

Urban building land use change mapping from high resolution satellite imagery, active contours and Hough voting

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Abstract: In this paper we propose a novel approach for updating the building layer of a high-scale land use digital map using a more recent high resolution panchromatic Quickbird image. A preliminary map-to-image fine matching is carried out by edge-based and shape constrained active contours. This step reduces exogenous discrepancies between the map and the image and makes a subsequent Hough voting change detection reliable. Promising experimental results are shown over Beijing city area.

1. Introduction

As the urban population is growing worldwide, a reliable analysis of the urban land use is essential to develop a sustainable environment for citizens. The monitoring of urban sprawl, water resources and vegetation are common tasks of urban planning to achieve such goal and can be substantially supported by the wide range of spectral signatures of remote sensing data. With the advent of very high resolution optical sensors on board of observation satellites, detailed land use change mapping in urban areas is becoming affordable at a large-scale. The regular revisit capabilities of satellites also enable a high frequency of acquisition for a ‘continuous’ survey and monitoring. However, the interpretation of high resolution optical images remains challenging especially for urban areas and therefore requires new fusion tools to accomplish land use updating.

In this paper we propose a novel approach for updating the building layer of a high-scale land use digital map using a recent very high resolution panchromatic image. The method consists in verifying if each building of the map appears in the image. The proposed two-step approach relies on a preliminary map-to-image active contours based matching, followed by Hough voting based change detection. We show experimental results using a Quickbird image acquired in 2002 and 1:10,000 scale GIS data over Beijing city.

2. Method

Assuming that building land use and imagery data are first globally registered, the following scheme is performed to carry out land use map updating:

2.1. GVF active contours with shape constraint for map-to-image fine matching

Each building from the map is finely matched to its counterpart representation in the image. In case no change has occurred between the map and the image for a considered building, the fine matching step enables increased consistency between the cartographic and remote sensing representations. It alleviates the problem of map-to-image exogenous variabilities (incorrect registration, mistakes in the map, etc...) which could be wrongly interpreted as a change. As a result, the fine matching makes the final change detection decision more reliable. In case a change has occurred, the fine matching fails and the building disappearance may be confirmed by the final change detection step.

In (Bailloeuil et al., 2005) a method was proposed to achieve digital building map refinement. This scheme was shown to effectively overcome urban artifacts (occlusions, poor contrast, and shadows) but was limited to deal with buildings having a homogenous roof reflectance. In this paper, we propose to extend the approach of (Bailloeuil et al., 2005) to heterogeneous buildings.

We choose to use edge-based information to drive the active contour to the considered building outline in the image. Gradient information is invariant and robust towards the type of building to be matched. Nevertheless, the use of edge information raises two problems: i) edges are numerous in high resolution images of urban environments, which may influence the active contours and the subsequent matching result. ii) edge information is intrinsically local; as a consequence, an active contour initialized too far from the target building in the image might not be attracted to its roof outline. To alleviate the first problem, we extract segment primitives by chaining high gradient pixels derived from an edge detection performed on the image. This pre-processing is filtering the gradient information as it only retains segments from the satellite image which are relevant to characterize buildings. To deal with the second issue, we make use of the Gradient Vector Flow (GVF) technique formerly proposed in (Xu and Prince, 1997). This approach consists in spatially diffusing the gradient information into a vector field $[\mathbf{u}, \mathbf{v}]$ which tends to drive the active contour to high gradient areas, even remotely. More recently, GVF-based active contours were formulated in a level

set approach (Osher and Setian, 1988) in the work of (Paragios et al., 2004). The level set representation allows active contours to undergo topological changes and ease the incorporation of shape constraints. Adapting the scheme of (Baillioleul et al., 2005) while replacing the region-based information term by the simplest GVF-based model of (Paragios et al., 2004), the level set evolving equation of an active contour intended to achieve fine matching with an inhomogeneous building becomes:

$$\phi_t(\mathbf{x}, t) = \beta\kappa|\nabla\phi| - \langle [\mathbf{u}, \mathbf{v}], \nabla\phi \rangle + 2\lambda\delta(\phi)(H(\phi) - H(\psi)) \quad (1)$$

where ϕ and ψ are the level set functions representing the active contour and the cartographic object respectively, κ is the level set curvature at the location \mathbf{x} . $[\mathbf{u}, \mathbf{v}]$ is the GVF built from the segment primitives derived from edge detection and (β, λ) are positive constants weighting the smoothing curvature flow and the shape constraint respectively. $H(\cdot)$ and $\delta(\cdot)$ are regularized approximations of the Heaviside and Dirac functions and $\langle \cdot, \cdot \rangle$ is the inner product.

2.2 Change detection based on Hough voting

An Hough voting approach (Hough, 1962) is used to confirm the *changed* or *unchanged* status of each building and relies on a preliminary active contours fine matching: correspondences between segments of the refined cartographic building and segments primitives extracted from the image are evaluated and accumulated in a Hough voting space which aims at estimating the best translation $\boldsymbol{\mu}_{Hough}$ matching both representations. The maximum value of the Hough accumulator is an indicator of change: a low score means that a few segments in the image match the land use map object and detects a change. Conversely, a high score acknowledges that a similar building in the image was found. The simultaneous evaluation of a high Hough voting score and a small translation amplitude $|\boldsymbol{\mu}_{Hough}|$ confirms the unchanged status of the building. The Hough voting algorithm is as follows:

A. Let S and S' be the two sets containing the segments related to the refined cartographic building and the image. S is obtained by vectorization of the active contour achieving refinement; segments of S' are extracted with a similar procedure as explained in section 2.1.

B. For each s_i in S :

i) For each s'_i in S' :

- If s_i and s'_i are almost colinear, the minimum and maximum translations $\boldsymbol{\mu}_{ij, \min}$ and $\boldsymbol{\mu}_{ij, \max}$ enabling the superimposition of each extremity of s_i and s'_i are estimated.
- In a two-dimensional accumulator (μ_x, μ_y) , the segment $[\boldsymbol{\mu}_{ij, \min}, \boldsymbol{\mu}_{ij, \max}]$ is added with a weight

equal to $\min(|s_i|, |s'_i|)$, where $|s_i|$ is the length of s_i .

D. The translation $\boldsymbol{\mu}_{Hough}$ is estimated at the maximum location of the Hough accumulator. This maximum value is normalized by the perimeter P of the cartographic polygon ($P = \sum |s_i|$) to finally yield the normalized Hough score s_{Hough} .

3. Experimental results

We show experimental results with a building land use map of 1996 and a panchromatic Quickbird satellite image of Beijing city acquired in 2002 (0.6 m/pixel). The outdated urban digital map is the building layer of a 1:10,000 scale GIS data. The satellite image was rectified from terrain variations by the Beijing Institute of Surveying and Mapping (BISM) to reach 0.4 m geocoding accuracy.

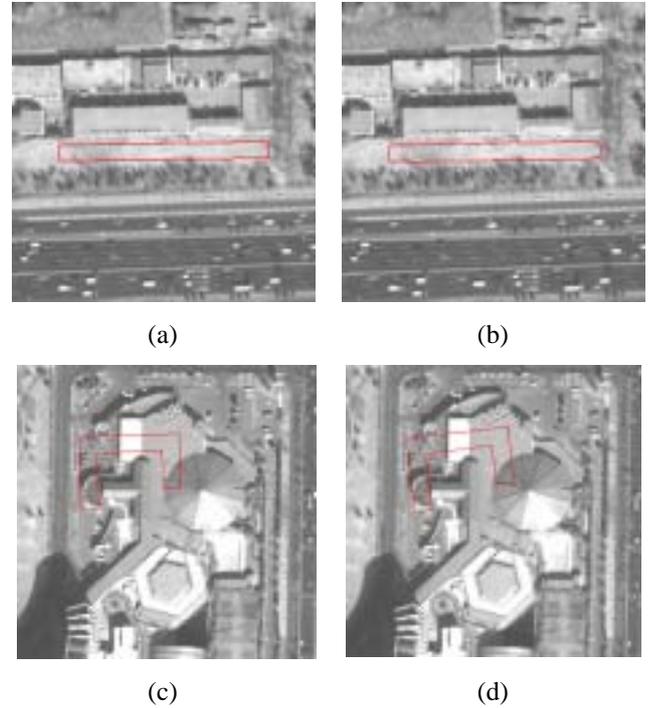


Fig. 1. Change detection results. (a-c): initial overlay of the cartographic building on the image. (b-d): refined cartographic object after active contours matching. (a) $s_{Hough} = 0.08$ (b) change confirmed, $s_{Hough} = 0.2$ and $\boldsymbol{\mu}_{Hough} = (1, 0)$; (c) $s_{Hough} = 0.15$ (d) simulated change confirmed, $s_{Hough} = 0.2$ and $\boldsymbol{\mu}_{Hough} = (-4, -5)$

Since both cartographic and remote sensing data are geocoded in the same cartographic system, their initial registration is straight-forward. Active contours matching was carried out with $\beta = 0.1$ and $\lambda = 5$. The figure 1.a illustrates an obvious change between the map and the image. The whole

building was destroyed and replaced by a grass land. The active contours matching fails as the building disappeared, which is confirmed by the final Hough voting low score $s_{Hough} = 0.2$.

The second experiment is a simulated change which is less univocal as the first one: the cartographic building is replaced by a complex one (fig. 1.c). Like in the first experiment, the matching fails and the Hough vote confirms the absence of the map object ($s_{Hough} = 0.2$). In both experiments, Hough scores after fine matching are higher than before. This observation is consistent with the fact that active contours drive the cartographic object close to high gradient segments of the image which might contribute to the Hough vote.

The two last experiments illustrate cases where buildings are correctly confirmed as unchanged (fig. 2). We notice that in both cases, the refined cartographic object is closer to the building boundaries. However some local discrepancies remain. These are due to local shape inaccuracies in the map inherent to simplification effect or mistakes. Such local variabilities cannot be overcome by active contours as they are embedded in the shape constraint. Nevertheless, we notice that such minor discrepancies do not affect the matching process which increases the Hough voting score in a significant way and thus makes it more reliable (see caption of fig. 2 for quantitative results).

4. Conclusion

We have presented a novel approach for urban building land use change mapping from high resolution satellite imagery. Our scheme relies on a preliminary map-to-image fine matching step achieved by active contours. The fine matching process was extended in the present paper to any kind of inhomogeneous buildings by using the GVF technique coupled with the shape constraint derived from the map. A Hough voting approach yielding two map-to-image change indicators was proposed. This method was proved, from experiments, to be efficient while being combined to the fine matching process. Future works may attempt to merge the Hough normalized score and the estimated translation in a stochastic framework to estimate a probability of change for each building of the map. Incorporation of geometric variations due to the active contours matching as well as additional building cues such as shadows and multispectral signature is also under consideration.

Acknowledgment

This project is supported by the Chinese MOST 863 programme as well as Alcatel Alenia Space.

References

- [1] Bailloeuil, T., V. Prinnet, B. Serra, P. Marthon, P. Chen, H. Zhang (2005). Digital building map refinement from knowledge-driven active contours and very high resolution optical imagery. Proc. ISPRS Hannover Workshop.
- [2] P. V. C., Hough (1962), Methods and means for recognizing complex patterns. U.S. Patent 3 069 654.
- [3] Osher, S., J.A. Sethian (1988), Fronts propagating with

curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. Journal of Computational Physics, 79, 12-49.

- [4] Paragios, N., O. Mellina-Gottardo, V. Ramesh (2004). Gradient Vector Flow Fast Geometric Active Contours. IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 402-407.
- [5] Xu, C., J. Prince (1997). Gradient Vector Flow: A New External Force for Snakes. Proc. of Computer Vision and Pattern Recognition, 66-71.

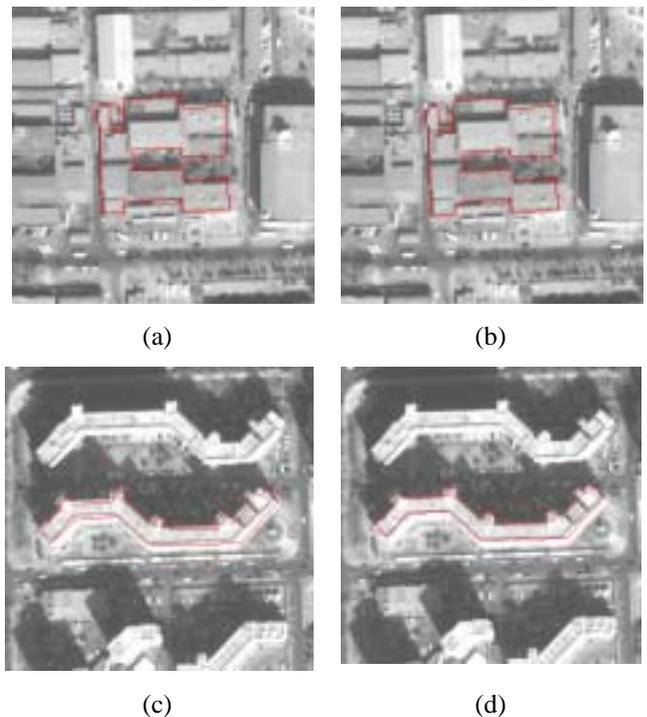


Fig. 2. Change detection results. (a-c): initial overlay of the cartographic building onto the image. (b-d): refined cartographic object after active contours matching. (a) $s_{Hough} = 0.34$ (b) no-change confirmed, $s_{Hough} = 0.7$ and $\mu_{Hough} = (1,0)$; (c) $s_{Hough} = 0.57$ (d) no-change confirmed, $s_{Hough} = 0.8$ and $\mu_{Hough} = (1,0)$

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