Urban Change Detection Based on Edge Line Segments and Texture

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Abstract

In this paper, a novel approach based on edge line segments and texture is presented for urban change detection. First, we extract edge line segments based on Canny edge detector and line-support regions based on gradient orientation, Then changed edge line segments are found and grouped into clusters as potential changed regions which are finally validated using the difference of pixels and texture features. The main novelty of our approach is that the combination of different features, such as edge line segments and textures, is used for change detection and validation. The experiments with real *Quickbird-II* images show the promising performance of the proposed method.

Keywords: urban change detection, edge line segments, texture.

1 Introduction

Urban change detection is very important in urban area monitoring such as the detection of new buildings or the discovery of modifications in the existing ones. Very high resolution (VHR) image pairs are very useful for analysing significant urban changes. At present, change detection with such image pairs is primarily performed by human operators, which is time consuming and tedious. We aim at developing algorithms that can automatically extract urban change detection. Many existing methods perform comparisons between various image components such as image pixels (M.J. Carlotto 1997, R.J. Radke 2005), lines (N.C. Rowe 2001), blocks (M. Borchani 2004) and blobs (O. Miller 2005), segments (J. Li 2003). As to urban change detection using VHR images, we find that straight line segments are appropriate image features. Line segments are abundant in the urban scene and less sensitive to illumination changes and local image intensity variations. In addition, the texture is very important for change detection, so we incorporate edge line segments and texture in our work. Our algorithm contains the following main steps: (1) Extraction of edge line segments. (2) Grouping pixels into line-support regions via gradient orientation. (3) Finding and grouping the changed line segments. (4) Validation of the changed regions. The proposed approach is summarized in Fig.1.

This paper is organized as follows: In section 2, our method is elaborated step by step. Section 3 reports our experimental results with *Quickbird-II* VHR images, Section 4 are some concluding remarks.

2 Algorithm description

2.1 Edge line segments extraction

Due to the noisy nature of remote sensing image, standard edge detectors failed to perform adequately. Neither the Roberts Cross, the Sobel operator, nor Prewitt operator are able to detect the edges of the object while removing all the noise in the image. Since the LoG filter is calculating a second derivative of the image, it is quite susceptible to noise, particularly if the standard deviation of the smoothing Gaussian is small. Thus it is common to see many spurious edges detected away from any obvious edges. Canny edge detector performed the best both visually and quantitatively based on the measures such as mean square distance, error edge map and signal to noise ratio (M. Ali 2001). In this paper, a technique based on Canny edge detector is used to extract edge line segments. First, Gaussian filter is used to perform image smoothing. Then, edge line segments are extracted from the smoothed noisy image by using Canny edge detector. The Gaussian smoothing in the Canny edge detector fulfils two purposes: first it can be used to control the amount of detail that appears in the edge image and second, it can be used to suppress noise. Using the implemented Canny edge detector as an efficient tool for extracting edge line segments from VHR images, the result was robust and achieved a very high enhancement level.

2.2 Grouping pixels into line-support regions via gradient orientation

According to Burns (J. B. Burns 1986), pixels are grouped into line-support regions of similar gradient orientation. A similar algorithm is used to extract line-support regions in this paper. The detailed algorithm is as follows:

1) Computation of gradient magnitude and orientation for image *I*. The local gradient orientation was computed by

$$\tan^{-1} G_V(i,j)/G_H(i,j)$$

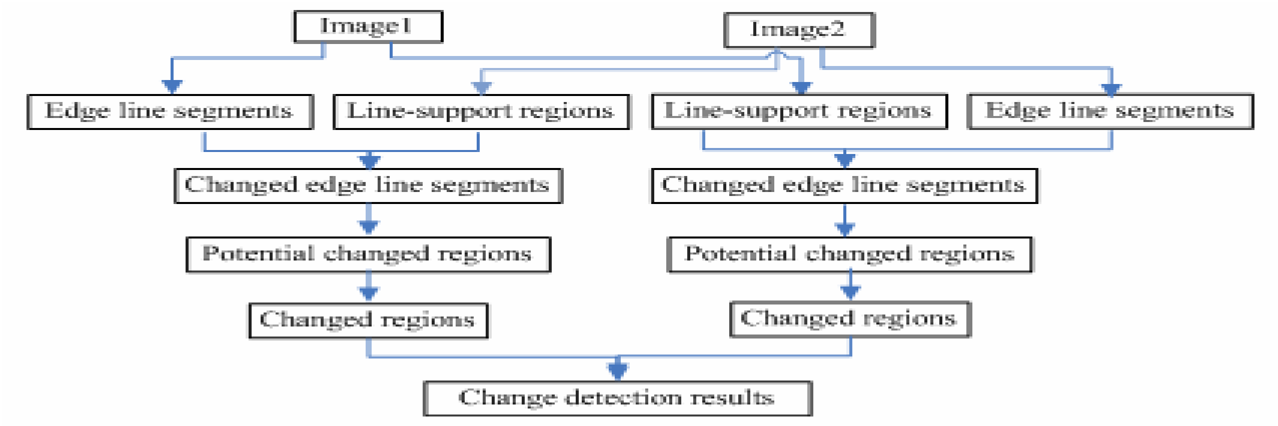


Fig.1 Flowchart of the proposed method

where $G_V(i, j)$ and $G_H(i, j)$ are the vertical and horizontal components of the gradient obtained at pixel (i, j) .In our paper, $G_V(i, j)$ and $G_H(i, j)$ are estimated by convolving the image with two masks $\begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix}$ and $\begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix}$.

2) Extraction of line-support regions. Pixels are grouped into line-support regions of similar gradient orientations. The 360 degree range of gradient direction is arbitrarily quantized into a small set of regular intervals, say, eight 45 degree intervals. Each gradient vector is labelled according to the partition into which it falls. A simple connected-components algorithm is then used to form distinct line-support regions for groups of adjacent pixels with the same orientation label.

The edge line segment sets extracted from $I(t_1)$ and $I(t_2)$ are denoted by $Line(t_1) = \{l_i^{(1)}\}$ and $Line(t_2) = \{l_j^{(2)}\}$, the correspondent line-support regions by $ori(l_i^{(1)})$ and $ori(l_j^{(2)})$ respectively.

2.3 Finding changed line segments

Inspired by the work of Burns (J. B. Burns 1986), we propose to make comparisons between edge line segments from one image and the gradient orientation field of the other image. Then $l_i^{(1)}$ is regarded changed if the following inequality holds:

$$\frac{\sum_{x \in \Omega(l_i^{(1)})} MA(l_i^{(1)}(x), ori(l_i^{(2)}(x))}{length(l_i^{(1)})} \le thresh1$$

where $\Omega(l_i^{(1)})$ is the support of $l_i^{(1)}$, $MA(l_i^{(1)}(x), ori(l_i^{(2)}(x))$ is a 0-1 function that thresholds the angle perpendicularity between $l_i^{(1)}$ and $ori(l_i^{(2)})$ at x. $length(l_i^{(1)})$ is the length of $l_i^{(1)}$. In this paper, $thresh1 = 0.7$. $l_i^{(2)}$ is treated similarly. Therefore we obtain two sets of changed lines: $Change(t_1) = \{l_i^{(1)}\}$ and $Change(t_2) = \{l_i^{(2)}\}$. In addition, differences between pixels are important for change detection, so if the sum of squared differences between the line segments $l_i^{(1)}$ and its correspondent pixels in the other image is larger than a threshold, $l_i^{(1)}$ is also regarded as changed.

2.4 Grouping changed line segments

Making comparisons between two sets of line segments is a very difficult problem due to the unreliable low-level line extraction process and the complex content of urban scene, so we group the changed line segments $Change(t_i)$ into different clusters such that within each cluster the maximized distance between any two line segments is smaller than a predefined threshold. We observe that the isolated short changed line segments are mainly induced by noise while a cluster of changed line segments spanning certain image regions are usually significant urban changes. Therefore the clusters whose total line segment lengths are smaller than a threshold are removed. Then, from each resulting cluster, the corresponding minimum rectangular region containing all the line segments of this cluster is outputted as the potential changed regions for further validation in the next step.

2.5 Validation of changed regions

For potential changed regions, further validation needs to be performed to get the regions that did change. Many features can be used for this task, the differences of pixels and texture features between two regions are selected in this paper. Color moments in RGB space and histogram in HSV space are important features to describe the texture. The first and second moments are used for channels R, G and B, so its dimension is 6. Since HSV decouples the intensity (i.e., value) from color (i.e. hue and saturation), it is reasonably insensitive to illumination effects. Normalised histograms in the HSV space are used and the channel V is rejected, in our work, 32 bins are used to represent the histogram. Thus we got two kinds of texture features for every potential changed region: color moments and histogram features. For predefined thresholds *th1~ th4*, the detailed algorithm for validation is described as follows:

1) Compute the maximized average difference $d(I(t_1), I(t_2))$. $I(t_1)$ and $I(t_2)$ can be decompose of some subregions, i.e.

$I(t_i)=\bigcup_{k=1}^{m} R_k^{(i)}$, $R_n^{(i)} \cap R_l^{(i)} = \varnothing$, $(n \neq l)$, where $R_l^{(i)}$ is a 15*15 patch. Let $d(\mathrm{R}_i^{(1)}, \mathrm{R}_i^{(2)})$ denote the average difference between $R_l^{(1)}$ and $R_l^{(2)}$, among which the maximized $d(\mathrm{R}_i^{(1)}, \mathrm{R}_i^{(2)})$ is set to $d(I(t_1), I(t_2))$,

2) If $dif > d(I(t_1), I(t_2)) * th1$, then the changes between R_1 and R_2 exist, where dif is the average difference between them.

3) If $dif <= d(I(t_1), I(t_2)) * th1$, but the distance of the normalized histogram features $D_{\mathrm{h}}(X, Y) > th2$, the changes between R_1 and R_2 exist.

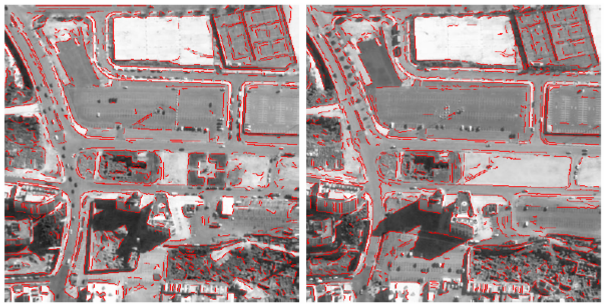
4) If $dif < d(I(t_1), I(t_2))$, but $D_{\mathrm{h}}(X, Y) > th3$ and the distance of the normalized color moments features $D_{\mathrm{m}}(X, Y) > th4$, the changes between R_1 and R_2 exist.

5) Otherwise, no changes take place.

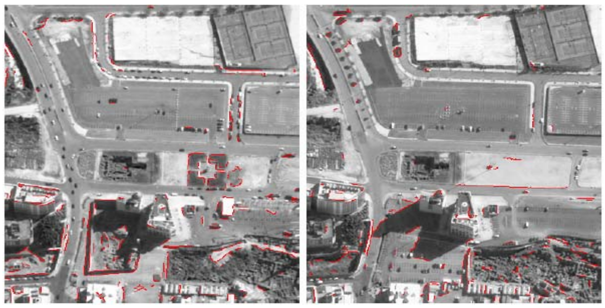
3 Experimental results

We test our method with two *Quickbird-II* images taken in Dec.2003 and Feb. 2005 for the city of Beirut. This is a typical scene in urban area, there are various urban architectures such as dense building with complex roofs, parking lot, vehicles, grasslands. Both view angle and illumination vary between two images. Fig.2 (a) is the direct difference image of $I(t_1)$ and $I(t_2)$ in which changes are difficult to separate from each other. Fig.2 (b) shows the extracted edge line segments and (c) the changed edge line segments. Fig.2 (d) is the change detection results using our method. Fig.2 (e) shows the actual changed regions. The red rectangular indicate the significant changes, while the sub-significant changes are denoted by the purple rectangular. In our paper, four predefined thresholds used to validate the changed regions are 0.8, 0.6, 0.2 and 0.12 respectively, which mainly depend on our experience. By comparison of these regions, most of actually changed regions are correctly detected by our automatic detection algorithm. This shows the robustness of our method. But as Fig.3 illustrated, some subtle changes fail to be detected using our method due to the complex pattern formed by both parallax and illumination changes. This needs to be improved in our future work.

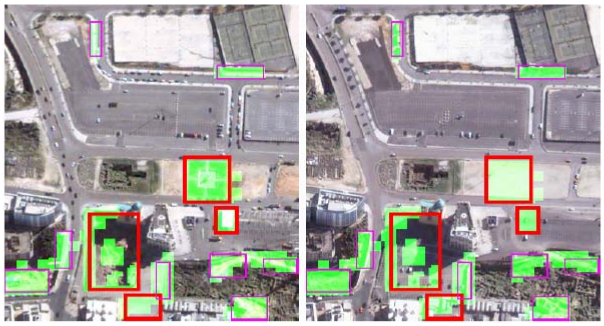
(a) Difference image



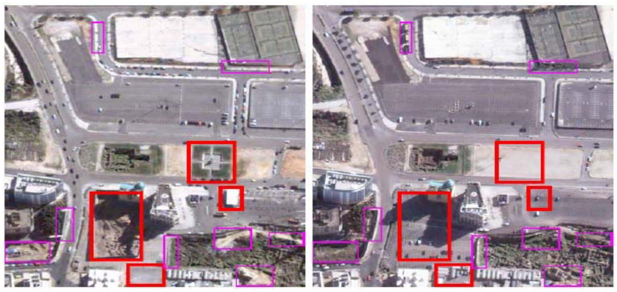
(b) Extracted edge line segments



(c) Changed edge line segments



(d)Final change detection results



(e)Manual change detection results

Fig.2 Change detection results

Fig.3 An example of information loss

4 Conclusions

A novel approach based on edge line segments and texture is proposed in this paper for urban change detection. The main novelty of our approach is that the combination of different features, such as edge line segments and texture, is used for change detection and validation. Our method can extract not only building changes but also other significant urban structure changes such as plazas, roads and grasslands. The experiments show the promising performance of the proposed method. However, many thresholds must be predefined, which limits the generalization of the proposed method, this need to be improved in the future. In addition, the algorithm will be tested on more types of datasets, and its performance will be compared to other change detection techniques.

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