AN IMPROVED APPROACH FOR AUTOMATIC DETECTION OF CHANGES IN BUILDINGS

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ABSTRACT:

Automatic detection of buildings and changes in buildings from airborne laser scanner and image data is discussed. A new, improved method for change detection between an existing building map and building detection results has been developed. Corresponding building objects between the two datasets are found by analysing the overlaps of the buildings. Depending on the correspondences, change detection is carried out, and new, demolished and changed buildings are found. Detection of changed buildings is based on analysing overlap percentages or investigating the building detection results inside and outside buildings on the map by using buffers. Additional rules were developed to investigate tree cover or a digital surface model (DSM) in cases where misclassifications in the building detection stage are likely. The change detection method was evaluated by using suburban test areas covering 4.5 km^2. Reference results were created by applying the same method to two real building maps. Accuracy estimates for different change classes and building sizes are presented. For all buildings, the completeness and correctness were about 70%. Further tests on building detection with a classification tree based approach are also presented. The method was applied to a new dataset containing laser scanner data and an ortho image created from digital aerial images. Generally, the results are in agreement with our earlier tests and show a mean accuracy of 89% for buildings when compared with a building map, pixel by pixel. Contrary to our earlier study, however, the use of the aerial imagery clearly improved the results.

1. INTRODUCTION

Airborne laser scanning (ALS) has now become an operational technique for topographic mapping. For example, in Finland, laser scanning of the entire country began in 2008. The data are used to improve the quality of digital elevation models (DEMs), but there is also potential for other applications, such as the updating of map databases (Kareinen, 2008). In mapping organisations, there is high interest to develop automatic tools to assist the updating process, for example, to detect changes in buildings automatically (Knudsen and Olsen, 2002, 2003; Champion, 2007; Holland et al., 2008). Still today, mapping is mainly based on visual interpretation and manual digitising, and updating requires time-consuming work for human operators to search for changed objects. The availability of laser scanner data with accurate height information, as well as digital aerial images with multispectral channels, has clearly improved the possibilities to develop useful automatic tools for the process.

In the field of automatic change detection of buildings from ALS data, several studies have been carried out in recent years. If old and new datasets are available, change detection can be carried out by comparing these. Murakami et al. (1999) presented a simple approach based on subtracting one digital surface model (DSM) from another. Vögtle's and Steinle's (2004) method also compared multitemporal DSMs, but it was object-based and analysed building objects that were first extracted from the DSMs. Another basic approach for change detection is to detect buildings from new data and compare the results with an existing building map to detect changes. Knudsen and Olsen (2002, 2003) presented a method that is based on the pixel-based spectral classification of image data followed by change detection. Further developments of the method include the use of DSM data obtained, for example, from laser scanning (Olsen, 2004). Vosselman et al. (2004, 2005) used laser scanner data, colour imagery and a segment-based classification approach. To take into account differences between database objects and extracted building objects in the change detection process, they used morphological operations, shifting of objects and mapping rules. The method developed by Rottensteiner (2007, 2008) uses a DSM and multispectral imagery and includes pixel-based and region-based classification steps. In change detection, special attention is paid to the topology of buildings. The method also exploits existing map data in the building detection stage to give additional support for deciding whether a pixel belongs or does not belong to a building. Methods solely based on aerial image data and DSMs created from them have also been developed (e.g. Jung, 2004; Champion, 2007; Holland et al., 2008). Holland et al. (2008) reported a production trial with promising results. Recently, a EuroSDR (European Spatial Data Research) test comparing different change detection approaches for buildings has also been carried out (Champion et al., 2008, 2009).

Our research has concentrated on a two-step approach including automatic building detection and change detection. The idea is that the results could be utilised in further steps of the updating process, which could be either manual or automatic. An operator or a further automatic process could concentrate on determining the boundaries of changed buildings and bypass the unchanged ones, which could save a lot of time, as most buildings are normally unchanged. If the process is manual, even the building detection results, visualised with the map data, could be helpful in finding changes. The basic approach and first tests were presented in Matikainen et al. (2003, 2004) and further development of the building detection method in Matikainen et al. (2007). The objective of the present paper is to

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present a new, improved version of the change detection method and test results obtained when it was applied to test areas covering 4.5 km^2. Reference results for the study were created by applying the same method to two real building maps. This was different from previous studies, which have used a smaller number of real or simulated changes for analysis. In addition to change detection, building detection results from a new dataset are presented.

2. DATA

Testing of the methods was carried out in the suburban study area of Espoonlahti in Espoo, near Helsinki. The area included a training area of about 0.8 km^2 and five test areas covering about 4.5 km^2 in total (see Figure 1). ALS data, an aerial colour ortho image and two building maps were used in the study. All data were processed into raster format with a pixel size of 30 cm × 30 cm.

The laser scanner data were acquired on 12 July 2005 with the Optech ALTM (Airborne Laser Terrain Mapper) 3100 laser scanner. The point density in areas covered by single strips is about 2-4 points/m^2. The classification routines of the TerraScan software (Terrasolid, 2009) were used to classify the laser points into ground points and points clearly above ground (threshold value 2.5 m). Two raster DSMs – a maximum DSM and a minimum DSM – were also created in TerraScan (maximum and minimum values for pixels). The ortho image mosaic with red, green, blue and near-infrared channels was created from digital aerial images acquired with the Intergraph Digital Mapping Camera (DMC) on 1 September 2005.

Buildings of the Topographic Database from 2000, produced by the National Land Survey of Finland (NLSF), were used to create an old map to be updated (this was not the newest version of the database but was used to create realistic circumstances for the test). The required positional accuracy for buildings in the database is 3 m (NLSF, 1995). An up-to-date map used as reference data was created from a building map obtained from the city of Espoo. The map data were originally from 2008 but were modified to represent the situation in 2005. The city map presents the buildings in more detail and has a generally higher accuracy than the Topographic Database. In an earlier study, we estimated that the positional accuracy of buildings is 0.5 m or higher. For the purposes of the study, it is important to note that buildings appear different on the maps and in remotely sensed data. An obvious difference, in addition to generalisation, is that the maps represent the ground plans of the buildings instead of roof edges. A 100% correspondence between building detection results and map data cannot thus be reached. The use of the two different maps as reference data for change detection was also challenging.

3. METHODS

3.1 Building detection

The main idea of the building detection method (Matikainen et al., 2007) is to first segment a laser scanner derived DSM into homogeneous regions using the height information and then to classify the segments on the basis of their properties in the laser scanner and aerial image data. The first classification step is conducted to distinguish high objects, i.e. buildings and trees, from the ground surface. The preclassified laser points are used for this. Buildings are then distinguished from trees by using the classification tree method (Breiman et al., 1984). Postprocessing of the classification results is possible, for example, by eliminating very small regions classified as buildings. Definiens (Definiens, 2009) and Matlab (The MathWorks, 2009) software were used in the building detection.

3.2 Change detection

The change detection method is based on comparison of an existing building map with the building detection results. The method was implemented in Matlab. It uses input data in raster format, but it is object-based, i.e. individual building objects are analysed. Compared with the previous version of the method, the new one includes matching of buildings between the two datasets and improved change analysis. The matching allows one-to-one comparison and consistent labelling of the buildings as will be described in the following. The improved change analysis includes two alternative approaches for detecting changed buildings and the possibility to rely on the existing map in cases where misclassifications in the building detection stage are likely.

It was assumed that there are not large shifts between the map and the building detection results. Matching of buildings can thus be based on their overlaps. Small differences in the location and appearance of the buildings are allowed by change detection rules, which use overlap percentages or morphological operations. Similar approaches have also been utilised in previous studies (Vosselman et al., 2004; Rottensteiner, 2007). It was also assumed that buildings are detached objects because this is the normal case in Finland. If there are blocks of buildings connected to each other, these are treated as one object.

If there is any overlap between a pair of buildings on the map and in the building detection results, these are considered as corresponding buildings. Change detection is based on these correspondences. Different alternatives include:

- One building on the map corresponds to one in the building detection (1-1). This is an *unchanged* (*OK*, class 1) or *changed* building (class 2).
- No buildings on the map, one in the building detection (0-1). This is a *new* building (class 3).
- One building on the map, no buildings in the building detection (1-0). This is possibly a *demolished* building (class 4).
- One building on the map, more than one in the building detection (1-n), or vice versa (n-1). This can be a real change (e.g. one building demolished, several new buildings constructed), or it can be related to generalisation or inaccuracy of the map or problems in building detection. These buildings are assigned to class 5: *1-n/n-1*.

Map buildings and new buildings smaller than a threshold value (20 m^2 in this study) and buildings including outside pixels (e.g. missing data) are excluded from the analysis and assigned to class 6: *not analysed*. For the detection of unchanged and changed buildings (classes 1 and 2), two different alternatives are possible: overlap percentages or a buffer approach. The user can select which of these is used and determine threshold values. If the overlap approach is used, the percentage of overlapping area is considered both for the building on the map and the detected building. Both of these percentages must be on a required level to label the building as unchanged. If the buffer approach is used, a buffer is created around the boundary of the building on the map by using morphological operations dilation and erosion. The building is considered unchanged if the inner part of the building is detected as a building and the detected building does not extend outside the buffer area. The buffer approach is better suited for the detection of subtle changes in the outlines of the buildings than the overlap approach. Some misclassifications can be allowed by using percentage thresholds. If the buffer covers the building completely, it is assigned to class 6.

If a building seems to be demolished or changed so that it is smaller in the building detection results than on the map, additional correction rules can be applied. The objective of these rules is to rely on the existing map data in cases where misclassifications are likely. The rules are used to investigate tree cover and DSM in the case of demolished buildings and tree cover in the case of changed buildings. First, it is tested if over 90% of a demolished building, or over 90% of the missing area of a changed building, has been classified as tree. In this case, it is likely that tree cover has prevented proper detection of the building. On the other hand, a demolition or change is less likely, supposing that the majority of buildings should be unchanged. These buildings are assigned to class 7: *assumed to be OK after examining tree cover*. If the tree cover condition is not satisfied for a demolished building, the DSM is examined by comparing the mean height of the building on the map with the height of the surrounding pixels (located 3.6-3.9 m from the boundary in this study). To exclude trees, only pixels classified as ground are considered. If the height difference is over 1.5 m for at least 25% of the surrounding pixels, this is considered as an indication of a building, and the building is assigned to class 8: *assumed to be OK after examining DSM*. This rule can detect buildings lower than 2.5 m, which was used as a threshold value in the original building detection. It can also detect car parks or other buildings that are located on a hill slope and have part of the roof on or near the ground level.

The buildings of the map and building detection results are labelled separately but so that the labels are consistent. For example, if three buildings on the map correspond to one in the building detection, all four of these buildings are assigned to class 5. Different presentations can be easily created from the change detection results. For example, new and changed buildings can be taken from the building detection results, others from the map. The results are also provided as text files that can be imported as attributes to vector maps, i.e. the existing building map or the building detection results converted into vectors. The extraction and correction of boundaries of changed buildings, as well as actual updating of the database, remain tasks of further stages in the updating process.

3.3 Classification experiments

The minimum DSM was segmented and high objects (buildings and trees) were distinguished. Training segments for buildings and trees were defined automatically by using the up-to-date building map of the training area. Some corrections to these were made after visual checking. Altogether, 47 attributes were determined for the training segments. In addition to the DSMs and image channels, the difference between the two DSMs and a filtered slope image calculated from the minimum DSM were used as input data for calculating the attributes. The attributes included mean values, standard deviations, texture attributes, 26 shape attributes, the normalised difference vegetation index (NDVI), and the mean squared error (MSE) obtained when fitting a plane to the minimum DSM values inside a segment. Attributes, except the plane fitting MSE, were obtained from the Definiens software. The 47 attributes were given as input data to the classification tree method, which automatically selected the following attributes for the final classification tree to distinguish buildings from trees: NDVI, mean slope, Grey Level Co-occurrence Matrix (GLCM) homogeneity calculated from the maximum DSM, and GLCM homogeneity calculated from the near-infrared channel of the aerial image. In postprocessing, two slightly different algorithms were tested. The first one removed buildings smaller than 20 m^2; the second one also removed buildings smaller than 30 m^2 if they had a solidity value (a shape attribute from Matlab) lower than 0.8. After visual and numerical quality evaluations, the results of the first approach were selected for the low-rise area and the results of the second approach for other areas. The classification was also tested by excluding attributes calculated from the aerial image data. In this case, attributes selected in the tree included the mean slope and GLCM homogeneity calculated from the maximum DSM.

The results obtained by using both laser and aerial image attributes were better and were thus used as a basis for change detection. In this article, results obtained by using the buffer approach to detect changed buildings are presented. The width of the buffer was 2.1 m (inside building boundary) + 3.6 m (outside). The number of misclassifications allowed inside and outside the building was 5%, calculated separately for both cases as a percentage of the area of the inner part. The tree cover and DSM correction rules were in use.

3.4 Accuracy estimation

The building detection results were compared pixel by pixel with the reference map, and completeness, correctness and mean accuracy were calculated (for more information and references, see Matikainen et al., 2004, 2007). For evaluating the change detection results, reference results were created by carrying out change detection between the old and new building maps. The method and parameter settings were the same that were used for the actual change detection, but naturally, the tree cover and DSM correction rules were not applied. A confusion matrix was created, and completeness and correctness were estimated separately for different classes and buildings of different sizes. This accuracy estimation was building-based. Two sets of accuracy estimates were calculated. In the first case, classes 1-5 were considered. In the second case, class 5 was excluded. Classes 7 and 8 were included in class 1 in both cases. There can be many reasons for classifying a building to class 5 (see Section 3.2), and errors are not always related to building detection. The true accuracy is thus likely to lie somewhere between the two estimates. Similar to Rottensteiner et al. (2007) and Champion et al. (2009), curves showing the accuracy estimates as a function of building size (buildings ≥ threshold value) were created.

4. RESULTS AND DISCUSSION

4.1 Building detection

Pixel-based accuracy estimates for the building detection results are presented in Table 1. Table 2 shows a comparison of the accuracy estimates before and after postprocessing. Considering all test areas and the results obtained by using both laser and image attributes, the mean accuracy of buildings was about 89%, which corresponds well with our earlier results obtained by using a different dataset (Matikainen et al., 2007). Interestingly, the accuracy was lowest in the new residential area, but there are some understandable reasons for this, such as buildings or building parts missing from the map, low car parks and buildings under construction.

Evaluated both visually and from the accuracy estimates, the use of the aerial image data clearly improved the results in this study. When image attributes were not used, many additional small 'buildings' were detected, which reduced the correctness, except in the new residential area. This is different from our previous study, which suggested that results can be equally good if only laser scanner data are used. Reasons for this difference can be twofold. Firstly, the laser scanner data used in the previous study had a higher point density, were acquired in leaf-off conditions, and thus had a clear difference between first and last pulse data, which was advantageous for building detection. Secondly, the aerial ortho image used in the present study was better for distinguishing buildings and trees because it contained the near-infrared channel. The effect of the postprocessing on the pixel-based accuracy estimates was small. The completeness decreased and the correctness increased slightly. Visually, the effect was more positive because a large number of small erroneous building objects were removed. The effect was more remarkable when aerial image data were not used.

Table 1. Pixel-based accuracy estimates for the building detection results in different test areas (see Figure 1) with/without the aerial image data.

	Low-r.	High-r.	New res.	Industr.	All
Image used					
Completeness	89.7%	90.0%	89.2%	96.9%	91.3%
Correctness	83.8%	89.3%	77.7%	90.6%	87.1%
Mean acc.	86.6%	89.6%	83.1%	93.7%	89.1%
Image not used					
Completeness	88.8%	89.5%	88.1%	96.5%	90.7%
Correctness	76.8%	84.9%	78.0%	87.7%	82.7%
Mean acc.	82.4%	87.2%	82.8%	91.9%	86.5%

Table 2. Pixel-based accuracy estimates for the building detection results with/without the aerial image data and before/after postprocessing. All test areas included.

	Image used		Image not used	
	Before postp.	After postp.	Before postp.	After postp.
Completeness	91.5%	91.3%	90.9%	90.7%
Correctness	85.9%	87.1%	79.6%	82.7%
Mean acc.	88.6%	89.1%	84.9%	86.5%

4.2 Change detection

The buffer approach and parameters were selected to detect rather subtle changes (or differences in the appearance of the buildings). The total number of changes was thus relatively large. The change detection results are presented in Figure 1. New and changed buildings for the figure were taken from the building detection results, others from the old map. The confusion matrix for the change detection results is presented in Table 3 and the accuracy estimates in Figure 2.

Table 3. Confusion matrix for the change detection results. All test areas and buildings included (threshold value ≥ 20 m^2); class 5 included.

	Reference results							
	1	2	3	4 *)	5	6	Not new b.	Sum
1	**470**	24	0	12	19	3	–	528
2	112	**82**	0	3	4	1	–	202
3	0	0	**171**	0	0	0	139	310
4	2	2	0	**13**	0	2	–	19
5	71	10	0	3	**95**	2	–	181
6	2	1	0	2	0	91	–	96
Not new b.	–	–	79	–	–	–	–	79
Sum	657	119	250	33	118	99	139	1415

*)10 of the reference buildings for class 4 (demolished) did not really belong to class 4, see text.

Supposing that the updating process is based on changes found in the change detection, real changes should be found well, i.e. the completeness of changed, new, demolished and 1-n/n-1 buildings and the correctness of unchanged buildings should be high. High correctness for the different types of changes and high completeness for unchanged buildings are also desirable, but not necessarily so critical, at least if the updating process is manual. An operator could check all changes and bypass the false ones. However, to keep the process effective, the number of false changes must not be too large (see also Champion et al., 2009).

From Table 3, it can be estimated that about 40% of the 1336 (= 1415-79) buildings in the change detection results were labelled as unchanged (OK). In the actual updating process these buildings could be bypassed, which means a remarkable saving of time. The accuracy of this class was high. About 90% of buildings labelled as unchanged were also unchanged according to the reference results (correctness), which is very important, as discussed above. The completeness was about 70-80%, which means that some more buildings could have been labelled as unchanged. Investigation of buildings assigned to class 7 (OK after examining tree cover) showed that almost all of these were unchanged buildings. Most buildings in class 8 (OK after examining DSM) were also unchanged. In particular, this rule was useful in detecting car parks missed in the building detection stage. The effect of the additional correction rules was thus mainly positive, although a few demolished or changed buildings were incorrectly classified as unchanged. In practice, the best solution to avoid these types of errors might be to have the operator also check buildings assigned to classes 7 and 8.

The correctness of buildings labelled as changed was about 40%, i.e. many buildings were included that were not changed in the reference data. On the other hand, the completeness was higher, about 70-75% for all changed buildings, which means that real changes were found rather well. New buildings were also well detected. The completeness was about 90% for buildings larger than 60 m^2. For all new buildings, it was about 70%. New buildings not detected were thus mainly small in size. There were many false detections of new buildings, but these objects were also usually small. The correctness increased to about 90% when the minimum building size considered was 80 m^2.

The correctness of demolished buildings was high. The completeness seems low, but these results are misleading. The number of buildings in this class was small, and problems on the maps have a large effect on the results. Visual inspection of the demolished buildings in the reference results showed that 10/33 (30%) of them were not really demolished. Nine buildings were not included in the up-to-date raster map because they were missing, smaller than 20 m^2 or not presented as closed polygons on the original vector map. Five of these were car parks or other large constructions and four were small buildings. One large building was probably mislocated on the old map. If these 10 buildings are excluded from the analysis, the completeness rises to 57% (all buildings included) and errors occur in small buildings (most of them < 100 m^2, all < 200 m^2).

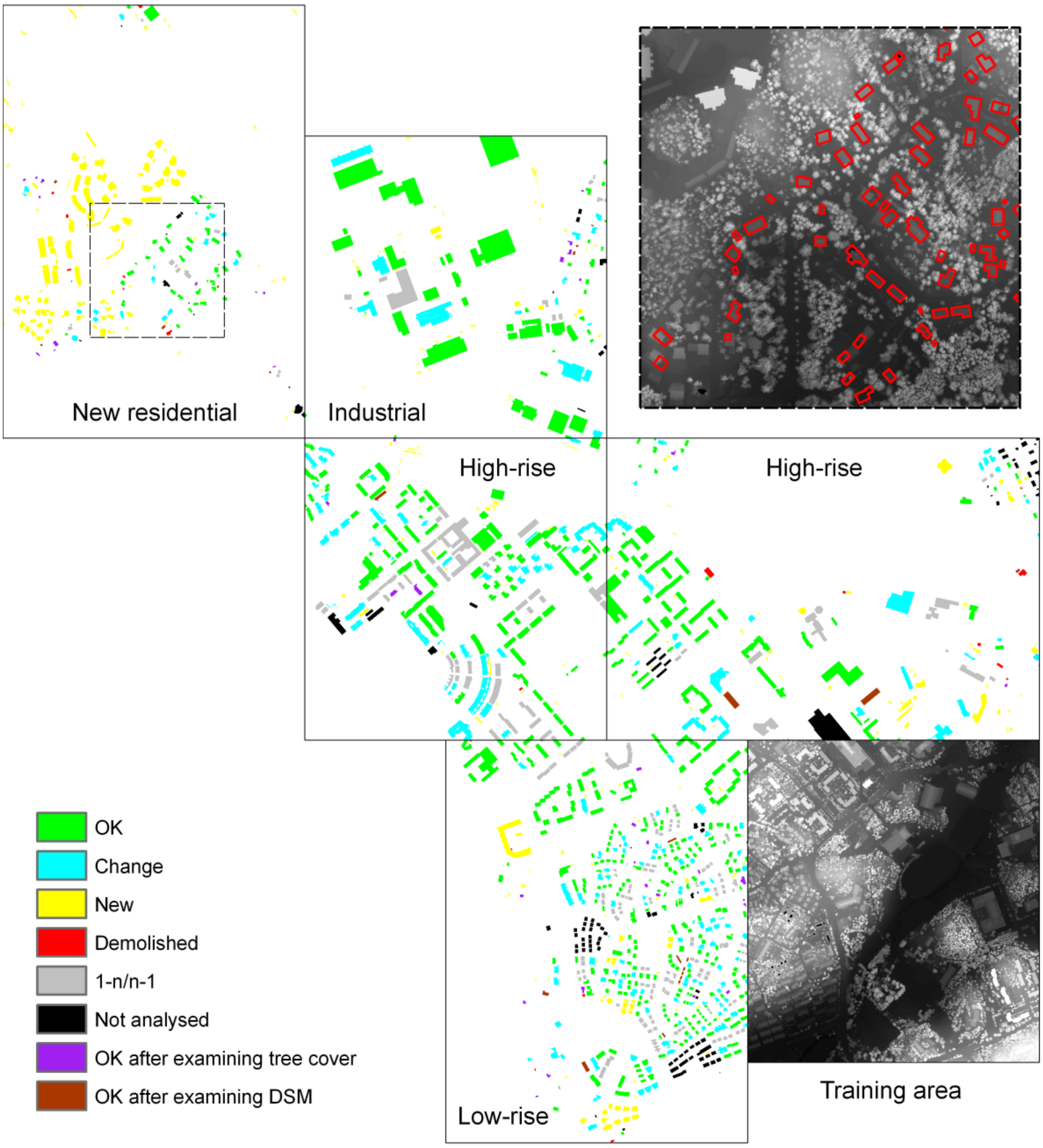
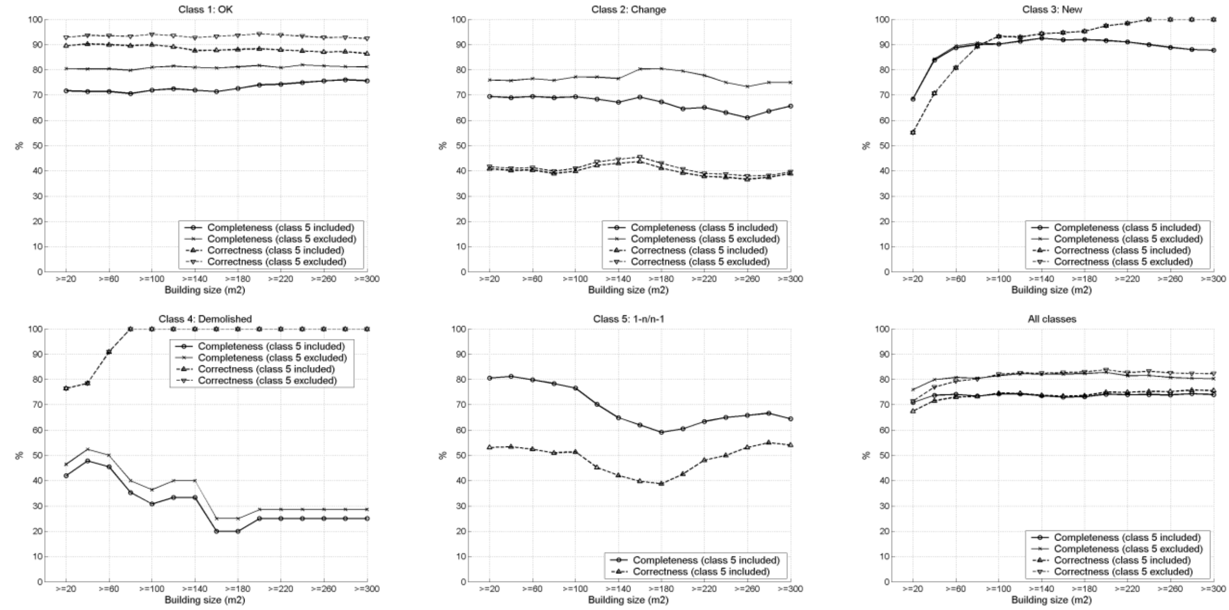


Figure 1. Change detection results for the test areas and minimum DSM for the training area. New and changed buildings were taken from the building detection results, others from the old building map. In the upper right corner of the figure, the minimum DSM and old map are shown for a subarea of the new residential area. Buildings of the old map © The National Land Survey of Finland 2001, permission number MML/VIR/MYY/219/09.



*)

Figure 2. Accuracy estimates for the change detection results. The results are presented for different classes as a function of building size. Class 5 (1-n/n-1) was included or excluded. *) 30% of reference buildings for class 4 (demolished) were not really demolished, see text.

As previously discussed, class 1-n/n-1 is problematic because it can occur in many different cases: due to real changes, due to representation of buildings on the map, or due to errors in the building detection. Considering all buildings, the completeness of this class was about 80%, which is a good result. For larger buildings it decreased, which indicates that correct detection of the class was not easier for large buildings. The correctness was about 50%. Many buildings that were unchanged according to reference results were assigned to this class. This was mainly related to problems in building detection, such as missing parts in buildings or nearby buildings connected to each other, but sometimes also to the maps.

Considering all classes and buildings, the completeness and correctness were about 70%. Excluding class 5 from the analysis, and considering buildings larger than 60 m^2, the estimates increased to about 80%. This is a satisfactory result, remembering that all the accuracy estimates presented here include some uncertainty related to the representation of buildings on the maps. Numerical comparison of different studies is not reasonable, but the trend that completeness in detecting changes was higher than correctness was similar to many other change detection studies (e.g. Holland et al., 2008; Champion et al., 2009). Some false detections are inevitable to assure a high enough completeness in detecting changes. In our study, however, the number of false detections was moderate. Similar to Champion et al. (2009), the results improved, especially for new and demolished buildings, as the size of the buildings increased, which was an expected result.

5. CONCLUSIONS

A new, improved method for automatic change detection between a building map and building detection results was developed and tested. In addition, a previously developed building detection method was tested by using a new dataset containing airborne laser scanner and digital aerial image data. The completeness and correctness of the change detection results were about 70% when considering all buildings larger than 20 m^2 (building-based comparison with reference results created from two building maps). The results were mainly successful when considering that real changes should not be missed in change detection. Completeness and correctness of new buildings were high, except for the smallest buildings (completeness about 90% for buildings larger than 60 m^2). In the case of demolished buildings, the small number of buildings in this class and problems with the maps complicated the evaluation. Visual evaluation revealed, however, that errors occurred only in small buildings. Relatively many unchanged buildings were labelled as changed, but this problem is not as severe as the omission of real changes. An operator could consider these buildings and bypass them if changes are not needed in the database. On the other hand, if the goal is only to detect the major changes, another approach and parameter settings (overlap percentages) could be used to decrease the number of buildings labelled as changed. Results obtained by using this approach will be presented in a later article. Further development of the method should concentrate on improvements related to the problematic cases. For example, the number of false detections of small new buildings might be reduced by using appropriate shape criteria. However, caution is needed here to avoid missing the real new buildings. The mean accuracy of the building detection results was 89% (pixel-based comparison with a building map). The use of the aerial image data clearly improved the results. It is likely that the results of automatic building detection and change detection could provide useful information for map updating, but further study is needed to confirm this.

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