PRACTICES AND TRENDS IN GEOSPATIAL CHANGE DETERMINATION

C. Armenakis*, J. Jung, G.Sohn

Department of Earth and Space Science and Engineering
Geomatics Engineering, GeoICT Lab
York University, Toronto, Canada
{armenc} {jwjung} {gsohn}@yorku.ca

Commission IV, ICWG IV/VIII

KEY WORDS: Change detection, updating, methods, practices, trends

ABSTRACT:

There is a constant effort by the data providers to maintain up-to-date geospatial databases. Multi-temporal coverage of the same geographic area using aerial and satellite images and airborne laser scanning data is the most common approach for directly generating and updating geo-databases from raw source data. Geo-databases can also be updated indirectly from multi-source multi-scale up-to-date geo-databases. The patterns of spatial changes in the existing data sets are detected and determined by determining mismatches in the state of a feature over different times. For the determination of spatial changes it is essential that the multi-temporal multi-source data sets are co-registered by mapping one data set over the other using appropriate transformation functions. Invariant corresponding features are matched between the two data sets for the determination of the transformation parameters. The methods and quality of data alignment are important in order to reduce registration errors as any difference is interpreted as potential change. In the actual determination of spatial changes factors such as level of change detection, types of data used for change detection, level of processing, types of changes, and turn-around time all influence the method applied. The change detection methods between existing and new features are based on approaches, which depend on the data types, level of pre-processing and on proximity and/or similarity measures. In this paper, using examples, we present methods and common practices applied for change determination in vector databases and identify trends for future approaches. Emphasis is on the use of automated methods due to the increasing data volumes and new types of data.

1. INTRODUCTION

The determination of spatial changes is required for updating the databases and for providing impact indicators related to both scientific knowledge and decision-making. The determination of spatial changes is required for addressing economic, environmental and scientific issues, and safety concerns.

The improvement of change detection methods for updating the geo-spatial databases is still an active research area. Spatial change occurs when the spatial elements of shape, location and attributes of features are not similar between two datasets. Change detection is the process of identifying differences in the patterns of two datasets, usually generated at different times (t_1 and t_2)or by different methodology or different sources. Thus, change is determined by a comparison operation between two datasets and identifying any mismatches.

Change detection can be performed interactively by a human operator. However, considering the amounts and heterogeneity of the data this is a tedious and laborious task. While full automation is highly desirable, presently several semi-automated operations contribute to the improvement of the change detection process.

Spatial changes can be distinguished in actual changes and in apparent changes. Examples of apparent changes are differences detected in the data due to different accuracies, scales, atmospheric conditions or perspective views. Actual changes are those that truly have changed the shape, the location, or the attributes of a feature.

An important factor affecting the change detection operations is the high heterogeneity of data. Change detection may be required between various types of data, such as image and vector data, between image and image data, between image and map data, between vector and vector data, and between map and map data. Data can be vector or raster type, their sources could be geodatabases, raster maps, airborne and/or spaceborne images with various spatial and radiometric resolutions and multi-temporal in nature. The complexity of the comparisons of heterogeneous datasets can be reduced by determining the domain of comparison, thus the actual comparison is conducted with homogeneous types of data.

2. CHANGE DETECTION PRACTICES

As significant number of vector-based geospatial databases exists, this type of data constitutes the existing data sets to be updated. The sources of new data are newly acquired aerial/satellite images and lidar 3D points. In several cases newer vector databases, usually of larger scale, are updated. The large number of earth observation satellites and the high temporal acquisition frequency of images contribute to the creation of image-based databases, thus image to image change detection methods are used. Thus, the comparison can be performed either in the object or image space, while the change can be performed using vector or raster data in the domain of comparison. Obviously the comparison of similar thematic

* Corresponding author.

layers facilitates the change detection. If the source of the new data is imagery, then feature extraction is usually performed through image segmentation and classification (Walter, 2004). Features can be also formed from extracted edges in the imagery. The extracted new features are used either as vector or raster data and in most of the case are projected in reference system of the existing data.

In a thematic vector-based approach, the changes can be defined as the difference between the spatial union of the vector data sets and their spatial intersection (Armenakis et al., 2003). In a thematic raster approach, raster algebra (e.g., difference, ratios) is easily applied (Lampropoulos et al., 2004). In the case of urban environments, DSM and lidar data support the extraction of the "new" buildings data (Champion et al., 2009), while the changes of the buildings footprints can be determined using the raster approach by converting the existing vector building polygons to raster objects (Olsen and Knudsen, 2005).

The accuracy of the spatial change determination highly depends on: a) the accurate co-registration of the two data sets, and b) the establishment of the correspondence of features between the two data sets. Accurate co-registration ensures the spatial alignment of the data sets and eliminates the apparent error changes. Feature correspondence is obtained by overlaying the two spatially aligned data sets. There are five possible change outcomes in the "life" of a feature: confirmation, addition, deletion, partly addition and partly deletion.

The quality measures of completeness and correctness (Heipke et al., 1997) can be used to evaluate the change detection approach, where

$$Correctness = \frac{TP}{TP + FP} \in [0,1]$$

$$Completeness = \frac{TP}{TP + FN} \in [0,1]$$

and TP, FP, and FN refer to True Positive, False Positive, and False Negative, respectively. A TP is an object of the database reported as changed that is actually changed in the reference data. A FP is an object reported as changed by the change method that has not actually changed in the reference data. A FN is an object that was reported as unchanged by the change algorithm, but has actually changed in the reference data. Obviously we are interested in ensuring that the change detection method has minimum erroneous change detections, that is to have FN and FP as close to zero as possible.

3. TEST CASES FOR CHANGE DETECTION

3.1 Test 1 – Existing 2D building vectors vs new lidar data

The existing building map consists of a raster image with ground resolution of 1m generated from the building layer of existing vector map by vector to raster conversion (Fig. 1). Lidar data was used to create the new building map (Fig. 2). Building points of lidar data were manually extracted by TerraScan and the new building map is generated from building points in the shape of raster image with resolution of 1m.

A simple change detection test is carried out based on papers written by Rottensteiner (2007), Matikainen et al. (2007), and Olsen and Knudsen (2005). Although many change detection algorithms include methods to extract the new building map from DSM, lidar and/or optical image, this process is omitted in this example.

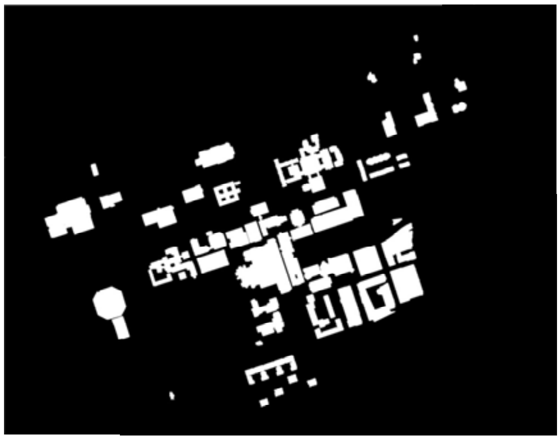

Figure 1. Existing building raster database.

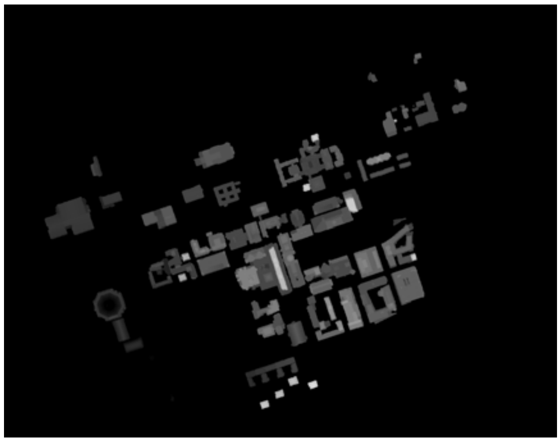

Figure 2. New extracted building raster database from lidar data.

The change detection method is based on a comparison of the existing label building images L^e and the new building images L^n obtained by grouping the building pixels into building regions in the raster domain. The existing label image L^e generated from the existing building map contains the building labels $l^e \in L^e$, and the "new label image" generated by lidar data contains the building labels $l^n \in L^n$. The following figures show existing label image and new label image.

The existing label map, (Fig. 3), and the new label map, (Fig. 4), are superimposed and compared to each other to generate the change map in the object space. For each building co-occurrence of two labels, the overlap ratios $p_{ne} = n_{n \cap e} / n_n$ and $p_{en} = n_{n \cap e} / n_e$ are computed to determine the building changes, where n refers to the total number of pixels. Small ratios p are eliminated using a user-defined threshold, for example T=10%. If p_{en} =1, then we have confirmation; if p_{ne} =1, then we have addition of buildings. In between values indicate modifications. Then the change map is generated including confirmations, partly deletions, deletions, partly additions, and additions (Fig. 5).

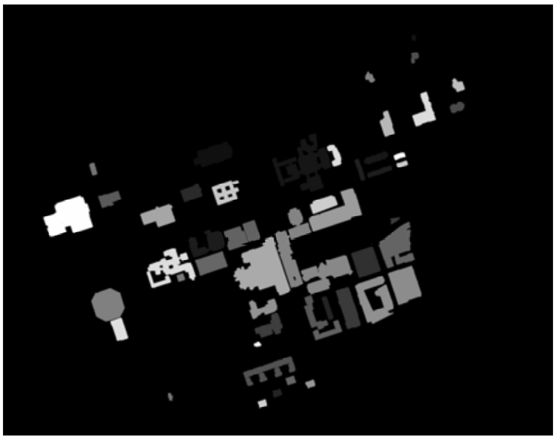

Figure 3. Existing label building image.

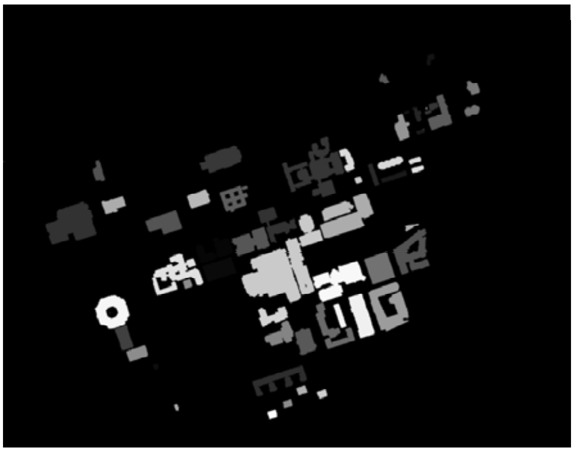

Figure 4. New label building image.

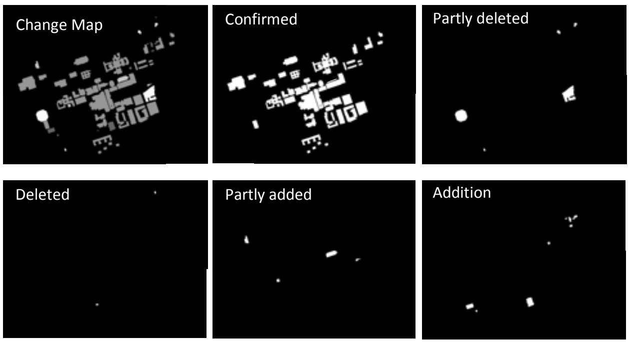

Figure 5. Change detection maps (Test 1).

3.2 Test 2 – Existing 2D building vectors vs new image data

In this second test, the source of the new building data is digital aerial images. Photogrammetricly generated DSM and the RGB ortho-image are used for the extraction of the new buildings, and compare them to the existing building database. The sources of the existing building database are the vector footprints converted to raster data as in Test 1. The domain of comparison is the object space.

The commercial object-based image analysis software Definiens is used to extract the new buildings. Buildings are segmented and extracted from the RGB ortho-image and the DSM by setting the segmentation scale to an approximate building size and then by using various rule set functions (elevation information, shape characteristic, context information, etc.) to support the extraction of building polygons. The results obtained by the Definiens software were edited manually to improve the extracted building results (Fig. 6). The final building polygons were exported in .shp format and then were converted into raster data (Fig. 7 and 8).

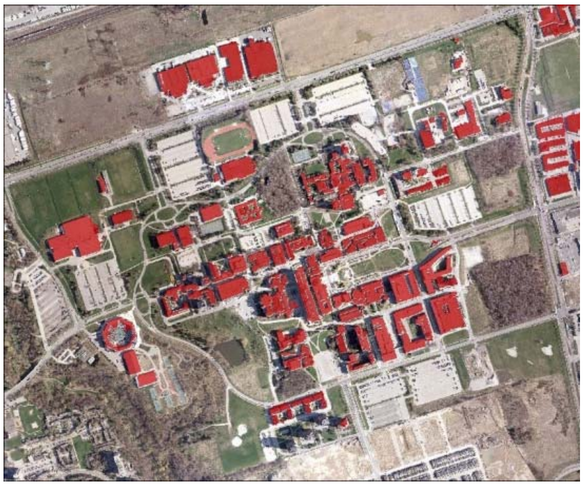

Figure 6. New buildings extracted from imagery.

Figure 7. Polygons of new the buildings extracted from imagery.

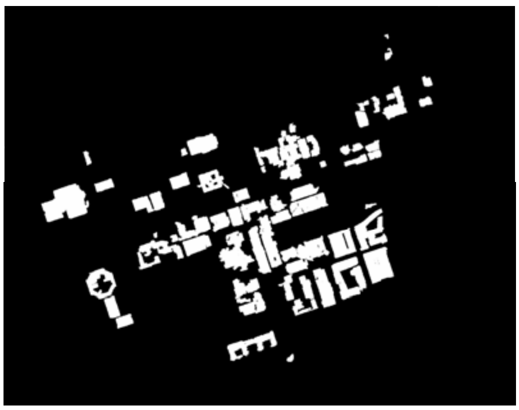

Figure 8. Extracted new building image.

Similar to the test 1, new label image is generated by a grouping algorithm to separate individual buildings and to group the pixels into building regions, (Fig. 9), and the result is compared to existing label image. Again using a user-defined threshold T=10%, the buildings are classified into confirmed, partly changed, new, and deleted building (Fig. 10).

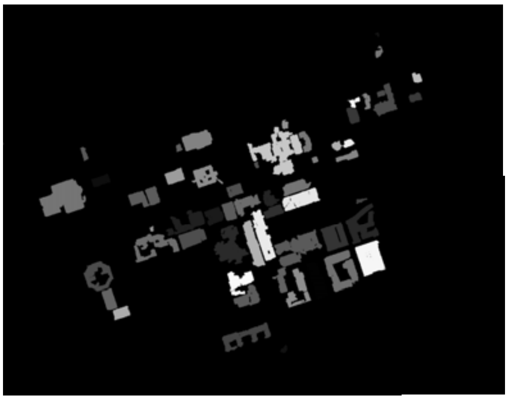

Figure 9. New label building image.

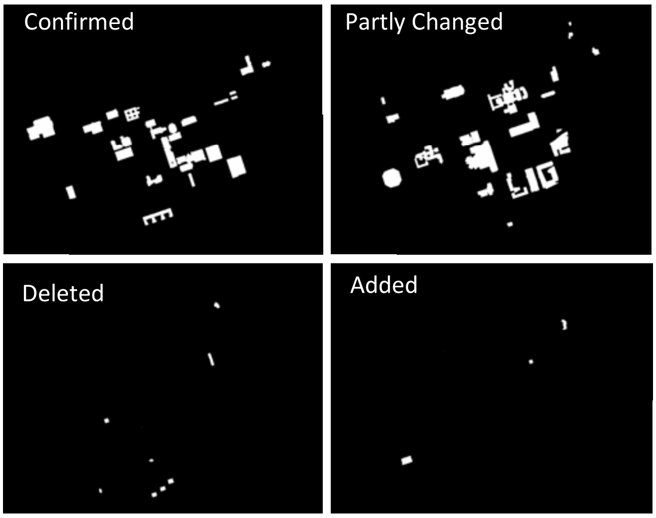

Figure 10. Change detection maps (Test 2).

3.3 Test 3 – Existing 3D building models vs new image data

In this case we examine a database-driven change detection approach between an existing 3D building model database and newly acquired digital aerial images. The selected domain of comparison is the image space. For detecting building changes, one image and a 3D existing building model are used. Initially image lines are extracted by the Burns algorithm (Burns et al., 1986) in the image (Fig. 11). Then the 3D existing building models are back-projected into image space using the exterior and interior camera parameters. A buffer zone is created around each projected image building vector (Jung et al., 2010). The change detection process begins by scoring the sum of the extracted image line lengths contained in the buffer zone of the projected existing building vectors. The ratio of the lengths between existing building vectors and sum of image lines is computed and then changed buildings are extracted with a threshold T=50%. In Figure 12, blue lines show changed buildings and green lines depict confirmed buildings. This change determination method cannot detect new buildings as changed buildings because it uses the 3D existing building models as the basis primitives for the comparison.

Figure 11. Extracted image lines in the new image.

Figure 12. Detected building changes in the image space.

3.4 Evaluation of the results

The results obtained by the three methods as applied to each test case were evaluated by comparing them to reference data. The quality measures of completeness and the correctness of the results were derived for each test case (Tables 1 and 2).

Table 1. Correctness and completeness of the three methods

	Correctness	Completeness
Test 1	1	0.55
Test 2	0.80	0.23
Test 3	0.61	1

Table 2. Measures of correctness and completeness of the changes

	Lidar (Test 1)	Image(Test 2)	Image (Test 3)
TP	10	8	14
FP	0	2	9
FN	8	26	0

The assessment of the change detection for each case indicates the following:

- Test 1: The change detection approach is correct (FP=0) but about 50% incomplete (FN=8) as it detected 8 objects as unchanged, which actually had changed in the reference data.

- Test 2: The change detection approach is somehow correct (80% correct) but very much incomplete (23% completeness) as it has detected a large number of false negative changes (FN=26), but it did not detect well actual changes as it should. This is most probably due to the poor extraction of new buildings from the new image.

- Test 3: The change detection approach is not very correct (correctness is only 60%), but it is a very complete approach (FN=0). The approach cannot detect new buildings, so it is not very correct, however it works very well when confirming no changes and detecting modifications in the existing buildings.

4. CONCLUDING REMARKS

The development of automated algorithms for spatial change detection is still an area requiring much research effort. The implementation of a higher level of automation in the change detection operations is highly desirable to reduce both the production time and the cost involved, especially when dealing with large areas and the continuous dwindling of resources.

As most existing geodatabases are of vector type, updating is required from new data sources, such as high resolution images, simultaneous availability of panchromatic and multispectral images, lidar and polarimetric SAR data. Considering the complexity of the geographic spaces, the change detection methods are based on thematic layers (e.g., buildings, roads, vegetation, and water).

The main difficulty is not the change detection method but the extraction of the new thematic features from the new data sources to be compared with the existing ones for the actual change determination. As presented in the test cases, change detection can be very well performed with vector or raster data, either new or existing. The extraction of the new data is supported by image segmentation and classification of the new multispectral images, and the use of photogrammetric and lidar elevation models.

As more and more 3D building models are becoming available in urban environments methods for 3D change detection will need to be developed. Test case 3 presented initial results for a database-driven change detection in 3D building models from new aerial images. However, the tested approach does not detect new buildings; it detects only changes or no changes to the existing 3D building database.

As more images become available, image based methods for change detection will be used more often in the future. The use of multi-temporal images for the formation of “pseudo-models”, (Armenakis and Faig, 1986) and the detection of 3D changes based on the mismatching of images (Jung, 2004) will also contribute to 3D change detection. It will also be possible to reliably detect spatial changes in a wide variety of situations using a combination of temporal image and range coming from various sensors (Heller at al., 2001). For 2D change detection between images there is a variety of successfully applied approaches (Singh, 1989; Lu et al., 2004; Radke et al., 2005).

It is foreseen that the main trend for the determination of spatial changes will be a synergistic one, created by integrating photogrammetric, image analysis and GIS methods. The integrated use of these methods will allow for the development of algorithms, which will significantly improve the change detection methods and results.

ACKNOWLEDGEMENT

This research is supported by a grant (07KLSGC03) from the Cutting-edge Urban Development – Korean Land Spatialization Research Project funded by Ministry of Land, Transport and Maritime Affairs of Korean government. The authors also would like to acknowledge the many valuable datasets provided by John Knowles at First Base Solutions Inc., Bob Gaspiric at City of Toronto, Dr. Glenn Farrington at Optech Inc., and Trudy Bodak at York University.

REFERENCES

Armenakis C., W. Faig, 1986. On-line data acquisition for multi-temporal photography using the analytical plotter OMI AP-2C. *IAPRS*, Vol. XXVI, Part 5.

Armenakis C., F. Leduc, I. Cyr, F. Savopol, F. Cavayas, 2003. A comparative analysis of scanned maps and imagery for mapping applications. *ISPRS Inter. J PRS*, Vol. 57, No. 5-6, pp. 304-314.

Burns, J. B., Hanson, A. R. and Riseman, E. M., 1986. Extracting Straight Lines. *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 8, pp. 425-445.

Champion N., F. Rottensteiner, L. Matikainen, X. Liang, J. Hyyppä, B.P. Olsen, 2009. A test of automatic building change detection approaches. In Stilla U, Rottensteiner, Paparoditis N (Eds) CMRT09, *IAPRS*, Vol. XXXVIII, Part 3/W4.

Heipke C., H. Mayer, C. Wiedemann, O. Jamet, 1997. Automated reconstruction of topographic objects from aerial images using vectorized map information, *IAPRS*, Vol. XXXII, pp. 47-56.

Heller A.J., Y.G. Leclere, Q-T. Luong, 2001. A framework for robust 3-D change detection. *SPIE Proc. of the Inter. Symposium on Remote Sensing*, Toulouse, France.

Jung F., 2004. Detecting building changes from multitemporal aerial stereopairs. *ISPRS J PRS*, Vol. 58, No. 3-4, pp. 187-201.

Jung J., G. Sohn, C. Armenakis, 2010. Automatic co-registration of existing building models and digital image. *Korean Journal of Geomatics*, Vol. 28, No. 2, pp. 125-132.

Lampropoulos G.A., T. Liu, C. Armenakis, 2004. A robust change detection methodology for topographical applications. *IAPRS&SIS*, Vol. XXXV, Part B2, Com. II, pp. 772-777.

Lu D., P. Mausel, E. Brondizio, E. Moran, 2004. Change detection techniques. *Inter. J. Remote Sensing*, Vol. 20, No. 12, pp. 2365-2407.

Matikainen L., H. Kaartinen, J. Hyyppä, 2007. Classification tree based building detection from laser scanner and aerial image data. *ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007*, Espoo, Finland.

Olsen B.P., T. Knudsen, 2005. Automated change detection for validation and update of geodata. *Proc. 6th Geomatic Week*, Barcelona, Spain.

Radke R.J., S. Andrea, O. Al-Kofani, B. Roysam, 2005. Image change detection algorithms: A systematic survey. *IEEE Transactions on Image Processing*, Vol. 14, No. 3, pp. 294-307

Rottensteiner F., 2007. Building change detection from digital surface models and multi-spectral images. In Stilla U et al (Eds) PIA07, *IAPRS&SIS*, 36 (3/W49B), pp. 145-150.

Singh A., 1989. Digital change detection techniques using remotely sensed data. *Inter. J. Remote Sensing*, Vol. 10, No. 6, pp. 989-1003.

Walter V., 2004. Object-based classification of remote sensing data for change detection, *ISPRS J PRS*, Vol. 58, No. 3-4, pp. 225-238.