CLASSIFICATION TREE BASED BUILDING DETECTION FROM LASER SCANNER AND AERIAL IMAGE DATA

Leena Matikainen[*], Harri Kaartinen, Juha Hyyppä

Finnish Geodetic Institute, Department of Remote Sensing and Photogrammetry
P.O. Box 15, FI-02431 Masala, Finland – firstname.lastname@fgi.fi

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ABSTRACT:

A classification tree based approach for building detection was tested. A digital surface model (DSM) derived from last pulse laser scanner data was first segmented and the segments were classified into classes 'ground' and 'building or tree' on the basis of preclassified laser points. 'Building and tree' segments were further classified into buildings and trees by using the classification tree method. Four classification tests were carried out using different combinations of 44 input attributes. The attributes were derived from the last pulse DSM, first pulse DSM and an aerial colour ortho image. In addition, shape attributes calculated for the segments were used. The attributes of training segments were presented as input data for the classification tree method, which constructed automatically a classification tree for each test. The trees were then applied to classification of a separate test area. Compared with a building map, a mean accuracy of almost 90% was achieved for buildings in each test. The classification tree method appeared to be a feasible and highly automatic approach for distinguishing buildings from trees. If new data sources become available in the future, they can be easily included in the classification process. The results also suggest that satisfactory building detection results can be obtained with different combinations of input data sources. By using a statistical method, it is possible to find useful attributes and classification rules in different cases. The use of an aerial image or both first pulse and last pulse laser scanner data does not necessarily improve the results significantly, compared with a classification that uses only last pulse laser scanner data.

1. INTRODUCTION

Most methods presented for automatic building detection from laser scanner data use step-wise classification approaches to distinguish buildings from other objects (see, for example, Hug, 1997; Morgan and Tempfli, 2000; Vögtle and Steinle, 2000; Rottensteiner et al., 2005a; Forlani et al., 2006; Zhang et al., 2006). The methods normally begin by extracting the ground surface using a filtering algorithm. After this, the most important task is to distinguish buildings from trees. Features or attributes commonly used for building detection include height texture (e.g. Hug, 1997; Maas, 1999) or surface roughness (e.g. Brunn and Weidner, 1998), reflectance information from images (e.g. Haala and Brenner, 1999; Vögtle and Steinle, 2000) or laser scanning (e.g. Hug, 1997), the difference between first pulse and last pulse laser scanner data (e.g. Oude Elberink and Maas, 2000; Alharthy and Bethel, 2002), and shape and size of objects (e.g. Tóvári and Vögtle, 2004). The attributes calculated for predefined segments or single pixels are presented as input data for a classification method which can be a general-purpose supervised or unsupervised method but more commonly is a rule-based method or other similar method specifically designed for the task.

Each building detection method typically uses a certain set of attributes and rules selected by its developers on the basis of their knowledge and experience on the subject and/or training data available for the study. This approach is a feasible one and can lead to satisfactory results, as shown by many previous studies. The disadvantage of the approach, however, is that the development of the methods is time consuming. When new datasets become available, considerable time is needed to study their potential in building detection and include them in the methods. Comparative studies between different datasets and

input attributes are also rare (for examples of comparative studies, see Rottensteiner et al., 2005b; Pfeifer et al., 2007), which makes it difficult to evaluate the usefulness of and need for different datasets for practical applications. For example, many of the methods use aerial image data in addition to laser scanner data, but whether this improves the results significantly is largely an open question. The same applies to the combined use of first pulse and last pulse laser scanner data.

A method that has been increasingly used in the classification of remotely sensed data in recent years is classification trees (also called decision trees) (Breiman et al., 1984; Safavian and Landgrebe, 1991). Classification trees can be created automatically with data mining or statistical software tools, and they have many useful properties which make them attractive for the analysis of remotely sensed data (see Breiman et al., 1984; Safavian and Landgrebe, 1991; Hansen et al., 1996; Friedl and Brodley, 1997; Huang and Jensen, 1997; Lawrence and Wright, 2001; Thomas et al., 2003; Lawrence et al., 2004). The classification tree method is non-parametric and does not require assumptions on the distribution of the data. It is thus particularly interesting when multisource datasets with different types of possible input attributes are used. A large number of different attributes can be presented for the method, and it automatically selects the most useful ones. This makes the classification process highly automatic and different from most other approaches, in which the user must select suitable attributes before classification. Different attributes can be used for distinguishing different classes. The structure of the classification tree is easy to understand and it gives information on the roles and usefulness of different attributes in the classification task, although caution is needed in the interpretation of this information (see Breiman et al., 1984).

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[*] Corresponding author.

There are still few applications of the classification tree method to the analysis of laser scanner data. Hodgson et al. (2003) studied the mapping of urban parcel imperviousness using colour aerial photography and laser scanner derived height information. Ducic et al. (2006) used the classification tree method to classify laser points as vegetation points and non-vegetation points on the basis of full-waveform information. Matikainen (2006) tested the classification tree method for building detection to distinguish buildings from trees. This approach proved to be highly automatic and provided an accuracy that was very near the accuracy obtained earlier using the same dataset and manually created classification rules.

This article presents further tests of the classification tree method in building detection. A large set of input attributes derived from last pulse and first pulse laser scanner data and an aerial ortho image were used. In addition to testing the feasibility of the method, the objective of the study was to acquire basic information on the importance of different datasets and attributes in building detection.

2. STUDY AREA AND DATA

Data from a study area in Espoonlahti, near Helsinki, were used. The area is a suburban area with small hills and plenty of coniferous and deciduous trees, as well as lower vegetation. When the laser scanner data were acquired on 14 May 2003, some deciduous trees were without leaves and others had small leaves. Colour aerial images were taken on 26 June 2003, when all trees were in full leaf. Separate areas covering about 0.4 km^2 and 1.4 km^2 were used for training and testing the classification tree method. The test area was divided into two parts, one of which is mainly a high-rise residential area and the other is mainly a low-rise residential area.

The laser scanner data were acquired simultaneously in first pulse and last pulse modes with the TopoSys FALCON system. The flying altitude was 400 m above ground level (a.g.l.), which resulted in a point density of about 10 points per m^2. The average point density in the datasets, including overlap between adjacent strips, is about 17 points per m^2. First pulse and last pulse digital surface models (DSM) in raster format and with a pixel size of 30 cm × 30 cm were created using the TerraScan software (Soininen, 2005; Terrasolid, 2007). The highest (first pulse DSM) or lowest (last pulse DSM) value within the pixel was assigned to each pixel, and interpolation was used to determine values for pixels without laser points. The original laser points were also classified in TerraScan to detect points located above 2.5 m a.g.l.. This classification for the last pulse points was used for distinguishing buildings and trees from the ground surface before application of the classification tree method. An aerial colour ortho image with a pixel size of 30 cm × 30 cm was created from the aerial images, which were taken with a Leica RC30 camera and had red, green and blue channels. The images were acquired and scanned by FM-Kartta Oy.

Two additional raster images were derived from the DSMs: slope calculated from the last pulse DSM and difference between first pulse and last pulse DSMs. Both of these were filtered using morphological opening and closing operations to remove building edges and to smooth areas covered with trees.

A building map from 2003 obtained from the city of Espoo and a forest map obtained from FM-Kartta Oy were used as training data. The building map was also used for estimating the accuracy of the building detection results. The map data were converted from vector to raster format (pixel size 30 cm × 30 cm). Before this, neighbouring building polygons were merged to obtain one polygon for each building and polygons smaller than 20 m^2 were eliminated to exclude very small buildings and other constructions from the analysis. Compared with some ground measurements in the study area, the positional accuracy of buildings in the original building map is 0.5 m or higher. There are, however, many differences in the appearance of the buildings on the map and in the laser scanner and aerial image data. For example, building outlines on the map represent the ground plans of the buildings instead of roof edges. Some more details of the laser scanner, aerial image and map data can be found in Matikainen et al. (2004; 2007).

3. METHODS

3.1 Classification tree tools

The classification (and regression) tree tools available in the Statistics Toolbox of the Matlab software (The MathWorks, 2007) were used in the study. These tools can be used to construct a classification tree with a binary tree structure and to apply the tree to classification (for a detailed description of the classification tree method, see Breiman et al., 1984). A classification tree has a root node, non-terminal nodes and terminal nodes. The root node and each non-terminal node contain a question that asks whether a given attribute satisfies a given condition. Beginning from the root node, an object to be classified goes to the left or right descendant node, depending on whether or not it satisfies the condition of the node. Finally, it ends up at one of the terminal nodes and is assigned to the corresponding class. When a classification tree is constructed, the most useful attributes and splits are selected using a splitting criterion. The Gini's diversity index was used as the splitting criterion in our study. This criterion is a measure of node impurity and is defined as

$$impurity(t) = \sum_{i \neq j} p(i|t)\, p(j|t)\,, \qquad (1)$$

where t is the node, and $p(i|t)$ is the proportion of cases $x_n \in t$ which belong to class i ($\mathbf{x}$ is the measurement vector). At each node of the tree, a search is made for the split that most reduces node impurity. (Breiman et al., 1984; The MathWorks, 2003.)

The resulting tree is normally large and can overfit the training data. Therefore, it must be pruned, which means that a set of smaller subtrees is obtained. The best level of pruning can be estimated by computing the cost of each subtree in the optimal pruning sequence (for details, see Breiman et al., 1984; The MathWorks, 2003). This was carried out using the training data and 10-fold cross-validation. The costs were based on the misclassification costs of classes (default; 1) and probabilities of the terminal nodes. The best level of pruning was the level that produced the smallest tree within one standard error of the minimum-cost subtree. When the tree was initially created, a threshold value of 10 (default) was used for splitting nodes, which means that a node had to contain at least 10 training objects to be split.

3.2 Workflow for building detection

The building detection method used in the study included the following stages:

1. Segmentation of the last pulse DSM into homogeneous regions. The segments were the objects to be classified. The multiresolution segmentation method (Baatz and Schäpe, 2000) of the Definiens Professional software (Definiens, 2006; 2007) and a homogeneity criterion based completely on the height values in the DSM were used. The software also provides a large number of different attributes for each segment.
2. Exportation of the segments and various attributes for the segments from Definiens Professional.
3. Classification of the segments into classes 'ground' and 'building or tree' on the basis of the preclassified laser points. A segment was classified as 'building or tree' if most of the last pulse laser points within it had been classified as having a height value of 2.5 m or over (a.g.l.). Within each pixel, only the lowest point, which was also used in forming the last pulse DSM, was considered.
4. Definition of training segments on the basis of training data. A segment from the training area was defined as a training segment for building or tree if over 80% of its area was labelled as building or forest in the map data (some forest areas were excluded because they included a considerable area covered by roads). Segments classified as ground were excluded from the training data. The total number of training segments was 2464, which included 396 building segments and 2068 tree segments. The building segments covered an area of about 3.2 ha and the tree segments covered an area of about 0.8 ha.
5. Construction of a classification tree on the basis of the attributes of the training segments.
6. Classification of all 'building or tree' segments on the basis of their attributes and the classification tree.

The classification tree method has also been applied to segments and attributes obtained from the Definiens (previously eCognition) software in some previous studies. For example, Thomas et al. (2003) used this approach for land-cover/land-use mapping.

3.3 Attributes and classification experiments

Four sets of attributes were selected to be used as input data for the classification of buildings and trees (Table 1, left column). Attributes calculated from the last pulse DSM included standard deviation, texture and the mean slope of the segments. In addition to these more common attributes, two attributes that were available in the Definiens Professional software and were expected to be potentially useful were included. Contrast to neighbour pixels is an attribute that describes the difference (in this case, height difference) between a segment and its surrounding area. Standard deviation of neighbour pixels is the standard deviation of the surrounding area. The surrounding area of a segment consisted of pixels that were located inside the bounding box of the segment (extended by one pixel at the edges) but did not belong to the segment. Attributes calculated using the first pulse DSM comprised standard deviation, texture, and the mean difference between the first pulse and last pulse DSMs. Aerial image attributes included the mean value, standard deviation and texture in different channels. Shape attributes comprised 27 different shape descriptors available in Definiens Professional.

The texture attribute used in the study, Grey Level Co-occurrence Matrix (GLCM) homogeneity, is one of the texture measures originally presented by Haralick et al. (1973). It can take into account grey level variations between neighbouring pixels in different directions. We used the option 'all directions'. For a more detailed description and formulas of this and other attributes, the reader should refer to Definiens (2006).

Four classification tests were carried out, each with a different combination of attributes (Table 1, middle column). These tests could correspond to four practical situations with different data sources available. The last pulse DSM, which was also used for segmentation, was considered as the primary data source and was available in each test. The shape attributes calculated for the segments could also be used in each case.

3.4 Accuracy estimates

Completeness (corresponds to interpretation accuracy or producer's accuracy), correctness (corresponds to object accuracy or user's accuracy) (Helldén, 1980; Congalton and Green, 1999) and mean accuracy (Helldén, 1980) were calculated for buildings by comparing the classification results with the reference map pixel by pixel in the test area. As described in Section 2, the test area was separate from the training area.

4. RESULTS

Attributes selected automatically for the classification tree in each of the classification tests are listed in the right-hand column of Table 1. The corresponding pruning level is also mentioned (for example, 'pruning level 3/8' means that there were 8 pruning levels in the tree and level 3 was selected; level 0 is the full tree without pruning). In each classification test, the script created for the construction of the tree was run five times to find the best level of pruning. The estimated level may vary slightly between the runs because the subsamples for cross-validation are selected randomly. If different levels were selected as the best in different runs, the classification was carried out using each of these. The level that gave the best mean accuracy for buildings in the whole test area is shown in Table 1 and following figures and tables. In practice, the differences in mean accuracy between the different levels were very small (less than 1 percentage unit).

To give an idea of the relative importance of different attributes in the classification, the total number of training segments passing through nodes with a given attribute is shown in brackets in Table 1. Some training segments had undefined values for one of the shape attributes (main direction) and were not taken into account in the construction of the trees. The total number of training segments used by the algorithm was 2224 (391 building segments and 1833 tree segments). If one segment passed more than one node with the same attribute, it was counted more than once for this attribute. The number of training segments per attribute can thus exceed the total number of training segments.

The classification tree obtained for Test 3 is shown in Figure 1 (pruning level 3/8). Classification results for Test 1 and Test 3 in the high-rise area and Test 2 and Test 4 in the low-rise area

Table 1.   Attributes and classification tests. The complete set of attributes used in the study is shown on the left, attributes available for the classification tests are shown in the middle and attributes selected automatically by the classification tree method in the different tests are shown on the right. The number of training segments passing through nodes with the given attribute is given in brackets. The accuracy obtained in the classification (completeness/correctness/mean accuracy) is also shown for each test.

Attributes	Attributes available for the classification tests	Attributes selected for classification and accuracy obtained (completeness/ correctness/ mean accuracy)
Attributes from the last pulse (LP) DSM LP DSM, standard deviation LP DSM, GLCM homogeneity LP DSM, contrast to neighbour pixels LP DSM, standard deviation of neighbour pixels Slope from LP DSM, mean	**Test 1** Attributes from the LP DSM Attributes from the FP DSM Attributes from the aerial image Shape attributes	**Test 1** (Pruning level 3/8) Aerial image, blue, mean (2224 segments) FP DSM - LP DSM, mean (2186) Length of longest edge (1872) Average length of edges (38) Area (12) **-> Accuracy 92.0/85.8/88.8%**
Attributes from the first pulse (FP) DSM FP DSM, standard deviation FP DSM, GLCM homogeneity FP DSM - LP DSM, mean	**Test 2** Attributes from the LP DSM Attributes from the aerial image Shape attributes	**Test 2** (Pruning level 1/6) Aerial image, blue, mean (2224 segments) LP DSM, standard deviation (2183) Length of longest edge (1872) Aerial image, blue, standard deviation (1834) Slope from LP DSM, mean (344) Edges longer than 10 pixels (48) Average length of edges (38) **-> Accuracy 92.1/86.4/89.2%**
Attributes from the aerial image Aerial image, red, mean Aerial image, red, standard deviation Aerial image, red, GLCM homogeneity Aerial image, green, mean Aerial image, green, standard deviation Aerial image, green, GLCM homogeneity Aerial image, blue, mean Aerial image, blue, standard deviation Aerial image, blue, GLCM homogeneity	**Test 3** Attributes from the LP DSM Attributes from the FP DSM Shape attributes **Test 4** Attributes from the LP DSM Shape attributes	**Test 3** (Pruning level 3/8) FP DSM - LP DSM, mean (4022 segments) FP DSM, GLCM homogeneity (1881) Average length of edges (1805) LP DSM, GLCM homogeneity (1803) Slope from LP DSM, mean (560) LP DSM, standard deviation (343) Radius of largest enclosed ellipse (36) **-> Accuracy 92.5/87.4/89.9%**
Shape attributes Area Area (polygon-based, excluding inner polygons) Area (polygon-based, including inner polygons) Asymmetry Average length of edges Border index Border length Compactness Compactness (polygon-based) Density Edges longer than 10 pixels Elliptic fit Length Length of longest edge Length/Width Main direction Number of edges Number of inner objects Number of right angles with edges longer than 10 pixels Perimeter Radius of largest enclosed ellipse Radius of smallest enclosing ellipse Rectangular fit Roundness Shape index Standard deviation of length of edges Width		**Test 4** (Pruning level 3/10) Length of longest edge (2224 segments) Slope from LP DSM, mean (2189) LP DSM, GLCM homogeneity (1921) LP DSM, contrast to neighbour pixels (420) Area (330) LP DSM, standard deviation of neighbour pixels (55) **-> Accuracy 92.8/86.7/89.7%**

Table 2.   Numerical accuracy estimates for the building detection results (%) (Test 1/Test 2/Test 3/Test 4).

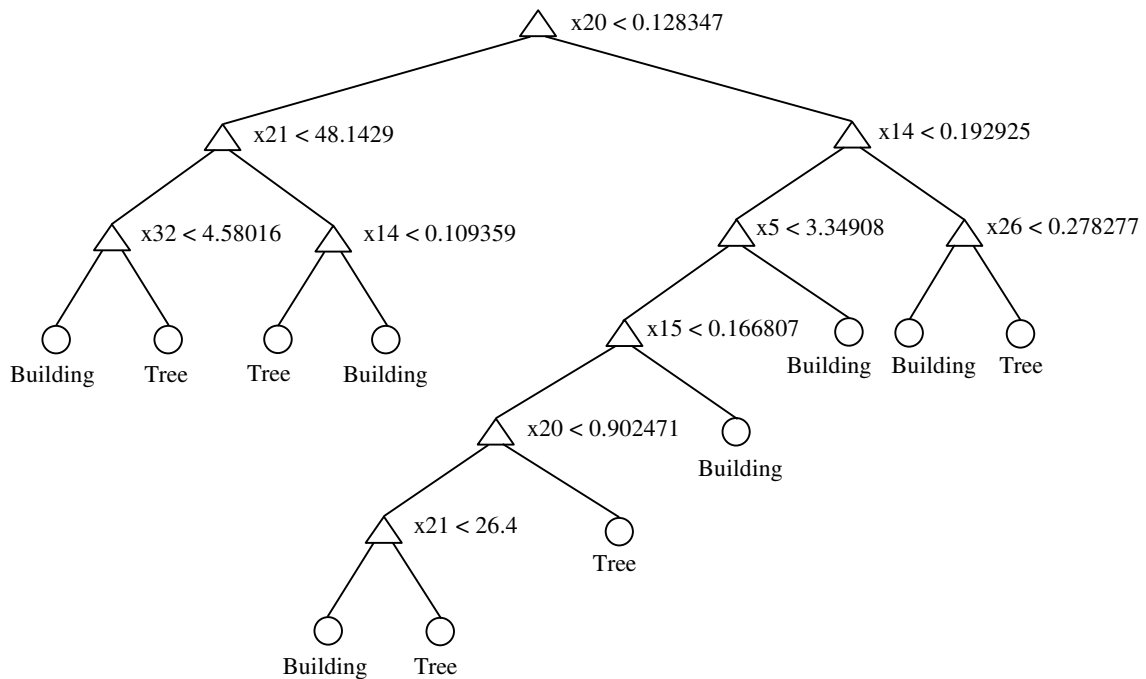|	Test area		
	High-rise residential	Low-rise residential	All
Completeness	92.6/92.3/92.6/92.3	91.5/91.9/92.5/93.2	92.0/92.1/92.5/92.8
Correctness	91.0/91.1/91.9/91.0	82.2/83.2/84.4/83.8	85.8/86.4/87.4/86.7
Mean accuracy	91.8/91.7/92.2/91.6	86.6/87.4/88.3/88.2	88.8/89.2/89.9/89.7
Buildings classified as trees	0.6/0.9/0.6/0.9	2.6/2.2/1.6/0.9	1.8/1.6/1.2/0.9
Buildings classified as ground	6.8/6.8/6.8/6.8	5.9/5.9/5.9/5.9	6.3/6.3/6.3/6.3

Figure 1. Classification tree obtained for Test 3. Attributes are: x20: FP DSM - LP DSM, mean; x21: slope from LP DSM, mean; x14: FP DSM, GLCM homogeneity; x32: LP DSM, standard deviation; x5: average length of edges; x26: radius of largest enclosed ellipse; x15: LP DSM, GLCM homogeneity.

are presented in Figure 2. Figure 3 shows classification results for Tests 1–4 in a smaller area of the low-rise residential area. Four input data sources derived from the laser scanner data are also shown for this subarea. The accuracy estimates for the building detection results are shown in Table 2. The percentage of building pixels classified as trees or ground is also presented (here, it should be noted that the ground classification was the same in each test). The accuracy estimates obtained for the whole test area are also shown in Table 1.

5. DISCUSSION

The classification tree approach allowed rapid and automatic testing of different attribute combinations for the classification of buildings and trees. Different attributes were selected for the trees, but the quality of the results, evaluated either visually or numerically, was very similar in each test and relatively good, taking into account the differences between the remotely sensed data and reference map. This suggests that satisfactory building detection results can be obtained with different combinations of input data sources. By using a large training dataset and a statistical approach, it is possible to find useful rules for separating buildings and trees in different cases. The highest mean accuracy, 89.9%, was obtained in Test 3, which used attributes calculated from the last pulse and first pulse DSMs, in addition to the shape attributes, which were used in each test. The mean accuracy obtained in Test 4, using the last pulse DSM alone, was only slightly lower, i.e. 89.7%. The lowest accuracy, 88.8%, was obtained in Test 1, which used both last pulse and first pulse DSMs and the aerial image. The difference in accuracy between this and other tests, however, was very small. The percentage of building pixels misclassified as trees was remarkably small in each test. Direct comparison of classification results from different studies is not possible, but the accuracy estimates are also in accordance with those

obtained in other studies (e.g. Rottensteiner et al., 2005a; 2005b).

Many of the attributes were selected in several trees. These included the mean value of the segment in the blue channel of the aerial image, the mean difference between first pulse and last pulse DSMs, the mean slope calculated from the last pulse DSM, standard deviation and texture calculated from the last pulse DSM, and shape attributes 'length of longest edge', 'average length of edges' and 'area'. These are obviously useful attributes for distinguishing buildings from trees. Some other attributes appeared occasionally in the trees, but most attributes were never selected. It should be noted, however, that there can also be useful attributes among those that were not selected (see Breiman et al., 1984). At each node, the algorithm selects the best split according to the splitting criterion, but there can be several attributes and splits that would be almost equally good. The lower splits in the tree also depend on the splits selected earlier. This can explain the difference in the attributes selected in different tests. The tree obtained in Test 2 was also different from the tree obtained in our earlier study (Matikainen, 2006), which used basically the same input data sources but somewhat different attributes and training data.

The classification tree based method seems to be a feasible approach for building detection. Satisfactory results can be obtained rapidly and with a high level of automation. When new data sources become available, they can be easily included in the classification. Once the input data are in the correct format, the construction of the tree can be carried out in seconds. This means a remarkable saving of time compared with the typical manual (or semi-automatic) process of attribute selection and rule development. The classification process itself is also fast. The method could thus be well suited to automatic processing of large areas. A training area with up-to-date map data, or manually delineated buildings and trees, is required for
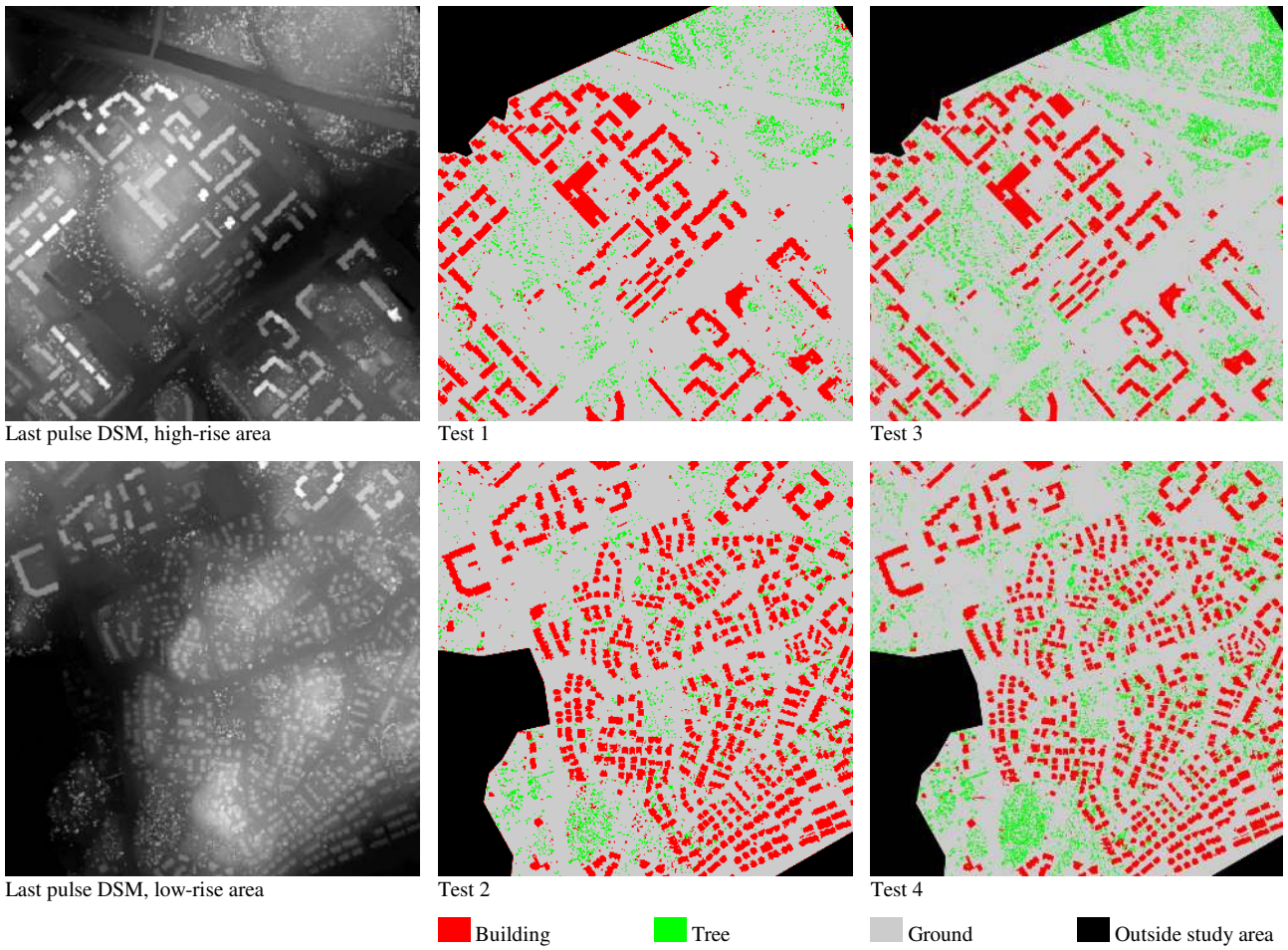
| Building | Tree | Ground | Outside study area |

Figure 2. Last pulse DSM and building detection results for Test 1 and Test 3 in the high-rise residential area and Test 2 and Test 4 in the low-rise residential area.
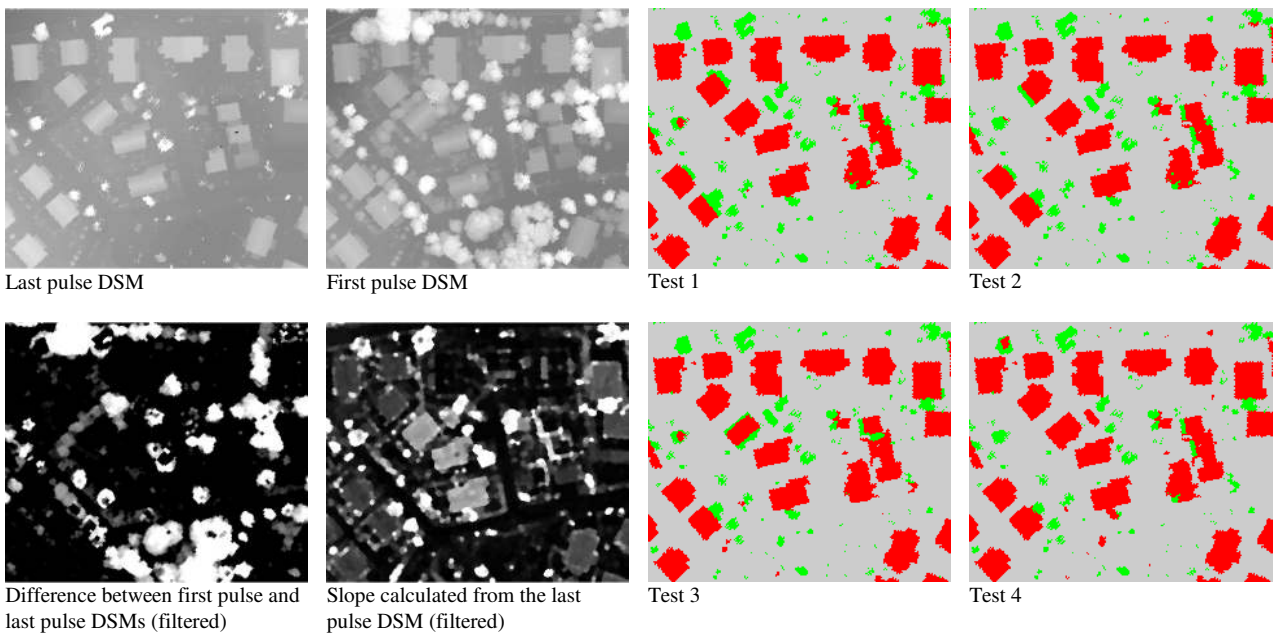

Figure 3. Four input data sources and classification results for Tests 1–4 in a subarea of the low-rise residential area.

training, but it is likely that the classification rules created in one training area could be applied to classification of other similar areas if the characteristics of the laser scanner and aerial image data are stable. For example, the rules from our training area could be largely applicable to other suburban areas in Finland. Further improvements of the classification method might be achieved by testing multivariate trees, alternative splitting rules and pruning methods, and advanced methods of using training data (see, for example, Breiman et al., 1984; Safavian and Landgrebe, 1991; Lawrence et al., 2004).

The classification tree based results can be improved by eliminating obvious misclassifications. This was tested by filling holes (classified as trees) in buildings and removing buildings smaller than 20 m^2. This increased the mean accuracy of the building detection results in Tests 1–4 to 90.0%, 90.1%, 90.6% and 90.4%, respectively. The use of aerial imagery with an infrared channel should also be tested in the future. The application of the classification tree method to the first classification step of building detection, i.e. distinguishing buildings and trees from the ground surface, could also be tested. Some preliminary experiments related to this were carried out and promising results were obtained, although further study is needed. The use of the classification tree method for ground classification too, could further speed up and simplify the process of building detection.

6. CONCLUSIONS

A classification tree based approach for building detection was tested. Segments derived from the last pulse DSM were first classified into classes 'ground' and 'building or tree' on the basis of preclassified laser points. 'Building and tree' segments were further classified into buildings and trees by using the classification tree method. Four classification tests were carried out by using different combinations of 44 input attributes. These included attributes calculated from the last pulse DSM, first pulse DSM and aerial colour ortho image, as well as shape attributes. The classification tree method appeared to be a feasible and highly automatic approach for distinguishing buildings from trees. The attributes of 2224 training segments were used as input data in the method, which automatically constructed a classification tree for each test. The trees were then applied to classification of a separate test area (1.4 km^2). Compared with a building map, a mean accuracy of almost 90% was achieved for buildings in each test. The best results were obtained using attributes derived from the last pulse and first pulse DSMs, and the shape attributes. The differences in accuracy between the different tests, however, were very small. The results thus suggest that satisfactory building detection results can be obtained with different combinations of input data sources. By using a statistical method, it is possible to find useful attributes and classification rules in different cases. Most importantly for practical applications, the use of only last pulse DSM may be sufficient. The use of aerial images or first pulse DSM does not necessarily improve the results significantly. However, if new and potentially useful data sources become available in the future, they can be easily included in the classification process.

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