OBJECT-BASED EVALUATION OF LIDAR AND MULTISPECTRAL DATA FOR AUTOMATIC CHANGE DETECTION IN GIS DATABASES

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ABSTRACT:

The automatic interpretation of aerial and satellite images is one of the main important research topics in photogrammetry and image analysis. The aim of the interpretation is the recognition or verification of objects in images. The quality of the interpretation results depends among other factors on the information content of the input data. The more information in the input data the easier is the interpretation process. In this paper an approach is described that increases the quality of the interpretation process by using existing GIS data as prior information on the one hand and by combining multispectral and LIDAR data on the other hand. The approach is used for automatic change detection and is based on the evaluation of automatically derived training data sets from existing GIS data. For that reason no data dependent tuning factors have to be defined and no human interaction is necessary.

1. INTRODUCTION

GIS databases are very dynamic and can change very rapidly over the time. Automatic interpretation procedures are needed in order to provide up-to-date databases. One of the standard approaches for the automatic interpretation of aerial or satellite images are pixel-based classification algorithms. With that kind of algorithms and appropriate input data it can be distinguished for example between vegetation pixels and non-vegetation pixels. Also the pixel-wise differentiation between different vegetation classes can be made very reliable. But it is not possible to distinguish between landuse classes that can only be detected by the evaluation of pixel groups and not of single pixels. For example it is not possible to distinguish between residential and industrial settlement areas only by evaluating single pixels. In order to distinguish between such landuse classes, we use an object-based classification approach that classifies not single pixels but groups of pixels that represent already existing objects in a GIS database. An n-dimensional vector of the feature space represents the objects. With that approach it is very easy to combine input data from different sources, like multispectral and LIDAR data or other data sources.

2. EXISTING WORK

Object based image analysis approaches for the interpretation of aerial and satellite images are already successfully applied to other problems. These approaches can be subdivided into approaches that use object-oriented classification rules without any GIS input and approaches that use existing GIS data to superimpose it on an image (also known as per-field, per-parcel or knowledge-based classification).

The difference to existing approaches is that in our approach the object interpretation is based on a maximum likelihood classification and all parameters are derived from existing training data. In own work it was shown that the result of a classification could be improved significantly by the combined use of multispectral and LIDAR data (Walter 1999). Furthermore it was shown that GIS-based classification can be successfully used to verify different object classes in the scale of 1:25.000 (Walter 2004).

Object-based image analysis is also used for example in (Benz et. al. 2004). The basic units in this approach are also image segments instead of single pixels. But these segments are derived from image segmentation techniques and not from existing databases. Therefore, this approach is more designed for the first acquisition of GIS objects and not for update or quality control. Most of the existing approaches that use GIS data as prior information are used for the detection and verification of roads (e.g. Zhang 2004) or buildings (e.g. Suveg and Vosselmann 2002).

3. OBJECT-BASED CLASSIFICATION APPROACH

In (Walter 2004) it was shown that it is possible to distinguish between the landuse classes *forest, settlement, greenland* and *water* with an object-based classification by using multispectral data. Because GIS databases contain typically more different landuse classes, this approach has to be refined. In the following we extend this approach and add LIDAR data as an input channel. This gives the possibility to evaluate more object characteristics. The approach will be tested on the example of the automatic classification of residential and industrial settlement objects.

3.1 Overview

The approach (see Figure 1) consists of two classification steps. In a first step, a pixel-based classification is calculated. The result of the pixel-based classification as well as the input channels (the multispectral and LIDAR data) are used as an input for the object-based classification that classifies not single pixels but groups of pixels that represent already existing
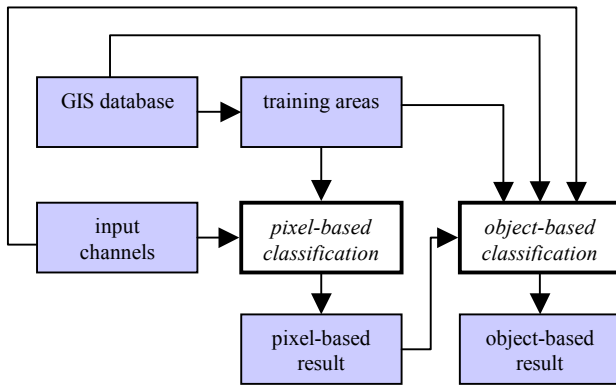
Figure 1. Workflow

objects in a GIS database. Both classification steps are based on a supervised maximum likelihood classification. The training areas are derived automatically from a GIS database in order to avoid the time consuming task of manual acquisition. In a pixel-based classification, the grayscale values of each pixel in different input channels and possibly some other pre-processed texture channels are used as input. For the classification of objects (groups of pixels), we have to define new measures that can be very simple (for example the mean gray value of all pixels of an object in a specific channel) but also very complex, like measures that describe for example the texture, the 3D shape, the homogeneity or the pixel-based classification result of an object.

3.2 Preprocessing of the input channels

The input channels for the pixel-based and object-based classification are multispectral bands, LIDAR data and a texture channel. In the following, the pre-processing of this data is described.

3.2.1   Pre-processing of the LIDAR data: In Haala and Walter (1999) it was shown that the result of a pixel-based classification can be improved significantly by the combined use of multispectral and LIDAR data because they have a complementary "behavior". There are two different kinds of information in LIDAR data: (a) the height of the terrain and (b) the local height of the objects on the terrain. For the classification only the local height is used. Therefore we use a Digital Terrain Model and "subtract" it from the LIDAR data. The result is a normalized DHM that contains only the local height of the objects (see Figure 2).
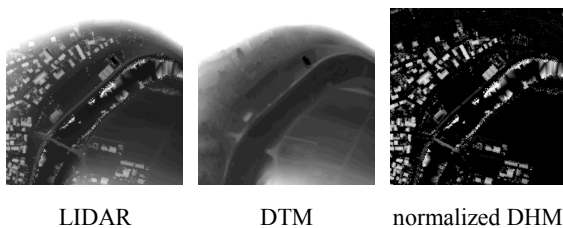

LIDAR   DTM   normalized DHM

Figure 2. Pre-processing of LIDAR data

3.2.2   Texture channel: Different landuse classes cannot be distinguished only by their spectral behavior but also because of different textures. In our approach, we use a texture operator based on a co-occurrence matrix that measures the contrast in a 5 * 5 pixel window. Figure 3 shows the used texture operator in an example. The input image is shown in Figure 3 a, the texture (calculated from the blue band) in Figure 3 b.
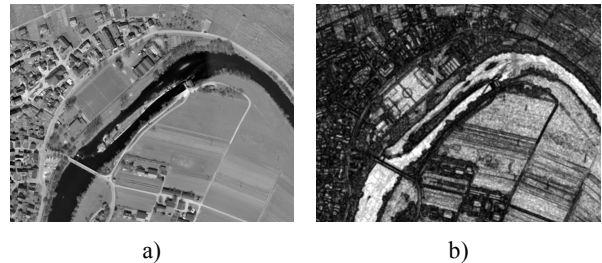

a)   b)

Figure 3. Calculation of the texture

3.3   Pixel-based classification

The result of the pixel-based classification is used as an additional channel for the object-based classification. The training areas are derived from an already existing GIS database in order to avoid the time consuming task of manual acquisition. This can be done, if it is assumed that the number of changes in the real world is very small compared with the number of all GIS objects in the database. That assumption can be seen as true because we want to realise update cycles in the range of several months.

In the pixel-based classification all pixels have to be classified into the landuse classes: *houses, streets, greenland, trees* and *water*. The GIS data (ATKIS; see section 4) that is used in this project is captured in the scale 1:25.000 and does not contain the object class *houses*. Therefore a heuristic is needed that derive automatically training areas for this class.

The training areas for *houses* are derived from the object classes of the GIS database that are representing settlements. In ATKIS there exist four settlement object classes: *residential areas, industrial areas, areas of mixed use* and *areas of special use*. The following three conditions are used to select pixels that are representing houses: (1) the pixels must be located in one of the four object classes for settlements, (2) the pixels must have a local height above the terrain and (3) the pixels must not represent vegetation.

Figure 4 shows the process chain to calculate the training areas for houses. First, all pixels are selected which are representing settlement objects. From these pixels all pixels are selected which are above the ground. A vegetation index is used in order to eliminate all pixels that are representing vegetation. The result contains only pixels that are likely to represent roofs of houses. Figure 5 shows the training areas for houses on an example. The input image is shown in Figure 5 a and the calculated training areas in Figure 5 b.
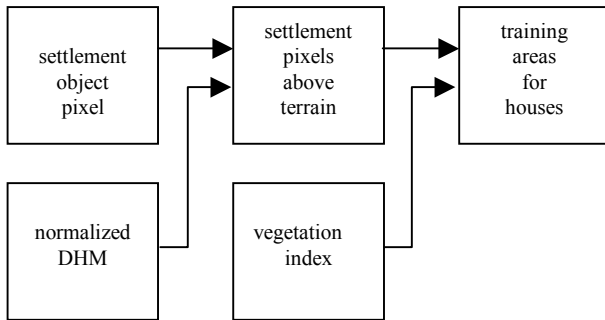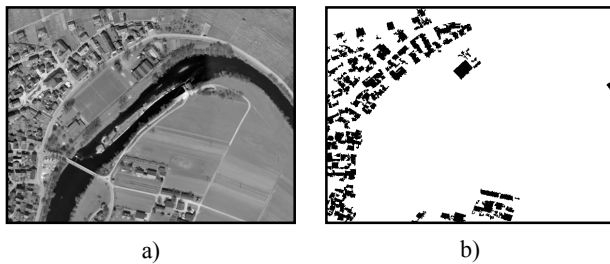
Figure 4. Calculation of the training areas for houses

a)   b)

Figure 5. Training areas for the landuse class *houses*

3.4 Object-based-Classification

The basic idea of object-based classification is to classify not single pixels but groups of pixels that represent already existing objects in a GIS database. Each object is described by an n-dimensional feature vector and classified to the most likely class based on a supervised maximum likelihood classification. The n-dimensional feature vector describes the spectral and textural appearance of the objects. Again, the trainings areas are derived automatically from an existing database.

3.4.1 Object characteristics: In order to distinguish between residential and industrial settlement objects we have first to describe the typical appearance of these two object classes. The following five characteristics can be used in order to decide if a settlement object represents a residential or an industrial area (these characteristics are especially valid in Germany – in other countries they may differ):

- *average size of the houses*: in industrial areas the houses are typically very large whereas in residential areas houses are typically smaller
- *average roof slope of houses*: in industrial areas are typically houses with flat roofs whereas in residential areas are typically houses with sloped roofs
- *percentage of trees:* trees can be found very often in residential areas but only rarely in industrial areas
- *percentage of sealed ground:* the percentage of sealed ground is typically higher in industrial areas as in residential areas
- *textural appearance*: the textural appearance of industrial areas is more homogenous as in residential areas

Not all characteristics must be valid for an object. Very often only three or four characteristics apply for a specific object but

this is not a problem because the object-based classification classifies the object into the most likely class. This is a very robust approach that can handle also fuzzy descriptions of objects. Figure 6 shows two typical examples of residential and industrial areas.
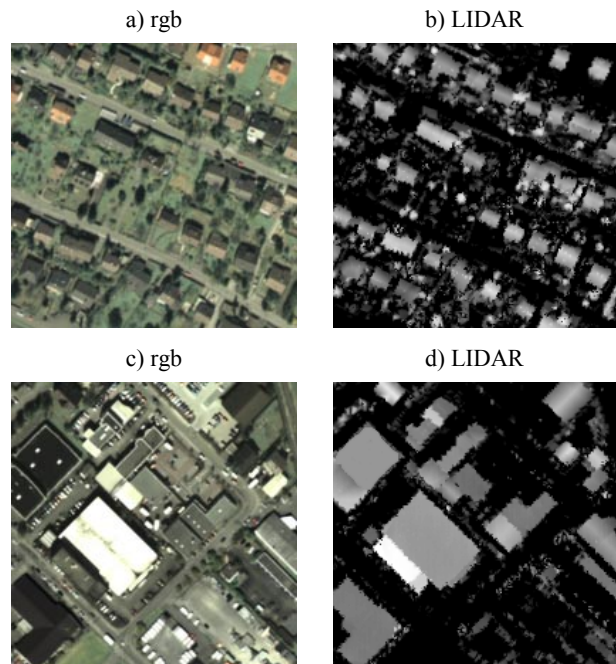
a) rgb   b) LIDAR

c) rgb   d) LIDAR

Figure 6. Comparison of residential (a) & (b) and industrial areas (c) & (d)

3.4.2 Calculation of the object characteristics: In order to represent the object characteristics as a feature vector we have to transform them into numeric values. Figure 7 shows the calculation of the different object characteristic on an example. Figure 7 a shows the calculation of the *average house size* per object. All pixels, which were classified as houses, are selected from the pixel-based classification result. Than, for each object, the average house size is calculated. It can be seen in the example that industrial settlement objects are having typically a larger average house size per object that is represented with brighter grey values and residential settlement objects are having typically a smaller average house size that is represented by darker grey values.

The calculation of the *average roof slope* per object is shown in Figure 7 b. All house pixels are selected from the pixel-based classification result and intersected with the normalized DHM. With that input data, the average roof slope per object can be calculated. High average roof slopes stand for areas with sloped roofs and are represented with bright grey values and low average roof slopes stand for areas with flat roofs and are represented with dark grey values.

Figure 7 c shows the calculation of the *percentage of trees* per object. All tree pixels are selected from the pixel-based classification result and for each object the percentage of trees is calculated. Trees can be found only seldom in industrial settlement objects. Therefore it can be seen in the example that industrial settlement objects are represented with dark grey values which stand for a low percentage of trees and residential settlement objects with bright grey values which stand for a high percentage of trees.
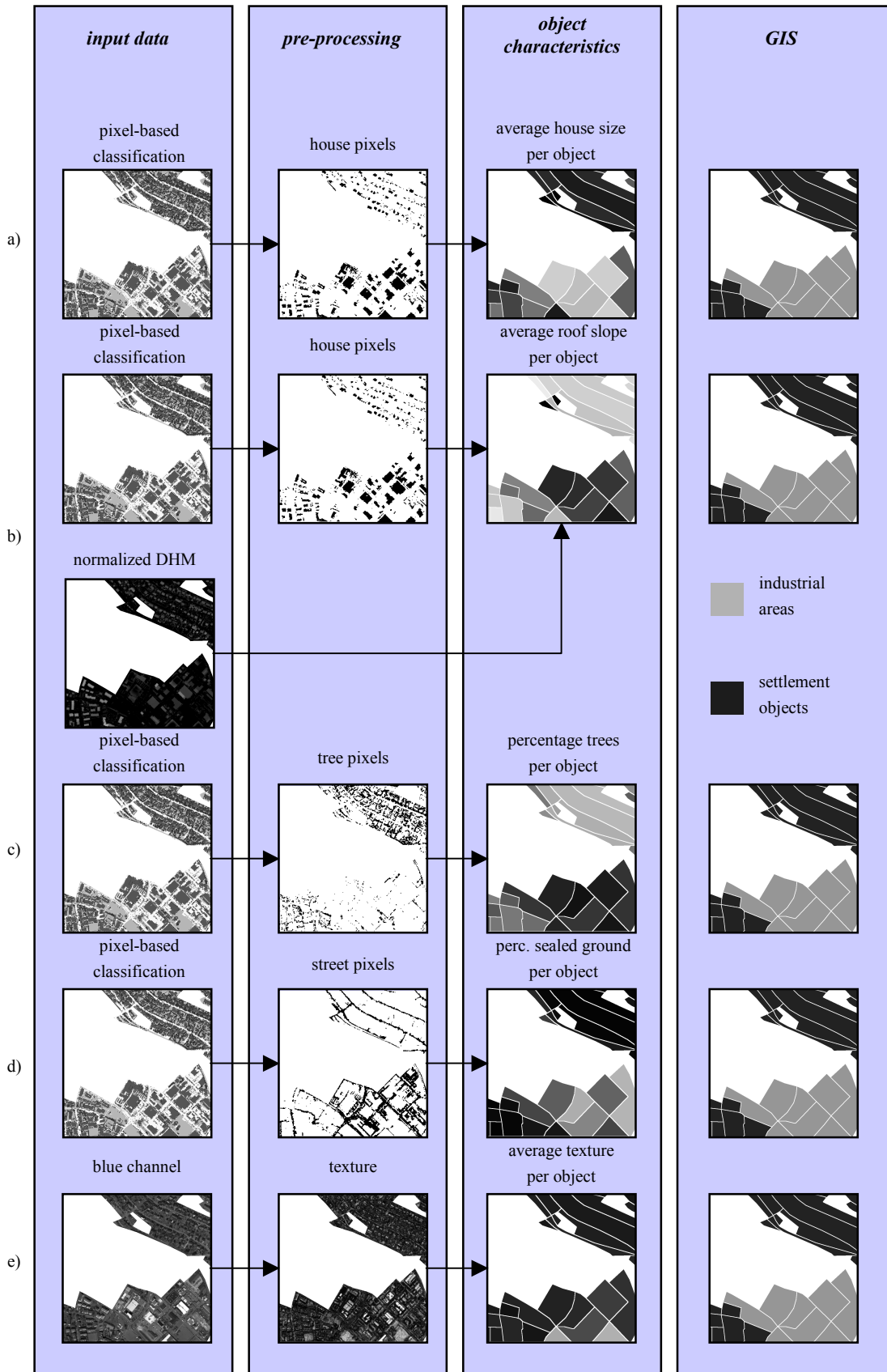
Figure 7. Calculation of the object characteristics

The calculation of *the percentage of sealed ground* is done in the same way as the calculation of the percentage of trees with the difference that all street pixels are selected from the pixel-based classification result (Figure 7 d). Industrial settlement objects have typically a higher percentage of sealed ground and are represented by bright grey values whereas residential settlement objects have typically a lower percentage of sealed ground and are represented with darker grey values.

The calculation of the *textural appearance* is shown in Figure 7 e. We use the same texture operator as described in section 3.2.2 and calculate the average texture per object. Industrial settlement objects are represented typically with brighter grey values because they have a more homogenous textural appearance whereas residential areas are represented typically with darker grey values because they have a more inhomogeneous textural appearance.

3.4.3   Classification: The five object characteristics span a 5-dimensional feature space. The feature vector of each object is evaluated and classified either to the object class residential settlement objects or industrial settlement objects. Table 1 shows the feature vectors of some objects of the test site. All values are mapped onto the interval [0..255], like in a typical pixel-based classification.

Table 1. Feature vectors of the objects

object number	average house size	average roof slope	percent. trees	percent. sealed ground	average texture
A01BH8D	93	85	20	99	55
A01BH85	25	29	8	34	102
A01BH86	25	56	11	76	61
A01BH7W	185	65	21	86	67
A01BH7X	191	48	7	34	50
…	…	…	…	…	…

In order to classify the objects, we use a maximum likelihood approach that classifies the objects into the most likely class based on the evaluation of training data. The objects of the existing GIS database represent the training data.

Figure 8 a shows the distribution of the percentage of trees for all objects of the GIS database and Figure 8 b the distribution of the percentage of tress for industrial settlement objects and residential settlement objects. It can be seen in the diagram that the higher the percentage of trees the higher is the likelihood that an object is representing a residential settlement area. But it can also be seen that there is an overlapping area where an object can represent a residential settlement object or an industrial settlement object with a similar likelihood.

In order to make the distinction between the two object classes clearer, we evaluate not only one object characteristic but more than one. Figure 9 a shows in a scatterplot the two-dimensional distribution of the two object characteristics 'percentage trees' and 'average house size' for all objects in the GIS database. Figure 9 b shows the same distribution only for residential settlement objects and Figure 9 c for industrial settlement objects. It can be seen that the distinction between the two object classes becomes clearer. The more object characteristics are evaluated the clearer becomes the distinction. All object characteristics are used in the object-based classification. That means that we evaluate a 5-dimensional feature space and classify the objects to the most likely class based on the statistical distribution of the training data.
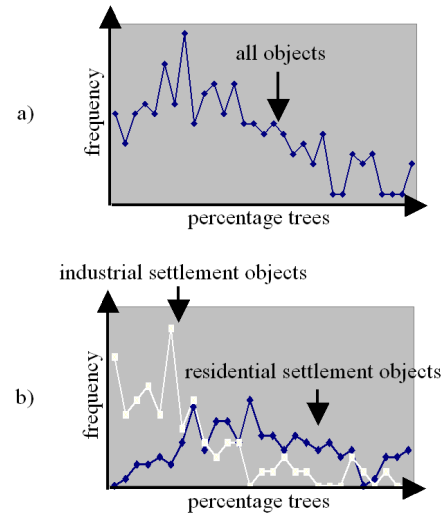

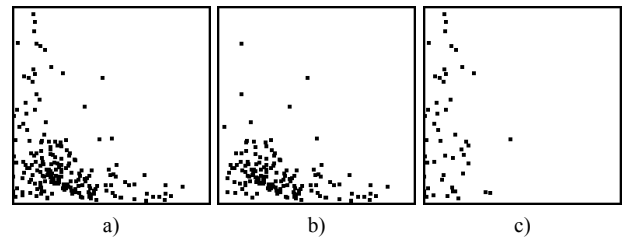Figure 8. Distribution of percentage of trees

Figure 9. Scatterplot (x-axis: percentage trees, y-axis: average house size)

4. RESULTS AND DISCUSSION

The approach was tested on a test area with 24 km² that contains 190 residential settlement objects and 84 industrial settlement objects. The test site is Vaihingen/Enz that is located in the southern part of Germany and represents a rural environment with smaller settlements. The multispectral data were captured with the DMC camera system, which is a CCD-matrix based camera system with 4 multispectral channels: R, G, B and Near Infrared (Hinz 2001). The LIDAR data were captured with the TopScan system and have an average point distance of approximately 1 m (Schleyer 2001). The LIDAR data and the multispectral data were resampled into regular raster images with a pixel size of 1m. The tests were carried out with ATKIS datasets. ATKIS is the German national topographic and cartographic database and captures the landscape in the scale 1:25,000 (ADV 1988).

In a manual classification all residential and industrial settlement objects of the databases were compared with the images and subdivided into the classes *OK*, *unclear* and *not OK* (see Figure 10). The class *OK* contains all objects with no change in the landscape (172 + 64 = 236 objects). The class *unclear* contains all objects where it was unclear if there was a change or not without evaluating additional sources (18 + 19 = 37 objects). The reason for the relatively high number of objects in that class is that the distinction between residential and industrial objects in ATKIS is not only done because of the spectral appearance but also because of non-visible criteria's (for example "non disturbing trade and repair businesses" have
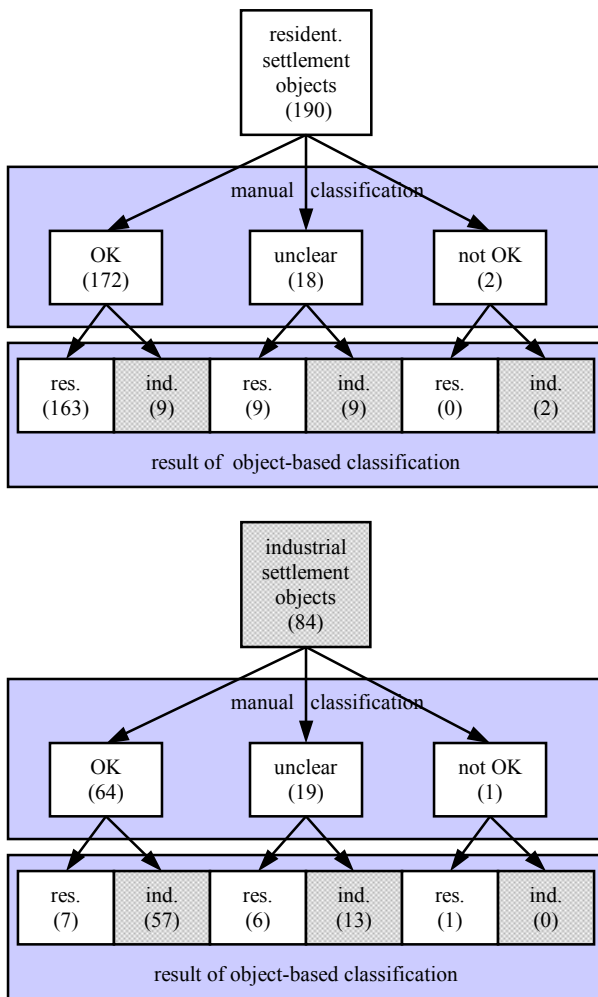
Figure 10. Results

to be captured as industrial settlement areas, but this characteristic cannot be seen in images). The class *not OK* contains all objects where a change in the landscape happened or which were captured wrongly. In this class were only 1 + 2 = 3 objects, because the GIS data was up-to-date and settlement objects change their object class only very seldom.

The result of the object-based classification can also be seen in Figure 10. The automatic approach classified 93% (163 + 57) of all objects of the class *OK* to same object class as they were collected in the GIS database. The classification of the objects of the class *unclear* reflects the situation that even a human operator is not able to classify these objects unambiguous: 60% (9 + 13) objects where classified to the same object class as they were collected and 40% (9 + 6) where classified to the other class. All objects (2 + 1) of the class *not OK* were classified into the other class, as they were collected. It is very important for a change detection approach that all objects, where definitely a change has happened, are found by the program. Otherwise an operator has to overwork the whole result of the automatic approach, which is nearly as much work as a manual change detection. If the automatic approach finds to many changes, is in opposition to that not a big problem. In our example 7% of the objects will be marked as a potential change by the object-classification and have to be controlled even there is actually no change.

The manual overwork of the object-based classification could be further decreased because the result is not only a classification of the objects into the most likely class but also a probability vector that describes the quality of the result. These quality measures can be used for an automatic evaluation of the results. This topic will be researched in future work. Another field of application for the automatically derived quality measures is the automatic quality control of GIS databases.

5. REFERENCES

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6. ACKNOWLEDGEMENTS