 3 and 4.

$$MP_{W\_TH}(d,s) = W\_TH(d,s) \qquad (3)$$

$$MP_{W\_TH}(d,0) = s \qquad (4)$$

(iii) Differential Morphological Profiles (DMP) of the white top-hat is calculated as Eq. 5.

$$DMP_{W\_TH}(d,s) = \left|MP_{W\_TH}\big(d(s+\Delta s)\big) - MP_{W\_TH}(d,s)\right| \quad (5)$$

where Δs is the interval of the profiles and $s_{min} \leq s \leq s_{max}$.

MBI is defined as the average of the DMPs of the white top-hat profiles defined in eq. 6 and 7 since buildings have large local contrast in different directions within the range of the chosen scales. Thus

$$MBI = \frac{\sum_{d,s} DMP_{W\_TH}(d,s)}{D \times S} \quad (6)$$

$$S = \left(\frac{S_{max} - S_{min}}{\Delta S}\right) + 1 \quad (7)$$

where D and S indicate the numbers of the direction and scale of the profiles, respectively. Four directions are considered in this study (D=4) since increase of D did not result in higher accuracy for building detection. According to spatial resolution of images and the characteristics of buildings, the size of SE (s_{max}, s_{min} and Δs) are set to (2, 52 and 5).

Step 3: Postprocessing of MBI

The building extraction process satisfies the following conditions and initial result of the building map is obtained by simply setting a threshold.

IF MBI(x) ≥ t1,
THEN $map_1(x) = 1$;
ELSE $map_1(x) = 0$;

where MBI(x) and $map_1(x)$ indicate the value of MBI and the initial label for pixel x. t1 is threshold value. To completely detect building feature, jointly approach of NDVI and entropy is used. Awrangjeb et al., recommend in [8] while the original algorithm was unable to detect green colored buildings using the NDVI only and detected a large number of false buildings in a densely vegetated area, the proposed improved algorithm preserves green colored buildings as well as removes non-green trees through a joint application of NDVI and entropy.

3.2 NDVI and Entropy

A high NDVI (normalized difference vegetation index estimated using multispectral images) value for a pixel indicates vegetation, whereas a low NDVI value generally indicates a non-vegetation pixel but it can't differentiate between trees and green buildings when both exhibit high NDVI values in [9].

In the improved method, texture information, namely entropy and NDVI are jointly employed to remove trees. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image given in [10]. Its adoption is based on the assumption that trees are rich in texture as compared to building roofs. While a high entropy value at an image pixel indicates a texture (tree) pixel, a low entropy value indicates a "flat" (building roof) pixel.

In order to calculate entropy *E(x)* at a point *P* of a grey-scale image, a 9×9 sub image *I* is, where *P* is the center point. A normalized histogram *H* for *I*, involving 256 bins and values between 0 and 1, is formed and entropy is calculated using non-zero frequencies in eq. 8.

$$E(x) = -\sum H_i log_2 H_i \quad (8)$$

where $1 \leq i \leq 256$ and $0 \leq H_i \leq 1$.

The use of entropy alone is insufficient because trees with self-occlusions and shadows may not contain enough texture information and in such cases NDVI helps to remove them. In order to extract building feature, then building map, vegetation index and entropy value are combined by following rules:

Rule 1: IF $map_1(x) = 0$; THEN map(x) = 0,
Rule 2: IF $map_1(x) = 1$ AND NDVI(x) ≥ t2 AND E (x) ≤ t3
THEN map(x) = 1

where *NDVI(x)* is the normalized difference vegetation index of pixel *x* and the shape attributes of texture information are computed based on *Entropy(x)* of satellite image. The *map(x)* produces result of building features and open space area can be calculated.

3.2 Matching-based Change Rule

After the building feature of urban areas is extracted using modified MBI, NDV and Entropy, region growing is carried out separately in both images. The objects growing from outliers especially differ from previous image are regarded as changed buildings. The building change detection is carried out based on the following rule

$$C(i) = \begin{cases} 1\ , \quad Obj(i) \in Obj_1(i) \cup Obj_2(i) and \\ |M_1(i) - M_2(i)| \geq T_{spec}, \qquad i \in \{1,2,\dots,N\} \\ 0\ , \qquad\qquad otherwise \end{cases}$$

where *C(i)* represents whether the object *i* is changed, with 0 and 1 for non-change and change, respectively. Obj_1,(*i*)and Obj_2 (*i*) denote the i^{th} pair of corresponding objects in the multi-temporal images, and M_1(i) and M_2(i)are their spectral means, respectively. Obj(*i*)is the union of Obj_1 (*i*)and Obj_2 (*i*). N is the number of pairs of the corresponding building objects.

4. Experimental Result

The experiments are conducted on Google Earth satellite images of Hlaing Tharyar Industry, Yangon, Myanmar. Figure 2(a) and (b) show Original satellite input image of 2003 and 2010.

(a) (b)

Figure 2: Original input image of (a) 2003 and (b) 2010.

Figure 3 compares two images to know they are same or different in building area using hue color histogram matching. This can be seen that the two images of pixels value difference are greater than defined threshold value. In this stage, pre-processing step can achieve better performance and reduce time consuming.

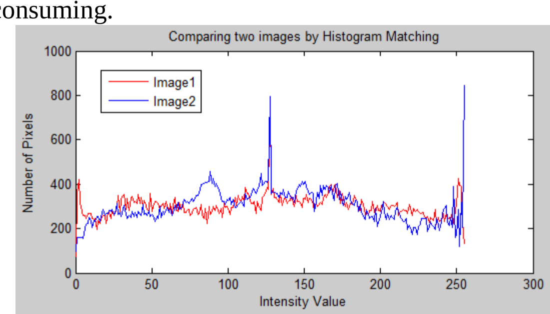


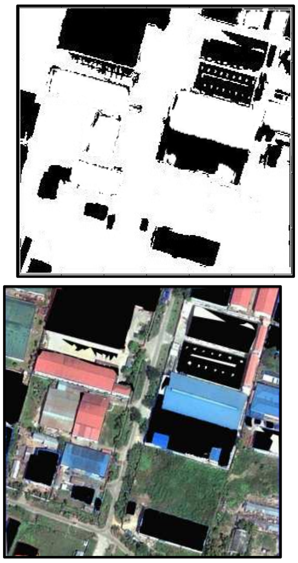
Figure 3: Hue color histogram matching

Then the two images are processed with modified MBI and join approach of NDVI and Entropy to extract building feature is shown in figure 4. In these figures, white area means building areas and black area indicates open space areas that have no buildings and can build anymore.

(a) (b)

Figure 4: The proposed Building Extraction of (a) 2003 and (b) 2010 images

Final change detection result obtained from using only matching-based change rule is shown in figure 5 in which the black areas are changed/increase building and others are without changed area between these two year and most changes have been correctly detected, with a high accuracy of 97%. However, several changed area are still missed.



(a) (b)

Figure 5: Output of proposed change detection result

The performance of the proposed modified MBI, jointly approach of NDVI and Entropy, and matching-based change rule is compared with change detection approach of MBI-based CVA in [6] and Multivariate alteration detection (MAD) transformation in [11]. MBI-based CVA focus on building change detection. The spectral bands are replaced by the multi-temporal MBI feature images for CVA. It contains the salt-and-pepper effects of pixel-based change detection approaches. Multivariate alteration detection (MAD) transformation approach gives good detection results for only simplified data but the variety of buildings shape and the heterogeneity of roof types limited the effectiveness of the proposed methodology.

Table 1: Accuracy assessment of the proposed method

Quantitative measures	MBI-based CVA	MAD	Proposed Method
Correctness	81.75%	77.43%	97.87%
Completeness	74.79%	88.03%	92.45%
Quality	64.09%	66.32%	89.07%

To test the performance of the proposed system, we first implement change detection of MBI-based CVA and MAD approach. The evaluation of change detection was accomplished using evaluation measures (completeness, correctness, quality).

$$Correctness = \frac{TP}{TP + FP}$$

$$Completeness = \frac{TP}{TP + FN}$$

$$Quality = \frac{TP}{TP + FP + FN}$$

where TP (True Positive) and FP (False Positive) are the numbers of changed pixels in the result, but changed and unchanged in the reference image, respectively. FN (False Negative) is the number of changed pixels in the reference image, but detected as unchanged in the result. Table 1 illustrates the accuracy assessment in three methods of change detection. A comparison between the proposed method and several recently developed change detection methods revealed that the proposed method reduced the number of commission and omission errors significantly.

5. Conclusion

In this paper, we have presented a building change detection method from satellite urban images, which is able to solve various intensity colors of building roof and uncertainly of building structure with the help of modified MBI result and joint NDVI and Entropy. Entropy ignores changes in color patterns and more effective differentiation of change types could be achieved by combining entropy change values with spectral information. It is not an easy task to automatically extract buildings without any supervised learning. Therefore, this can overcome as modified MBI is effective method for indication of buildings for even low quality resolution images. The qualitative and quantitative analysis of the changed detection result validates the effectiveness of the proposed system. The system also eases the constructor to find how area is free or already built and provides the free space of open area to build.

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