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Automatic GIS Updating from High Resolution Satellite Images

N. Champion[1,2*], G. Stamon[2] and M. Pierrot-Deseilligny[1]
[1] Institut Géographique National, MATIS Lab., 2/4 avenue Pasteur 94160 Saint-Mandé, France
firstname.lastname@ign.fr
[2] Université Paris Descartes, CRIP5-SIP Lab., 45 rue des Saints-Pères 75006 Paris, France
firstname.lastname@math-info.univ-paris5.fr

Abstract

Among all the issues involved in Geographic Information Science, automating the update of 2D building databases is a crucial and challenging issue. Such an update usually starts out with a manual change detection process. The main goal of this paper is to present a new method to automate the detection of changes in a 2D building database, starting from satellite images. The workflow of our approach is divided into 2 phases. Primitives, extracted from multiple images and from a correlation Digital Elevation Model (DEM), are firstly collected for each building and matched with primitives derived from the existing database to achieve a final decision about acceptance or rejection. A specific algorithm, based on the DEM and a computed Digital Terrain Model (DTM), is subsequently used to extract the new buildings of the scene. The method is here introduced and tested in two test areas, very different regarding the land use and topography. The outcomes of the method are assessed and show the good performance of our system, especially in terms of completeness, robustness and transferability.

1 Introduction

Traditionally, the mapping process, e.g. the practice of producing one representation of the Earth through a Geographic Information System (GIS) is carried out by field surveying: objects of interest (buildings, roads, etc.) are captured by operators on the field (with GPS), then processed and stored in the GIS as a vector database. Images are generally not considered in the workflow. At the end of the process, the question that immediately arises concerns the update of the database, more specifically the strategy to use for that purpose. This question is a topical issue in developed countries, as GIS databases - in particular 2D building databases - have been completed during the last decade.

1.1 Map Update Strategies

Many strategies exist to keep such databases up-to-date, such like the collaborative strategy found for instance in the Google Map Maker project[1], that consists of the aggregation of web maps generated by a group of individuals. Another strategy consists in collecting information about the update from external data such as airborne images and laserscanning data and also consists in comparing the existing database to more recent data in order to detect changes i.e. demolished, modified or new objects in the outdated database.
Among possible external data, images - in particular satellite images - have qualitatively advanced to a point where they become interesting input to solve mapping, here change detection issues. Thus, most satellite systems offer now a high spatial resolution (the panchromatic resolution is 1m for Ikonos, 60 cm for Quickbird, 50cm for Worldview-I, 50cm for the Pléiades-HR system that shall be ready for launch in early 2010) and have already and successfully been used in previous works for mapping purposes, e.g. for the automatic production of city 3D models [4]. Moreover, satellite systems have had their reactivity considerably upgraded during the last decade and are now capable to acquire a considerable amount of information in a relatively short amount of time, which complies with the reactivity required in a change detection procedure.

1.2 Related Works

A lot of change detection methods (Refer to [5] and [6] for two examples) can be found in literature. If it is difficult to compare them efficiently, as they have been developed in different contexts (regarding the specification of the database to update, the kind of input data to use, the level of user interactivity, etc.), almost all of them are based on a preliminary land cover classification of input data. The method described in [6] also splits the change detection procedure into three stages. First, a Dempster-Shafer fusion process is carried out on a per-pixel basis and results in a classification of the input data, here CIR (Colour InfraRed) images and a DEM, into one of four predefined classes: buildings, trees, grass land and bare soil. Connected components of building pixels are then grouped to constitute initial building regions and a second Dempster-Shafer fusion process is carried out on a per-region basis to eliminate regions corresponding to trees. The third stage corresponds to the actual change detection process, in which the detected buildings are compared to existing GIS data, which results in a very detailed change map. Another strategy is proposed in [1] and consists in splitting the procedure into two stages: the *verification of the database* that largely uses the initial description of the database to detect outdated objects and the *new building detection*. The key idea here is based on the

*The first author would like to thank the French Space Agency (CNES) for providing Pléiades-HR images.
[1]www.google.com/mapmaker, last date accessed: 03-06-2009.

assumption that the number of changes is small compared to the number of unchanged objects. [6] takes up this idea and also introduces a "bias" in the first per-pixel Dempster-Shafer classification, which translates the high probability of a building pixel of the map to still belong to a building in recent data.

1.3 Overview of the Method

The main goal of this paper is to present a new approach in order to automatically detect changes in a 2D building vector database from more recent satellite images. The input of our method is given by tri-stereoscopic CIR Pléiades-HR satellite images, with a base-to-height ratio of 0.15 and a spatial resolution of 50cm. A stereo-matching algorithm, based on [7] is used to compute a DEM and a vegetation mask is derived from the CIR satellite images through the Normalised Difference Vegetation Index (NDVI). Note that the DEM is given in the form of a matrix (regular grid) of height values (raster model). The output of the method is given by a change map, in which buildings are labeled unchanged, demolished, modified (e.g. having a wrong geometric description) or new.
The method described here is meant to be an alternative to the previously mentioned methods, mostly based on a preliminary land use classification and is based on two key ideas. The first one takes up [1] and consists in splitting the change detection procedure (known to be difficult to solve) into two subtasks easier to solve, the verification of the database (phase I) and the detection of new buildings (phase II). The second one consists in using massively 3D geometric primitives in the system.

2 Automatic Verification of the Database (Phase I)

This first phase also implements a knowledge-driven approach: the key idea here is to use the prior knowledge provided by the database about the geometric description of buildings and to collect 2D & 3D information from input sources in order to confirm or not their existence in the outdated database.

2.1 General Workflow

Geometric linear primitives are also extracted from input data. For each object (building) to verify, the primitives that fulfil a user-defined distance and orientation with it are selected. A similarity score is then computed per building: it is based on the coverage rate between the previously selected primitives and the building. This similarity score is used in a threshold-based module and a final decision about acceptance or rejection is achieved for each building. This first phase leads to a partially updated database, in which buildings are labeled demolished, modified or unchanged.

2.2 Extraction of Pertinent Information from Input Data

The performance of this phase is obviously related to the pertinence of primitives extracted from input data. Two kinds of primitives are used in our work, firstly 2D contours and secondly 3D segments.
The classical gradient operator [3] is firstly applied to the DEM and a hysteresis detector is used to extract the local maxima in the direction of gradients, which are then chained, polygonized and deliver the 2D contours. These 2D contours also correspond to the height discontinuities in the DEM. As the DEM is not surprisingly less accurate in shadow and vegetated areas, due to classical drawbacks of stereo-matching algorithms, the 2D contours are less reliable at such locations and other features consequently need to be extracted.
3D segments are thus injected in our system. They are generated directly from multiple satellite images with [8]. This algorithm can be divided into 4 stages. 2D segments are firstly extracted from source images (stage 1) with [3]. A set of so-called associations (i.e. possible correspondences) is subsequently determined (stage 2), by matching 2D segments from the Object Space through the well-known Sweep Plane technique (an association also corresponds to a set of 2D segments (in images), whose projections onto a plane (z = z_k) intersect each other in at least one voxel (x,y,z_k) of the Object Space). The set of associations is then pruned (stage 3), according to a geometric constraint and are lastly used to reconstruct the 3D segments (stage 4). More details can be found in [8].
These 3D segments are particularly interesting as they are shown to be accurate in planimetry and represent a good caricature of buildings in an urban environment (they are used as input data in a 3D city modeler).

3 New Building Detection (Phase II)

The goal of this phase is to detect new buidlings in the scene. The key idea here is to extract the above-ground objects that neither correspond to a building already present in the database nor a tree.

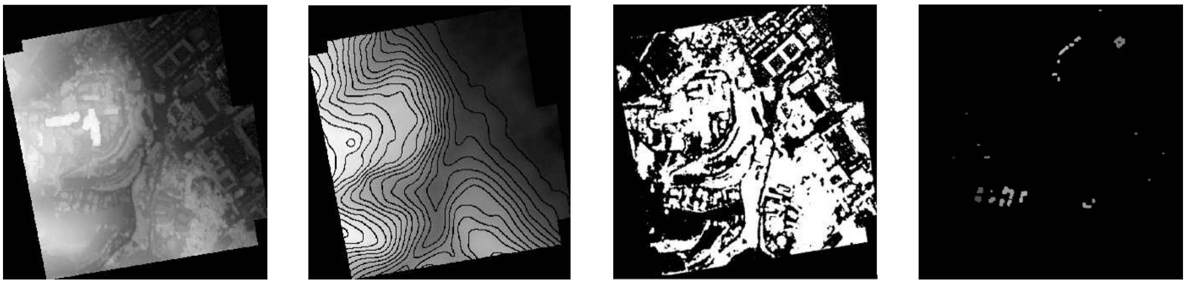
3.1 General Workflow

A specific methodology is proposed to achieve that goal (as illustrated in Figure 1). A DTM is calculated and a normalized DEM (nDEM = DEM - DTM)[2] is computed and applied a geometric threshold (here 2.5m) to build a new above-ground mask. This binary mask is then compared to the initial above-ground mask (composed of the vegetation mask and a building mask, easily derived from the database to update) with dedicated morphological tools: objects that appear in both masks are filtered out and remaining objects correspond to new buildings.

3.2 DTM Generation

The key issues of this phase are the computation of the DTM and its accuracy. In our work, the DTM is directly derived from the DEM and the initial above-ground mask. The DTM generation problem is considered solved when the terrain surface $z_{c,l}$ is determined at the nodes $p_{c,l} = (x_c, y_l)$ of the regular grid, already defined for the input DEM. Note that $(c, l) \in [1, M] \times [1, N]$ with M and N, respectively the number of columns and rows of the regular grid. The DTM generation is here formalised as the minimisation

[2] A Digital Terrain Model (DTM) is a 2.5D representation of the terrain surface. A Digital Elevation Model (DEM) is a 2.5D representation of the earth surface, including any above-ground objects, such as trees and human settlements. A nDEM also gives the height of above-ground objects in the scene.



(1) (2) (3) (4)

Figure 1: Detection of new buildings (illustration for the Toulouse test area). (1) : Initial DEM (lighter = higher). (2) : Processed DTM (with the contour lines superimposed). (3) : Processed above-ground mask. (4) : New building mask.

of a given energy $E(z) = K(z) + \lambda G(z)$, where K(z) refers to the regularisation term (i.e. a prior knowledge about the surface regularity) and G(z) refers to the data term. $obs_{c,l}$ correspond to observations e.g. DEM height points out of the above-ground mask and λ is a user-defined balance coefficient.

$$K(z) = \sum_{(c,l)\in[1,M]\times[1,N]} \left(\frac{\partial^2 z}{\partial^2 x_c}\right)^2 + \left(\frac{\partial^2 z}{\partial^2 y_l}\right)^2 \quad (1)$$

$$G(z) = \sum_{\substack{(c,l)\in[1,M]\times[1,N] \\ p_{c,l}\notin \text{Vegetation Mask} \\ p_{c,l}\notin \text{Building Mask}}} \rho\left(z_{c,l} - obs_{c,l}\right) \quad (2)$$

The main problem concerns the outliers i.e. above-ground points present in the DEM but not in the above-ground mask. They may correspond to cars, street furniture, inaccuracies in the vegetation mask (omitted trees) or inaccuracies during the DEM production (false correlation). As they systematically make the final DTM surface deviate from the true terrain, a specific module ρ is introduced in the data term to filter them. It consists of a dissymmetric robust Tukey-Huber norm (derived from the M-estimator theory [9]) that downweights observation points not close enough to the estimated model (typically outliers) and favours lower points (typically inliers i.e. true ground points). At the end of the iterative minimisation process, the terrain surface best fits inliers and the terrain shape is reconstructed accurately. The accuracy of the DTM is estimated with ground truth data and appears to be optimal: the height standard deviation, between a sample of reference height points (captured by an operator) and corresponding values in the DTM is 1.47m, which is in line with the theoretical value (ranging from 0.9m to 1.8m) expected for a tri-stereocopic computer-vision system such as Pléiades-HR.
Note that the DTM is all the more accurate as inliers are present in initial observations. As a consequence, the buildings, considered demolished in the first phase i.e. corresponding to potential ground points are removed from the building input mask for the DTM generation: here, the splitting of the change detection procedure appears to be crucial to improve the accuracy of the DTM and, at the end, the new building detection.

4 Experiments

The performance of the method is assessed in two test areas, Toulouse and Amiens (France), very different regarding the kind of land use and topography. Toulouse has an area of 1 km^2 and features a hilly and suburban area, with detached buildings, very different from each other with respect to the size, height, shape and roofing material. Amiens has an area of 0.5 km^2 and features a relatively flat and densely built-up urban area, composed of adjacent small houses, mostly covered with slate. A ground truth is available for both test areas and shows 51 changes for Toulouse (25 new buildings, 11 demolished buildings, 15 modifications) and 38 changes for Amiens (10 new constructions, 11 destructions, 17 modifications).

4.1 Evaluation Protocole

The evaluation procedure consists of a comparison of the change map delivered by the method to the ground truth. Two quality measures, the completeness and correctness, are also computed.

$$Completeness = \frac{TP}{TP+FN} \in [0;1] \quad (3)$$

$$Correctness = \frac{TP}{TP+FP} \in [0;1] \quad (4)$$

where TP (True Positive), FP (False Positive), FN (False Negative) - and TN (True Negative) - are denoted in the following confusion matrix.

Algo \ True	Change	No Change
Change	TP	FP
No Change	FN	TN

Table 1: Confusion Matrix.

From a practical point of view, the completeness refers to errors kept in the final database, once the change detection (and update) ended. The correctness refers to unchanged objects, unnecessarily checked by an operator. The optimal value for both quality measures is 1.

4.2 Results and Discussion

The evaluation outcomes are illustrated in Figure 2 (TP highlighted in green, FP in orange, FN in red and TN in blue). Table 2 gives the completeness and correctness, computed on a per-building then per-pixel basis. In a similar way as the other change detection approaches found in literature, our method delivers a lot of false alarms (the correctness is 41.6% for Toulouse and 34.5% for Amiens). The nature of these false alarms depends on the phase. In Phase I, they are almost entirely related to the building size (a lot

Quality Measure \ Study area	Toulouse	Amiens
Per-building Evaluation		
Completeness	96.2%	98.3%
Correctness	41.6%	34.5%
Per-pixel Evaluation		
Completeness	97.5%	97.7%
Correctness	75.3%	69.4%

Table 2: Per-building and per-pixel Evaluation.

of confusion occur with small buildings, which explains why the correctness is significantly higher, respectively 75.3% and 69.4%, when computed on a per-pixel basis). In Phase II, they are related to inaccuracies in input data: non masked trees in the vegetation mask and overestimated shadow areas in the DEM are systematically alerted as new buildings.
However, this drawback must be put into perspective. Firstly, the problem related to false alarms appears to be hard to avoid as it mainly concerns small buildings, for which pertinent information is known to be difficult to extract. Secondly, this problem only leads to a pointless verification for an operator and therefore does not alter the quality of the final database, which is guaranteed by a high completeness rate (respectively 96.2% and 98.3%). Thirdly, the system clearly and drastically speeds up the update procedure, as it gives only one quarter of the database to verify, with almost all the changes included. Lastly, similar quality measures are obtained for Toulouse and Amiens that are processed with the same parameters. The system also appears to have a performance independent of the test area (i.e. the land use and topography) and is therefore easily transferable: it is related to the use of geometric primitives (in particular 3D segments) and to the fact that the geometric appearance of buildings is relatively invariant (contrary to their radiometric appearance for example).

5 Conclusion

In this paper, we first show that GIS mapping procedures are nowadays mostly related to update and change detection issues and that satellite imagery has a major role to play in this industrial context. We then present an original method to detect the changes between a 2D building database and more recent high resolution satellite images. Two main contributions are presented here. First, we propose a semi-recursive approach: the objects present in the database are first verified (phase I) and the outcomes are used to improve the detection of new buildings (phase II). Second, the 2D database to update is plunged into a 3D environment by using invariant 3D primitives (in particular, 3D segments and DTM), reconstructed with tri-stereoscopic Pléiades-HR capabilities. These two contributions, combined together, give good results, both in terms of completeness and robustness (transferability). In the future, other experiments will be carried out on larger areas to confirm the robustness of the method. An ongoing work also deals with the comparison of our method with [5] and [6]. Interested readers could refer to [2] for details about the specific testbed used in this study, both including the comparison methodology and preliminary results.

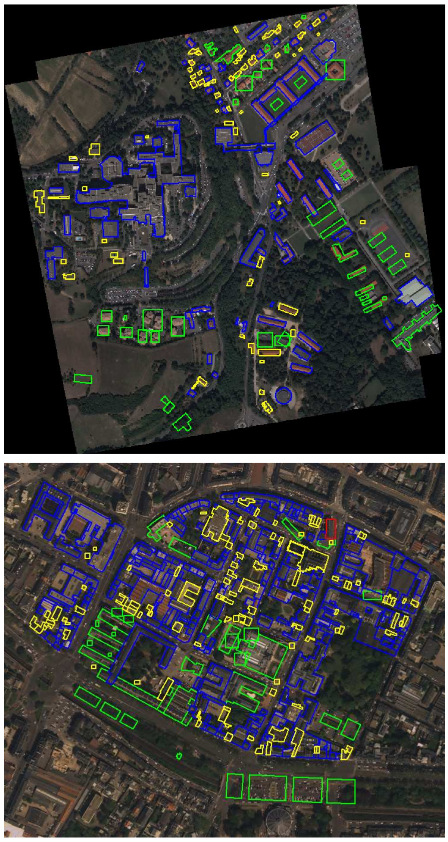


Figure 2: Evaluation in Toulouse (top) and Amiens (bottom). TP cases are depicted in green, FN in red, FP in yellow and TN in blue.

References

[1] A. Busch, M. Gerke, D. Grünreich, C. Heipke, P. Helmholz, C. E. Liedtke, S. Müller: "Automated Verification of a Topographic Reference Dataset using IKONOS Imagery", *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (IAPRS)*, vol. XXXVI/4, pp. 134-139, 2006.

[2] N. Champion, L. Matikainen, F. Rottensteiner, X. Liang, J. Hyyppä: "A Test of 2D Building Change Detection Methods: Comparison, Evaluation and Perspectives", *IAPRS*, vol. XXXVII/B4, 2008.

[3] R. Deriche: "Using Cannys Criteria to Derive a Recursively Implemented Optimal Edge Detector", *International Journal of Computer Vision*, vol. 1, no. 2, pp. 167-187, 1987.

[4] F. Lafarge, X. Descombes, J. Zerubia: "Building Reconstruction from a Single DEM", *Proc. IEEE Computer Vision and Pattern Recognition (CVPR)*, 2008.

[5] L. Matikainen, J. Hyyppä, H. Kaartinen: "Automatic Detection of Changes From Laser Scanner and Aerial Image Data for Updating Building Maps", *IAPRS*, vol. XXXV/B2, pp. 434-439, 2004.

[6] F. Rottensteiner: "Automated Updating of Building Data Bases from Digital Surface Models and Multispectral Images", *IAPRS*, vol. XXXVII/B3A, pp. 265-270, 2008.

[7] S. Roy, I. Cox: "A Maximum-Flow Formulation of the N-Camera Stereo Correspondence Problem", *Proc. of the IEEE International Conference on Computer Vision (ICCV)*, 1998.

[8] F. Taillandier, R. Deriche: "A Reconstruction of 3D Linear Primitives from Multiple Views for Urban Areas Modelisation", *IAPRS*, vol. XXXIV/3A, pp. 267-272, 2002.

[9] Z. Zhang, O. Faugeras: "3D Scene Analysis: A Stereo Based Approach", *Image and Vision Computing Journal*, 1992.