CLASSIFICATION OF GIS-OBJECTS FOR CHANGE DETECTION

Volker Walter

ABSTRACT:

In this paper an approach is introduced that classifies not only single pixels but groups of pixels which represent already existing object geometry's in a GIS database. This object structured classification result is than compared with the existing GIS objects and all objects are marked where the result of the classification is not the same as the object class of the object which is stored in the GIS database. The result is not only a change detection but also a classification into the most likely class.

ZUSAMMENFASSUNG:

Dieser Artikel präsentiert einen neuen Klassifikationsansatz, bei dem nicht einzelne Pixel, sondern ganze Objekte klassifiziert werden. Die Objektgeometrie leitet sich dabei aus bereits existierenden GIS-Objekten ab. Das Ergebnis der objektweisen Klassifikation wird dann mit den Objekten der Datenbank verglichen, um diejenigen herauszufinden, bei denen eine Änderung stattgefunden hat. Das Ergebnis ist nicht nur eine Änderungserkennung, sondern gleichzeitig eine Klassifikation in die wahrscheinlichste Objektklasse.

1. INTRODUCTION

Keeping spatial data up-to-date is a very time and cost intensive task. Every object of the database has to be checked by a human operator (for example by comparing it with an up-to-date orthophoto) to see if there has been a change in the landscape. Therefore the amount of work of updating a spatial database is nearly as high as the primary acquisition. But a large number of GIS applications rely on up-to-date data in order to solve their tasks. The higher the number of objects in the database the more difficult the problem. New satellite systems offer high resolution multispectral data in high quality with high repetition rates. This data can be used as an input for automatic change detection procedures. One approach is for example to classify each pixel of an image to one of several predefined landuse classes. Afterwards, the classification result can be compared automatically with the GIS database in order to detect updates. Whereas the classification is a very well understood and manageable problem, the matching is still a difficult task. Problems arise for example by objects which are not captured according their real shape but according ownership structures or by objects which have a very inhomogeneous appearance. Nevertheless a human operator can deal with that problems and distinguish between correct and incorrect acquisition with high certainty. The reason for this is that human image interpretation is not based on the interpretation on single pixels but on whole object structures and their relations between them.

In (Walter, 1999; Walter, 2000) a concept for the automatic update of GIS databases using multispectral remote sensing data is introduced. This approach can be subdivided into two steps. In a first step, remote sensing data are classified with a supervised maximum likelihood classification into different landuse classes. The training areas are derived from the 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. Because we want to realise update cycles in the range of several months, that assumption can be seen as true.

In a second step the classified remote sensing data have to be compared with the existing GIS objects in order to find those objects where an update occurred or which were collected wrongly. We solved this task by measuring object-wise the percentage, the homogeneity and the form of the pixels which are classified to the same object class as the object is stored in the database (Walter, 2001). All objects are classified into the classes *full verified, partly verified* and *not found*. This classification is done by using thresholds which can be defined interactively by the user.

The problem by using thresholds is, that they are data dependent. For example the percentage of vegetation pixels is varying significantly between data that was captured in summer or in winter. Other factors are light and weather conditions, soil type or daytime. Therefore we cannot use the same thresholds for different data sets. In order to avoid the problem of defining data dependent thresholds, we introduce an object-wise supervised classification approach. The object-wise classification works exactly in the same way as a pixel-wise classification with the difference that we classify not each pixel but we combine all pixels of an object and classify them together. Again, the training areas for the classification of the objects are derived from the existing database in order to avoid a time consuming manual acquisition.

In a 'normal' classification the greyscale values of each pixel in different multispectral channels and possibly some other pre-processed texture channels are used as input. For the classification of groups of pixels we have to define new characteristics which can be very simple (for example the mean grey value of all pixels of an object in a specific channel) but also very complex like measures that describe the form of an object. This approach is very flexible because it can combine very different measures for describing an object. We can even use the result of a pixel oriented classification and count the percentage of pixels which are classified to a specific landuse class.

2. OBJECT-WISE CLASSIFICATION

2.1 Input Data

The following tests were carried out with ATKIS data sets. ATKIS is the German national topographic and cartographic database and captures the landscape in the scale 1:25,000 (ADV 1988). In (Walter, 1999) it was shown that a spatial resolution of at least 2m is needed to update data in the scale 1:25,000. The remote sensing data was captured with the DPA system which is an optical airborne digital camera (Haala, N., Stallmann, D., Staetter, C. 1996). The original resolution of 0.5m was resampled to a resolution of 2m.

2.2 Classification Classes

Currently 63 different object classes are collected in ATKIS. There are a lot of object classes which have very similar appearance (for example industrial area, residential area, area of mixed used, special used area) and cannot be distinguished only based on remote sensing data without additional information (even for human operators). Therefore we subdivide all object classes into the five landuse classes *water, forest, settlement, greenland* and *streets*. The landuse class *streets* is only used for the pixel-wise classification. Because of the linear shape, streets consist of many mixed pixels in a resolution of 2m and have to be checked with other techniques (see Walter, 1998). The object-wise classification approach can also be used for streets if the input data has a higher resolution, so that streets are represented as areas.

2.3 Input Channels

Like in a pixel-wise classification we can use all spectral bands as input channels. The difference is, that in the pixel-wise classification each pixel is classified separately, whereas in the object-wise classification all pixels which belong to one object are grouped together. In order to analyse the spectral behaviour of objects, we calculate the mean grey value of each channel for all objects. Figure 1 shows on an example the original input data (b) and the mean rgb value (a) of all objects. The result of the pixel grouping is like a smoothing of the data. The spectral behaviour of the objects is equivalent to the typical spectral behaviour of the pixels. For example forest areas are represented in the green channel by dark pixels/objects whereas settlements are represented by bright pixels/objects.
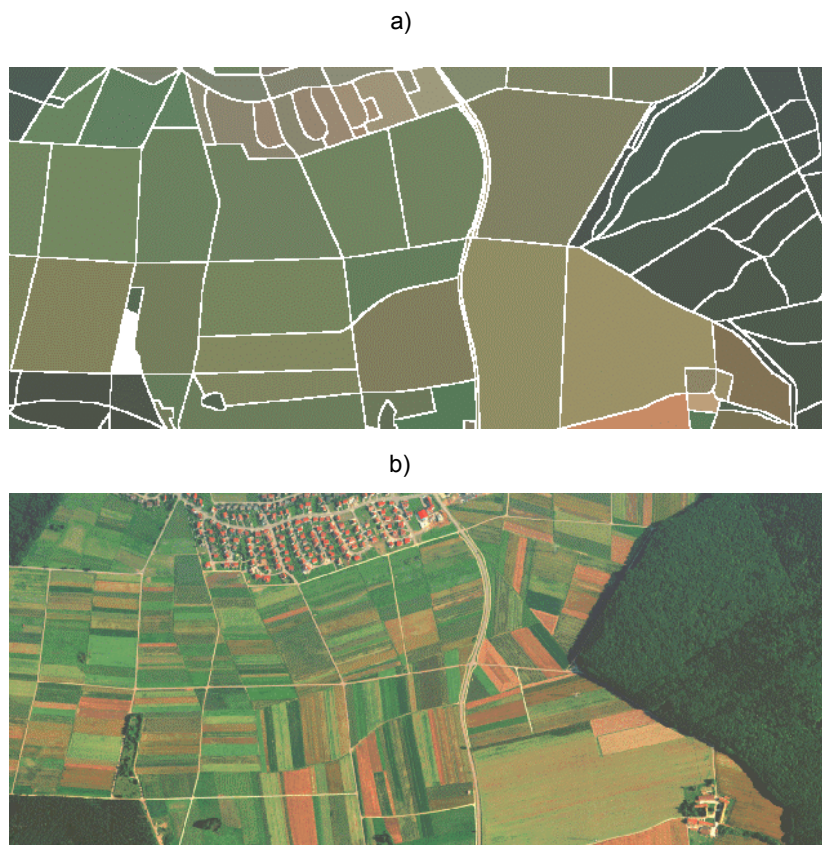
a)

b)

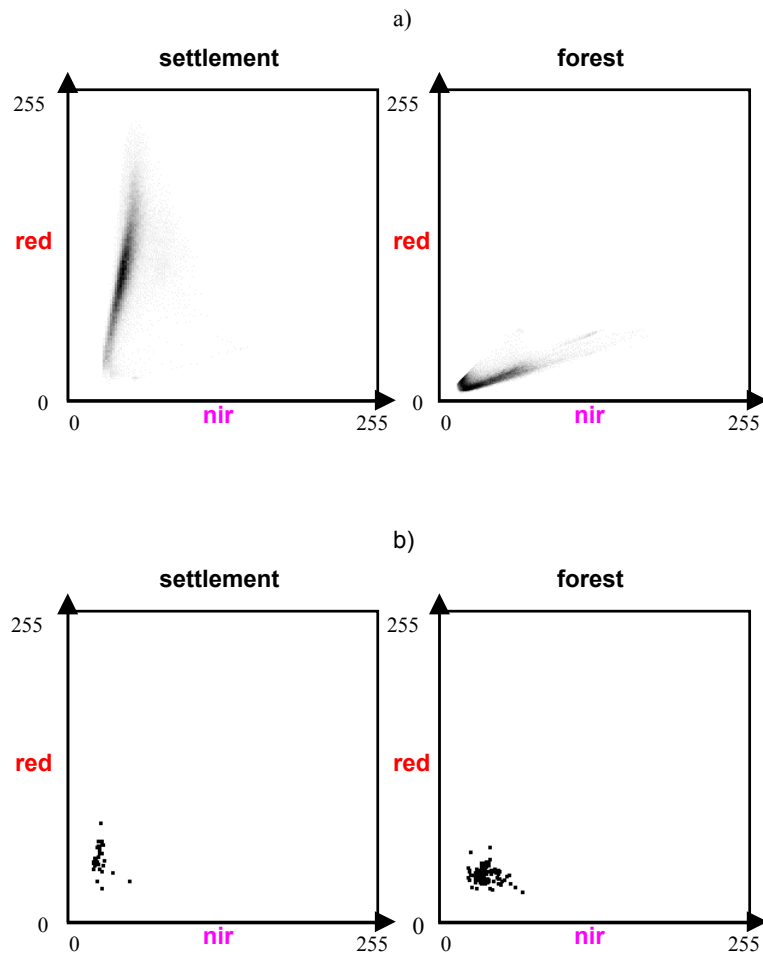Figure 1: Object-wise vs. pixel-wise classification

Figure 2: Scatterplot pixels vs. objects

This behaviour can also be seen in figure 2. The scatterplots show the distribution of the grey values of settlement and forest pixels (a) compared with the distribution of the mean grey value of settlement and forest objects (b) in the channels red and nir. It can be seen that the behaviour is similar but the separation of the two classes becomes blurred because of the smoothing. In the object-wise classification all multispectral bands of the DPA camera system (blue, green, red and nir) are used as input channels.

Different land use classes cannot only be distinguished by their spectral behaviour but also because of different textures. Texture operators transform input images in such a way that the texture is coded in the grey values. In our approach we use a texture operator based on co-occurrence matrices which measures the contrast in a 5 * 5 window. Figure 3 shows the used texture operator on an example. The input image is shown in figure 3 a, the texture image in figure 3 b and the object textures which were calculated again by the mean grey value for all object pixels in figure 3 c. Settlements are represented with dark pixels, greenland with bright pixels and forest with middle grey pixels.

The variance of the pixels of an object is also a good indicator about the roughness of a texture. Figure 4 shows the calculated variance in the blue band for all objects. Settlement objects have high, greenland objects middle and forest objects low variance values. Figure 5 shows the behaviour of the variance in the different bands: blue, green, red and nir. The best discrimination between the landuse classes using the variance can be seen in the blue band. In the nir band all landuse classes have a similar distribution which makes a discrimination in this band impossible.

Vegetation indices are very often used in pixel-based classification as an input channel to improve the classification result. They are based on the inverse spectral behaviour of chlorophyll which absorbs red light and reflects near infrared light. In our approach we use the most widely used (Campell, 1987) *normalised difference*:

$$ND = \frac{IR - R}{IR + R}$$

Figure 6 a shows the calculated vegetation index on pixel basis and figure 6 b on object basis which was calculated by the mean grey value of all object pixels. It can be seen that settlements are represented by dark areas whereas forests are represented by bright areas. The classification of green land is difficult because it can be represented by very bright areas (e.g. fields with a high amount of vegetation) as well as by very dark areas (e.g. fields shortly after the harvest).

a)

b)

c)

Figure 3: Calculation of the texture for pixels and objects
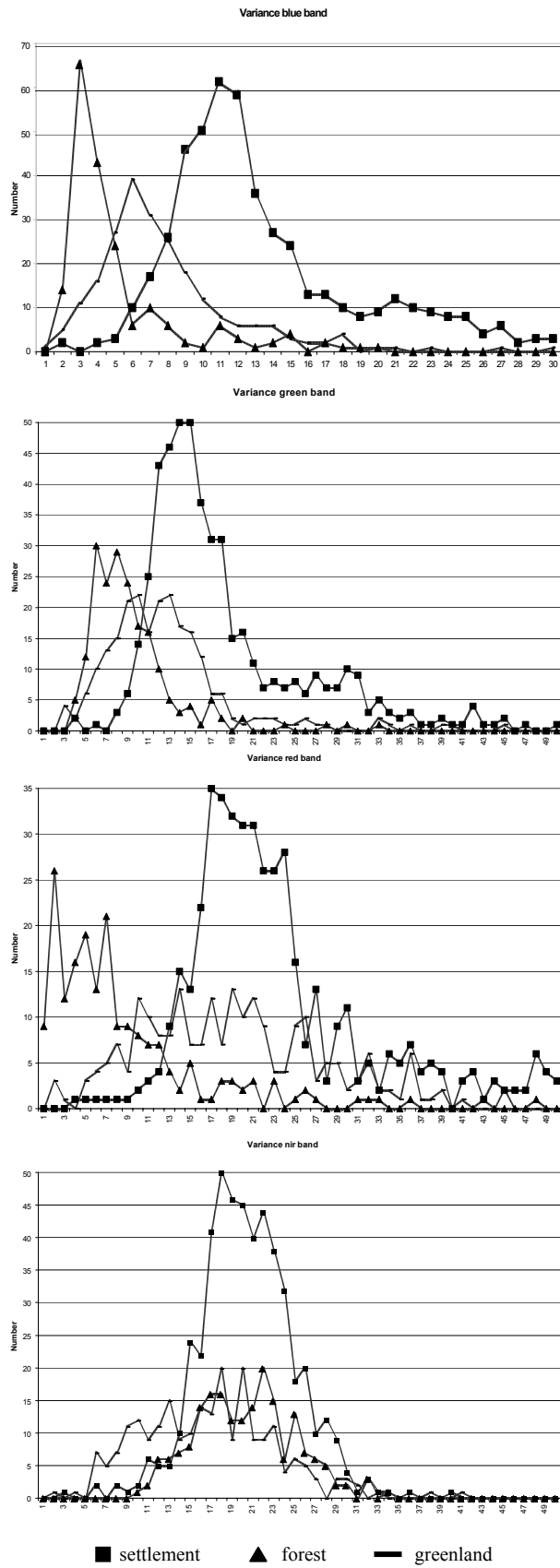

Figure 4: Variance of the objects
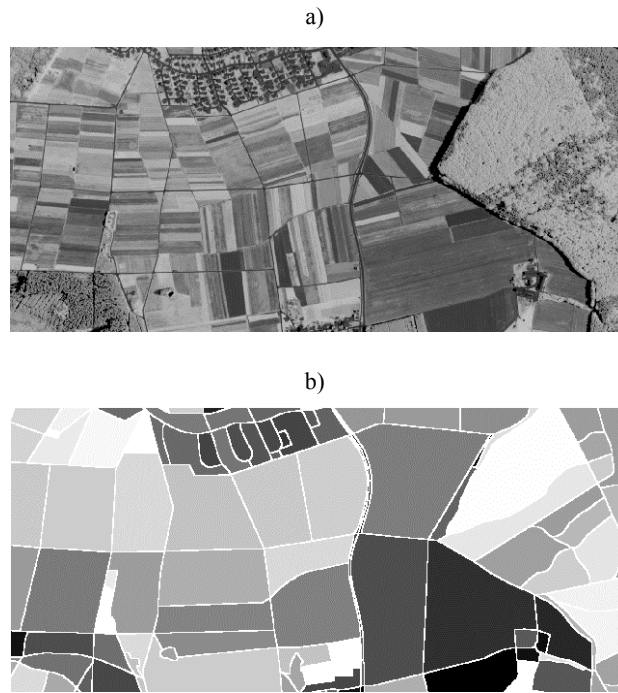
Figure 5: Object variance in different bands

a)

b)

Figure 6: Vegetation index for pixels and objects

All so far defined input channels are also used in 'normal' pixel-wise classification. In object-wise classification it is possible to add further input channels which describe not directly the spectral or textural characteristics. For example we can use the result of an pixel-wise classification and count the percentage of pixels which are classified to a specific landuse class.

The object-wise evaluation of the percentage of pixels which are classified to a specific landuse class is shown in figure 7. The input image is shown in figure 7 a and the pixel-wise classification result in figure 7 b. Figures 7 c shows for each object the percentage of pixels which are classified to the landuse class forest. White colour represents 100 percent and black colour 0 percent. Forest is a landuse class which can be classified with high accuracy in pixel-based as well as object-based classification.

Figure 7 d shows the percentage of settlement pixels. Because of the high resolution (2m) of the data, settlements cannot be detected as homogenous areas but they are splitted into different landuse classes depending on what the pixels are actually representing. Therefore settlement objects contain typically only 50 to 70 percent settlement pixels in a resolution of 2m. This can also be seen in figure 7 e which shows the percentage of greenland pixels. Whereas greenland contains up to 100 percent greenland pixels it can be seen that in settlement areas also pixels are classified as greenland.

2.4 Classification results

The approach was tested on two test areas which were acquired at different dates with together 951 objects. The input channels are:

- mean grey value blue band
- mean grey value green band
- mean grey value red band
- mean grey value nir band
- mean grey value vegetation index
- mean grey value texture
- variance blue band
- variance green band
- variance red band
- variance nir band
- variance vegetation index
- variance texture
- percentage forest pixels
- percentage greenland pixels
- percentage settlement pixels
- percentage water pixels

Figure 8 a shows the GIS data and figure 8 b the result of the object-wise classification on a part of one test area. Altogether 82 objects (which are 8.6 percent of all objects) were classified into a different landuse class as they were collected.

a)

b)
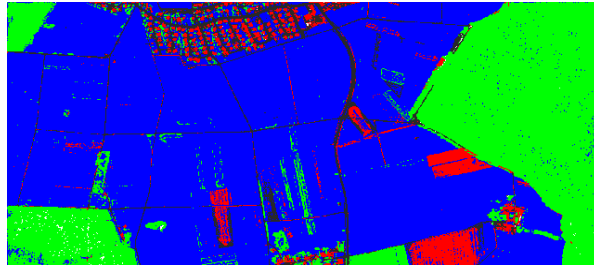
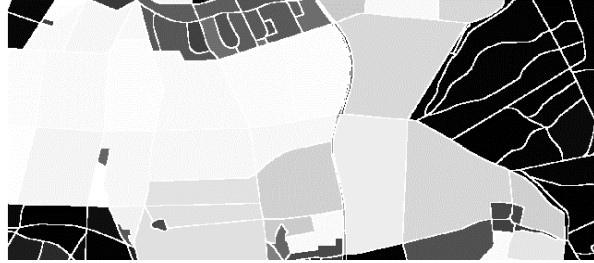■ street ■ greenland ■ settlement ■ forest

c)

d)

e)

Figure 7: Percentage right classified pixels

This objects can be subdivided into three classes. The first class contains all objects where a change in the landscape has happened and an update in the GIS database has to be done. In this class are 37 objects (43 percent). The second class contains all objects where it is not clear if the GIS objects were collected correctly. Further information sources are needed to decide if the GIS database has to be updated or not. In this class are 26 objects (31 percent). The third class contains all objects where the result of the classification is incorrect. In this class are 19 objects (23 percent).
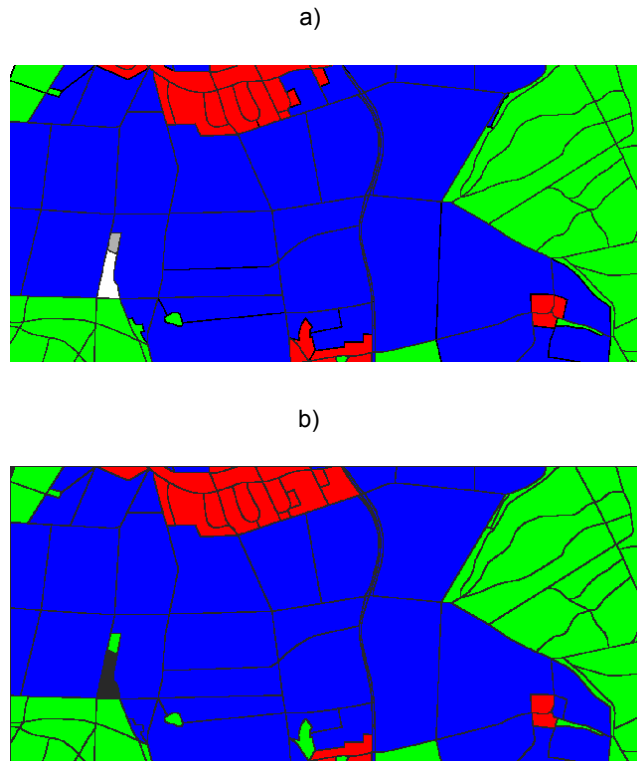
a)

b)

Figure 8: GIS data and result of the classification

3. DISCUSSION

The object-wise classification needs no tuning parameters like user defined thresholds. It works fully automatic because all information for the classification are "learned" from automatically generated training areas. The result is not only a change detection but also a classification into the most likely landuse class.

The results show that most of the changes which were found by the approach are real changes. That means that the amount of interactive checking of the data can be decreased significantly. On the other hand we have to ask if the object-wise classification finds all changes. Because it uses the existing object geometry, a change in the landscape can only be detected if it affects a large part of an object. If for example a forest object has a size of 5000 m^2 and in that forest object a small settlement area with 200 m^2 is built up, then this approach will fail.

The approach subdivides all objects into the classes *water, forest, settlement* and *greenland*. This can be refined if more information in the input data is available. This can be realised for example by the combined use of multispectral and laser data. With laser data further input channels can be created like slope, average object height, average object slope, etc. With information like that, it could be possible to distinguish for example between residential settlement areas and industrial settlement areas. Furthermore it was shown in (Haala, N., Walter, V., 1999) that also the pixel-wise classification result can be improved significantly by the combined use of multispectral and laser data.

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Dr.-Ing. Volker Walter is Head of the GIS research Group of the Institute for Photogrammetry (ifp), Stuttgart University
Adress: Institute for Photogrammetry (ifp)
University of Stuttgart
Geschwister-Scholl-Str. 24D
D-70174 Stuttgart
Email: Volker.Walter@ifp.uni-stuttgart.de