OBJECT-BASED CLASSIFICATION OF INTEGRATED MULTISPECTRAL AND LIDAR DATA FOR CHANGE DETECTION AND QUALITY CONTROL IN URBAN AREAS

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ABSTRACT:

Digital spatial data are underlying strong temporal changes. The typical approach of updating these changes is to check the data manually by superimposing them on up-to-date orthoimages from aerial or satellite camera systems. The update cycles of large data sets are in the range of several years because the manual inspection of the data is very cost and time consuming. However, spatial analyses for planning purposes are only meaningful if they are calculated with up-to-date data. Automatic data acquisition, update and quality control procedures are needed in order to provide up-to-date geo-databases. In this paper an approach is presented that increases the quality of the interpretation process on the one hand by using already existing data from Geographical Information Systems (GIS) as prior information and on the other hand by combining image data from different sources. The approach is based on the evaluation of automatically derived training data sets from existing GIS data. Therefore the approach is fully automatic and no human interaction is necessary. The result is not only a classification of the objects but also a distance vector that describes the quality of the classification. This distance vector can be used for an automatic evaluation of the automatic image interpretation as well as for automatic quality control of already existing GIS databases.

1. INTRODUCTION

A lot of research in the field of automatic data acquisition, update and quality control of spatial databases has been done. One of the main problems is, that the used methods are often based on a high number of data dependent tuning factors, like thresholds for example. This leads to the situation that the approaches work very well for specific test areas but become problems if there are variations in the input data. But especially remote sensing data have a very high variability because of different seasons, positions of the sun, atmospheric conditions, soil humidity, etc. In order to solve the problem of data dependent tuning factors, we suggest an approach that is based on the evaluation of automatically generated training areas (supervised classification). Supervised approaches are already used for pixel-based classification of remote sensing data since many years. In this paper we will show how this approach can be used for the classification of objects.

Another problem of the automatic interpretation of remote sensing data is that most of the existing approaches work only in rural areas. The interpretation of urban areas is still a problem because of the complexity of these areas. One approach to overcome this problem is to increase the information content in the input data. The information content is limited mainly by the spatial and spectral resolution of the images. If we combine data from different sources that have different spatial or spectral characteristics it can be possible to detect objects that are not detectable with only one of the sources. In our approach we combine multispectral and laser data. Using object information from an existing GIS database further supports the image interpretation.

2. EXISTING WORK

A comprehensive introduction into image data fusion can be found in [Pohl and Genderen 1998] and [Hahn and Samadzadegan 2004]. The fusion of multispectral and LIDAR data is applied in several approaches. [Zeng et. al 2002] discuss the use of IKONOS imagery and airborne LIDAR data for the classification of urban areas. It could be demonstrated that the classification accuracy can be considerably enhanced by the integrated use of LIDAR and multispectral data. Other approaches are for example [Collins, Parker and Evans 2004] which use multispectral imagery and multi-return LIDAR for estimating tree attributes, [Rottensteiner et. al. 2003] which use integrated LIDAR and multispectral data for the detection of buildings and roof segments or [Hu, Tao and Hu 2004] which extract roads in urban areas from integrated high resolution imagery and LIDAR data.

Object-based image analysis approaches for the interpretation of aerial and satellite images can be subdivided into approaches that use object-oriented classification rules without any GIS input (but use object-oriented modelling techniques [Blaschke et. al. 2000]) and approaches that use existing GIS data to superimpose it on an image (also known as per-field, per-parcel or knowledge-based classification). 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 Vosselman 2002]). The current status of the art of image analysis approaches that use existing GIS data is discussed in [Baltsavias 2004]. An example for a per-field classification approach is introduced in [Aplin et. al. 1999] in which first the image is classified into different landuse classes. Afterwards the fields (which are representing forest parcels from a GIS database) are subdivided into different classes, depending on the classification result by using thresholds. A similar approach can be found in [Arikan 2004] where also first a pixel-based classification is computed and then the parcels (which are representing agricultural areas) are subdivided into different object classes based on the distribution of the classified pixels.

Object-based image analysis is also used 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 the update of existing databases or for quality control.

The use of existing data for an automatic evaluation of GIS databases and for quality control is discussed on the example of road network data in [Wiedemann 2003] and in [Willrich 2002]. A method for quality assessment for roads using information extracted from aerial images is developed in [Gerke 2004]. Aspects of data quality management in GIS are discussed in [Veregin 1999] and [Devillers et. al. 2002]. A system for the semi-automatic quality control and management of linear and area features is introduced in [Busch et.al. 2004].

3. OBJECT-BASED CLASSIFICATION

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 objects in a GIS database. Both classification steps are based on a supervised maximum likelihood classification.

The pixel-based classification is a well-known approach and is not described further. In the following we describe how the object-based classification is calculated. An n-dimensional feature vector f describes each object in the object-based classification. The components of this vector are measures m_i that describe the spectral and textural characteristics of an object:

$$f = (m_1, m_2, ..., m_n)^T$$

In this paper we use the object-based classification to distinguish between residential and industrial settlement objects. The following five characteristics are 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):

- m_1 = *average size of houses*: in industrial areas houses are typically very large whereas in residential areas houses are typically smaller
- m_2 = *average roof slope of houses*: in industrial areas are typically houses with flat roofs whereas in residential areas are typically houses with sloped roofs
- m_3 = *percentage of trees:* trees can be found very often in residential areas but only rarely in industrial areas
- m_4 = *percentage of sealed ground:* the percentage of sealed ground is typically higher in industrial areas as in residential areas

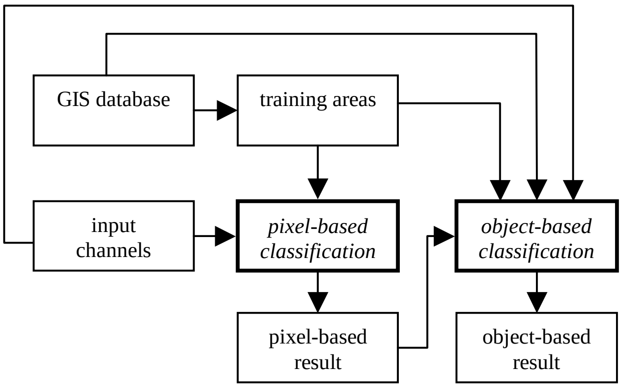


Figure 1. Workflow

- m_5 = *textural appearance*: the textural appearance of industrial areas is more homogenous as in residential areas

A detailed description how this measures are calculated can be found in (Walter 2004). 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 to the most likely class. This is a very robust approach that can handle also fuzzy descriptions of objects. Figure 2 shows a typical example of a residential and an industrial area.

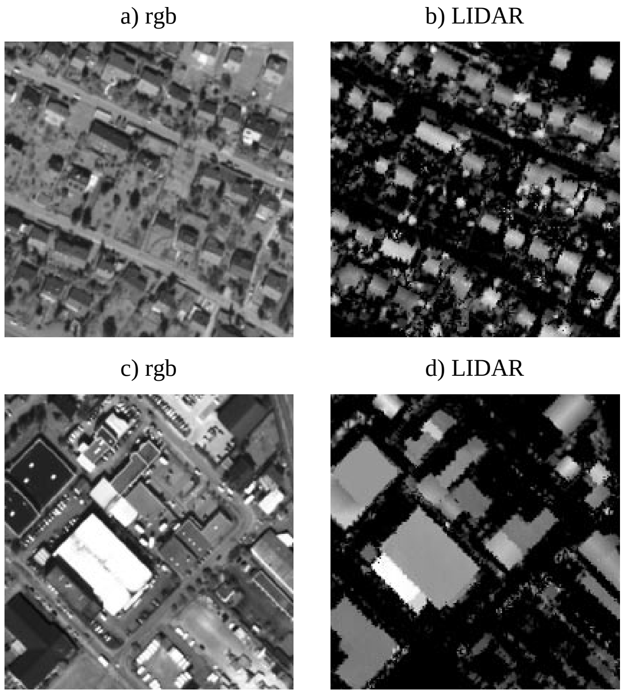


Figure 2. Comparison of residential (a) & (b) and industrial areas (c) & (d)

The decision to which object class K_i an object with vector f belongs is calculated with the distances d_i:

$$d_i(f) = p_1(K_i)\, p_2(f \mid K_i)$$

p_1 are the apriory-probabilities that an object is classified to an object class K_i. These probabilities are normally unknown and have to be estimated. p_2 are the conditional probabilities that an object with vector f is classified to an object class K_i. The distances are calculated for each object class and the object is classified to that object class where the distance d_i has its maximum. In the maximum likelihood classification an n-dimensional Gaussian distribution is assumed and the conditional probabilities are approximated with:

$$p_2(f \mid K_i) = \frac{1}{2\pi^{\frac{n}{2}}} \det(C_i)^{-\frac{1}{2}} \exp(-\frac{1}{2}(f - z_i)^T * C_i^{-1} * (f - z_i))$$

C_i is the covariance matrix and z_i is the mean vector of all training vectors that are derived automatically from a GIS database in order to avoid the time consuming task of manual acquisition. Because of the monotony of the logarithm it is possible to logarithmise the distance equation. This is done, because the logarithmised equation can be calculated faster. For the apriori-probabilities an equal distribution is assumed. Finally, after removing all constants parts, the distances are calculated with:

$$d_i(f) = -\frac{1}{2}\ln(\det(C_i)) - \frac{1}{2}(f - z_i)^T * C_i^{-1} * (f - z_i) \qquad (*)$$

4. QUALITY MEASURES

The workflow of fully automatic change detection approaches can be subdivided into two steps. First, a program is running autonomous without any user input. Then, in a second step, the results have to be controlled by a human operator because the approach can fail in situations where objects have an untypical spectral appearance although they were collected correctly. If the human operator has no information about the quality of the classification result, he has to control all objects of the database, which is nearly the same work as to make the change detection completely manually.

This problem can be solved with quality measures. In a maximum likelihood classification each object is described with a distance vector D that represents the classification distances for each object class:

$$D = (d_1(f), d_2(f), ..., d_n(f))$$

These distances can be evaluated in order to derive local quality measures that describe the reliability of the classification. For example a vector D_1(*Object*) = (55, 40, 1, 1, 1, 1, 1) represents a less reliable classification result as the vector D_2(*Object*) = (55, 7, 8, 7, 8, 8, 7) because the maximum distances in D_1 and D_2 are 55, but D_1 contains two object classes with high distances whereas D_2 contains only one object class with a high distance, whereas the other object classes have equal distributed low distances.

A global quality measure that describes the quality of the whole classification can be for example the average maximum distance of all objects. The higher the average maximum distance the more reliable is the result of the classification. Another quality measure can be the average difference between the highest and second highest classification distance of all objects. If this distance is low, then the differentiation between the object classes is difficult.

5. RESULTS

5.1 Classification

The approach was tested on a test area with 24 km^2 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 and 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). A detailed description of this test can be found in (Walter 2004).

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 3). The class *OK* contains all objects with no change in the landscape (234 objects). The class *unclear* contains all objects where it is unclear if there is a change or not without evaluating additional sources (37 objects). The class *not OK* contains all objects where definitely a change in the landscape happened or which were captured wrongly.

The result of the automatic classification can also be seen in Figure 3. The automatic approach classified 214 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: 24 objects were classified to the same object class as they were collected and 13 were classified to the other class. All objects of the class *not OK* were classified to 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.

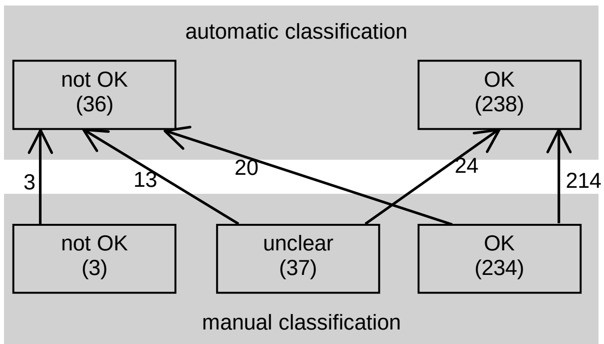


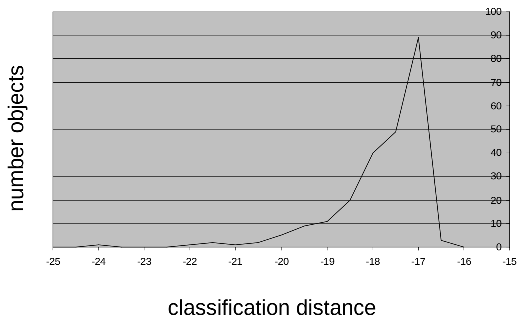
Figure 3. Classification result

5.2 Local quality measures

The object-based classification classified 36 objects to the class *not ok*. That means that approximately 13 percent of all objects have to be controlled by a human operator. The question is now, if the object-based classification can be extended that the objects are classified into three classes as in the manual classification in order to identify automatically those objects that are classified as *unclear* in the manual classification.

Two quality measures are used to identify objects where the classification result is not reliable. Figure 4 a shows the distribution of the maximum classification distance of the objects that are classified manually to the object class *OK* and Figure 4 b the distribution of the maximum classification distance of the objects that are classified manually to the class *unclear*.

a)



b)

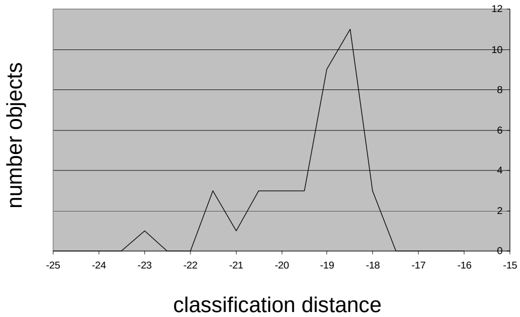


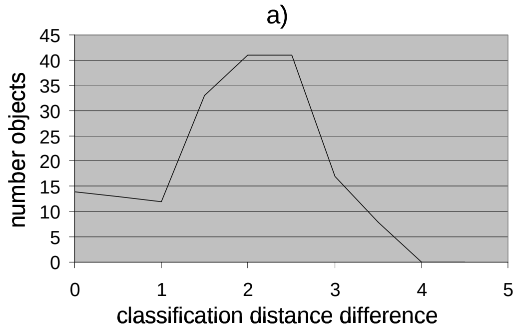
Figure 4. Maxmimum classification distance of (a) objects that are classified manually to the class *OK* and (b) objects that are classified manually to the class *unclear*

The maximum classification distance was calculated according equation *(*)* in section 2. It can be seen that the maximum classification distance of objects that are classified manually to the class *unclear* is tendential smaller than the maximum classification distance of objects that are classified manually to the class *OK*. Of course there is also an overlap area, but it represents the fact, that objects that are classified manually to the class *unclear* cannot be classified so reliable as objects that are classified manually to the class *OK*.

The second quality measure is the difference between the classification distances of both object classes (industrial and residential settlement objects). A small difference is an indicator that it is difficult to decide to which object class an object belongs.

Figure 5 a shows the distribution of the classification distance difference of the objects that are classified manually to the class *OK* and Figure 5 b the distribution of the classification distance difference of the objects that are classified manually to the class *unclear*.

a)



b)

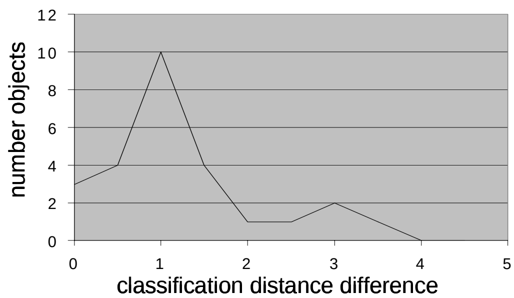


Figure 5. Classification distance difference of (a) objects that are classified manually to the class *OK* and (b) objects that are classified manually to the class *unclear*

Again there is an overlap area but it can be seen that the classification distance difference of the objects that are classified manually to the class *unclear* is tendential smaller than the classification distance difference of the objects that are classified manually to the class *OK*.

The two measures are used in order to identify the objects that are classified manually to the class *unclear*. The result can be seen in Figure 6. The automatic classification classified 38 objects to the class *unclear*. From the manually as unclear classified objects are 13 objects classified automatically to the class *not OK*, 13 to the class *unclear* and 11 to the class *OK*.

By changing the thresholds it can be influenced how strict the classification is. Figure 7 shows the result of a very strict classification where all objects, that are classified manually to the class *unclear*, are automatically classified to the class *not OK* or *unclear*. But this very strict classification has the side effect that only 139 objects are classified to the class *OK*. That means that 135 (36 *not OK* + 99 *unclear*) objects have to be controlled which is nearly 50 percent of the objects of the database.

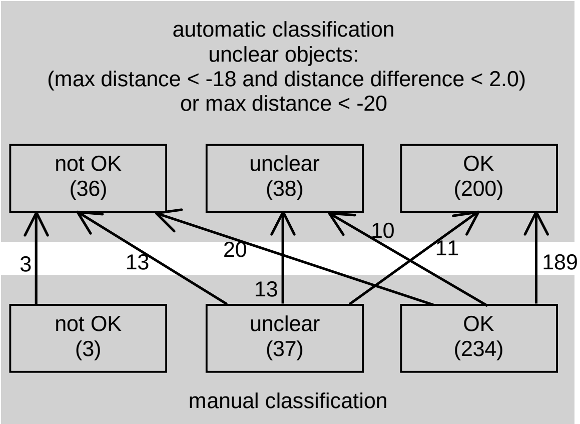


Figure 6. Classification result with 3 classes

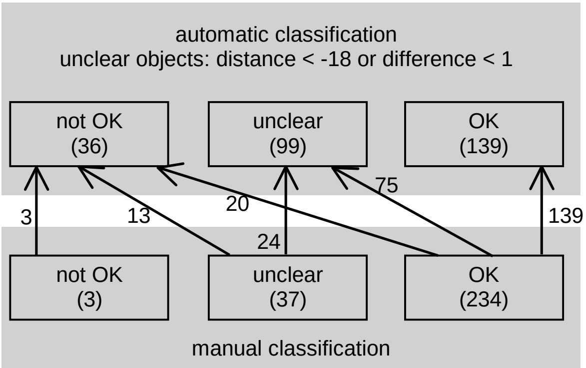


Figure 7. Classification result where all objects, that are classified manually to the class *unclear*, are automatically classified into the class *not OK* or *unclear*

5.3 Global quality measure

The calculation of the average maximum distance and the average distance difference shows the expected results (see Table 1). The class *OK* contains all objects where the human operator comes to the result that there is definitely no change. This is reflected with a higher average maximum distance and higher average distance difference. In the class *unclear* where the human operator was not sure how to classify the objects, the average maximum distance and the average distance difference are significantly lower.

	AVG maximum distance	AVG distance difference
class *OK*	-17.79	1.85
class *unclear*	-19.30	1.23

Table 1: Global quality measures

6. CONCLUSION

The basic idea of the approach is that image interpretation is not based only on the interpretation of single pixels but on whole object structures. Therefore, we classify not only single pixels but also groups of pixels which represent already existing objects in a GIS database. Each object is described by an 5-dimensional feature vector and classified to the most likely class based on a supervised maximum likelihood classification. The object-based classification needs no tuning parameters like user-defined thresholds. It works fully automatically because all information for the classification are derived from automatically generated training areas.

The object-based classification finds all changes where definitely a change in the landscape happened. In this paper we put our focus on identifying those objects where it is unclear if there is a change or not. In a manual classification we identified 37 objects where a human operator was not able to decide to which object class these objects belong without having further information sources.

Two quality measures have been defined in order to estimate the classification reliability. The maximum classification distance measures how likely the classification of an object is and the classification distance difference measures how difficult the differentiation between the two object classes is. If all objects should be automatically identified that are classified manually to the class *unclear*, only those objects can be accepted where the maximum classification distance and the classification distance difference are very high. But then, many objects where definitely no change in the landscape happened, are classified automatically to the class *unclear*. The approach has to be refined in order to overcome this problem. Increasing the dimension of the feature space by adding more object characteristics can do this. Another approach would be to use more different object classes in the object-based classification.

The results of the evaluation of the global quality measures are very promising. It could be shown that there is a significant difference of these measures if they are calculated on the one hand for all objects which are classified manually to the class *unclear* and on the other hand for all objects which are classified manually to the class *OK*. This enables a fully automatic quality control of databases with up-to-date remote sensing data.

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