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AUTOMATIC CLASSIFICATION OF REMOTE SENSING DATA FOR GIS DATABASE REVISION

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ABSTRACT

Geographic information systems (GIS) are dependent on accurate and up-to-date data sets. The manual revision of GIS data is very cost and time consuming. On the other hand more and more high resolution satellite systems are under development and will be operational soon - thus high resolution remote sensing data will be available. In this paper a fully automated approach for verification of GIS objects using remote sensing data is presented. In a first step a supervised maximum likelihood classification is performed. It is necessary that the training areas for the supervised classification are derived automatically in order to develop a fully automated approach. The already existing GIS data are used to compute pixel masks (which represent the training areas) for each object class. In order to find inconsistencies between the GIS data and the remote sensing data the result of the classification has to be matched with the GIS data. It is shown that different approaches are needed when dealing either with area objects or with line objects. Examples on both approaches are presented. The automatic verification was tested with ATKIS data sets and DPA high resolution remote sensing data. ATKIS is the German topographic cartographic spatial database and DPA (Digital Photogrammetric Assembly) is an optical airborne imaging system for real time data collection. This paper shows the results of the automatic verification of ATKIS objects represented in DPA data.

1 INTRODUCTION

Image classification procedures are used to classify multispectral pixels into different land cover classes. The input for the classification are multispectral bands and textural patterns which are computed from the multispectral data (see for example [R.M. Haralick and K. Shanmugam 1973]). There are numerous classification algorithms which can be divided into *unsupervised* and *supervised* approaches. In the unsupervised approach pixels are grouped into different spectral (and textural) classes by clustering algorithms without using prior information. After clustering, the spectral classes have to be associated with the land cover classes by an operator. Unsupervised classification algorithms only have a secondary role in remote sensing.

Two basic steps are carried out in a supervised classification. In a *training stage* an operator digitizes training areas that describe typical spectral and textural characteristics of the data set. In the *classification stage* each pixel of the data set is categorized to a land cover class. There exist a lot of different approaches for the classification stage such as minimum-distance, parallel-epiped or maximum likelihood classification [T. Lillesand and R. Kiefer 1987]. Very new approaches exist in the field of *Neural Network Computing* (see for example [K. Segl, M. Berger and H. Kaufmann 1994] or [A. Barsi 1996]). Whereas the classification stage can be done automatically, the training stage involves the work of an operator and requires a lot of experience because the quality of the training areas is a crucial factor for the quality of the classification result.

A further problem is that new training areas have to be digitized for every new data set. The reasons are for example atmospheric effects, different spectral diffusion depending on the sunlight, different spectral characteristics of vegetation depending on season or soil, vitality of the vegetation, etc. As the digitizing of the training areas is time intensive, a method is needed to generate the training areas in an automatic way. Having assumed that the number of wrongly captured GIS objects and the number of changes in the real world are substantially less than the number of all GIS objects of the data set, the training areas can be derived automatically from the already existing GIS data. This leads to high quantity but lower quality of training areas instead of low quantity but high quality. In the following it is shown how these training areas can be computed automatically and how the results can be matched with the GIS data sets.

2 PROJECT

This research is carried out by order of the surveying institute of the state Northrhine-Westphalia, Germany. The project is supported by the German Aerospace Center (DLR - formerly DARA).

3 DATA SETS

Two test areas with an extension of approximately 40 square kilometers were defined to test the approach. Figure 1 shows DPA data and ATKIS data of a part of one test area. The different object classes in ATKIS are represented by different grey values.

ATKIS is the German topographic cartographic spatial database [ATKIS 1988] and presently contains more than 60 different feature types for the whole area of Germany in the scale 1:25,000 (beside this scale there are further levels of data aggregation in the scales 1:200,000 and 1:1,000,000). The ATKIS datasets which are used for this work were collected in the years 1993 and 1994, whereas the DPA data were captured in the year 1997.

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Figure 1: DPA (a) and ATKIS (b) data

The Digital Photogrammetric Assembly (DPA) is an optical airborne imaging system for real time data collection. The ground pixel size is dependent on the flying height and is for example 0.60 m for multispectral data when flying 2300 m above ground. Beside the multispectral sensor, the DPA camera system offers also three panchromatic CCD line arrays for inflight stereo imaging (for more details of the DPA camera see: [M. Hahn, D. Stallmann and C. Staetter 1996]). In order to find a compromise between quality of the object verification and computing time the data were resampled to a pixel size of 2 m. This resolution is sufficient for the verification of ATKIS objects and it will be shown later that a higher resolution leads not necessarily to qualitative better results.

4 TRAINING AREAS

The supervised classification requires a quantitative description of the spectral and textural characteristics (in form of training areas) of the different land cover classes in order to be able to assign unknown pixels to one of these classes. The higher the quality of the training areas the better will be the result of the classification. Therefore the object geometry is not used as stored in the GIS database - a preprocessing has to be performed first.

It is very important that the training areas contain as little as possible mixed pixels. Mixed pixels arise especially at object borders where two different objects are neighbored to each other. Therefore a buffer is computed around the object border which has a width of four pixels. This buffer is also broad enough to eliminate wrong pixels which can arise because of inaccurate data acquisition.

In ATKIS the street geometry is not captured by areas but by lines which represent the street centerlines. This leads to the fact that neighboring area objects of streets are captured not by their exact geometry but they are enlarged by the half width of the street (this is the ideal situation - if the captured middle axis is not exactly on the middle of the street this leads to a more inaccurate geometry of the neighboring objects). Therefore we generate a buffer around all streets and cut this out from the training areas.

Figure 2 shows the training areas for the land cover classes *agricultural area, forest* and *settlement*. Additional training areas for the classes *water* and *street* are generated from the ATKIS data. In ATKIS many further object classes exist. These object classes can not be distinguished alone by their spectral and textural characteristics without addition of further information sources. Examples are the object classes *wood* and *grove* or *residential area, industrial area* and *area of mixed use*. Even a human operator is very often not able to distinguish these object classes without additional information. In addition, it is still added that the definition of these object classes are ambiguous and often not clearly delimitable from each other. Therefore, object classes of this kind are combined together to one of the five different spectral classes defined above.

Figure 2: Automatically generated training areas

Training pixels for the class *streets* are not cut out as areas because streets are typically very narrow and long objects and consist therefore of many mixed pixels. Additionally, the acquisition accuracy is a very important factor as already mentioned above. From that fact only those pixels are taken which are located exactly on the middle axis of the ATKIS streets. A further problem are streets in forest areas. Since streets are mostly hidden in forests, no training areas are generated here at all. But also in other areas streets are often hidden by trees. In order to avoid wrong pixels here, the vegetation index can be used. All pixels which have a high vegetation index are removed from the training areas for streets.

5 CLASSIFICATION RESULTS

The classification method used in our approach is a maximum likelihood algorithm. Figure 3 shows a schematical representation of the classification approach. The classification process is fully automatic.

Figure 4 shows the result of the classification procedure at an example. Forests are recognized being homogeneous and well detectable. Agricultural areas show sometimes inhomogeneities because of planting structures, but nevertheless they can be detected also very well. The land cover class which could be detected best is *water*. Larger streets are recognized without problems but sometimes street pixels are overlayed with pixels which represent house roofs because of their similar spectral characteristics. This applies in particular to flat roofs.

The land use class *settlement* can not be recognized as homogeneous uniform areas, but it is subdivided into several classes. It can be seen that pixels are only recognized as settlement areas if they represent house roofs. The other pixels are classified as streets, forest and agricultural area depending on the "ground truth". The reason for this result is the high resolution of 2 m. We also tested this approach with other resolutions. If the data sets have a lower resolution, settlements are recognized as uniform faces but the accuracy of the results detiorates and small settlement areas could not be detected anymore. If, however, the resolution is further increased, the results detiorates for settlements but improves for streets. For very high resolution data, it is necessary to define more land use classes as training areas which could be for example roofs, shadows, grass or hedges. Because this information is not available in ATKIS and the required accuracy is ±3 m, the used resolution of two meter is a good compromise between the quality of the result and the necessary computer time.

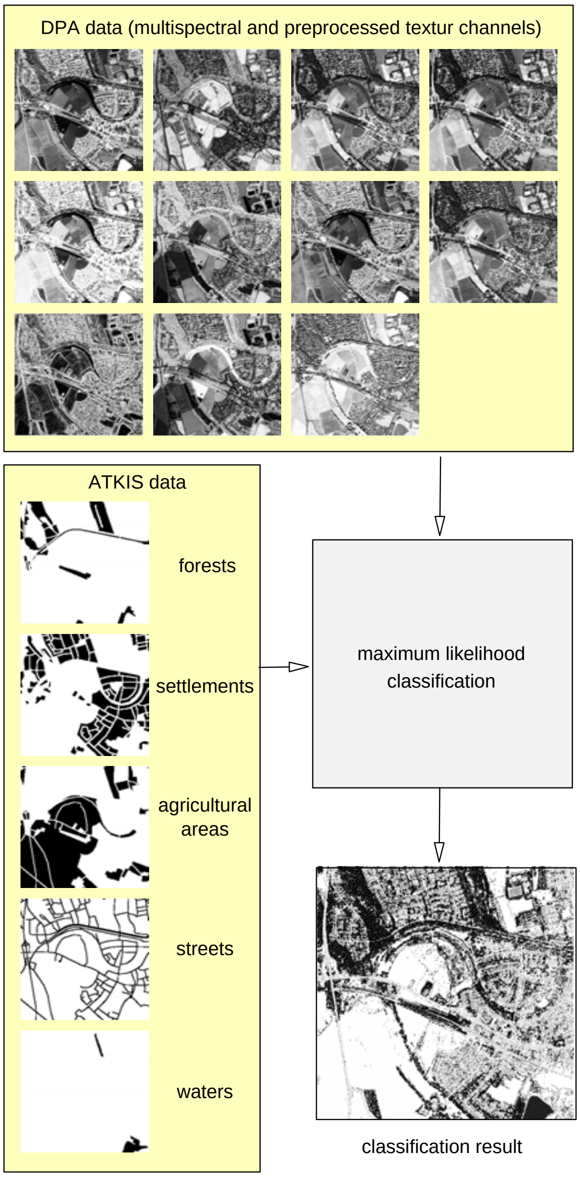

Figure 3: Input data for classification

6 MATCHING OF THE CLASSIFICATION RESULTS

After the classification, it must be decided which of the ATKIS objects do not match the DPA data. This can be objects where a change in the landscape has occured or objects, that were not collected correctly. Matching algorithms can be separated into approaches for area objects and line objects. The reasons for this distinction are represented in figure 5.

The representation of area objects results in considerably fewer mixed pixel than in the case of line objects. This situation is shown in figure 5 a). Because of the narrow shape of line objects most of the pixels are mixed pixels. The part of mixed pixels of an area object is small in relation to the total number of all pixels.

Furthermore, the acquisition accuracy is not as important for area objects than for line objects. In figure 5 b) an area object is shown which is captured very poorly. Nevertheless, most of the pixels which are represented by the area object are actually a part of that object. If a line object (for example a street) is not digitized exactly, almost all pixels of the line object belong actually to another object.

Shadow is a further problem which is represented in figure 5 c). While area objects are only concerned by shadow from other objects along the edge, line objects can completely be hidden by shadows and therefore may have other spectral characteristics than other objects of the same object class.

In summary, it can be said that on account of the problems represented above the matching of line objects is more difficult than the matching of area objects. Therefore we use two different approaches for the matching of the classification result which are described in the following.

6.1 Matching of area objects

All ATKIS area objects are subdivided into three different classes. The first class contains all objects which could be detected certainly in the DPA data, the second class contains all objects which are detected only partly and the third class contains all objects which could not be detected at all. The decision to which class an object be-

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longs is made by measuring the percentage of pixels which are classified to the same object class as the object itself belongs to. For example the matching of forest objects is done with the following rule:

$$class(\text{object}_{\text{forest}}) = \begin{cases} 1 & \text{if more than 66 percent of the pixels are classified as forest} \\ 2 & \text{if less than 66 percent and more than 33 percent of the pixels are classified as forest} \\ 3 & \text{else} \end{cases}$$

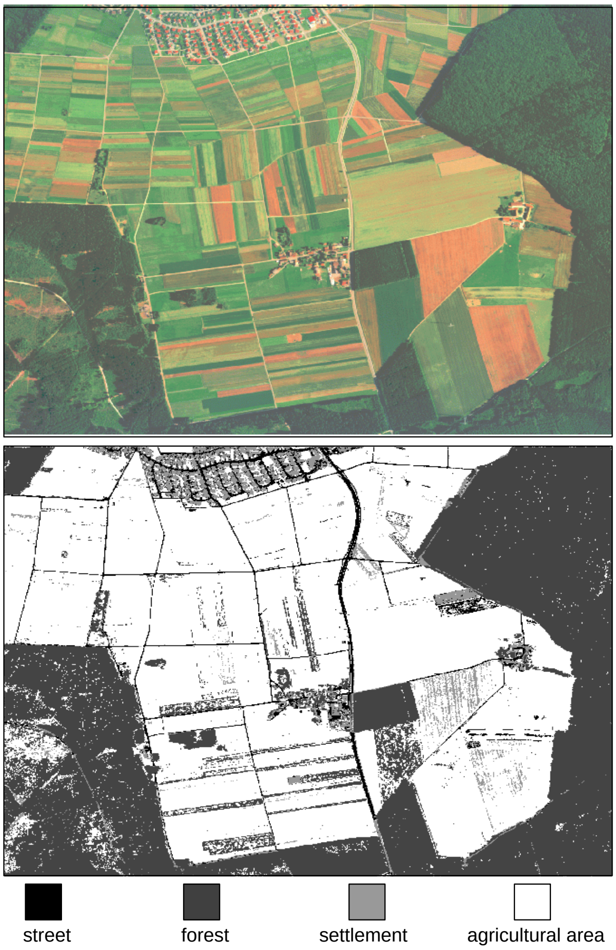

Figure 4: Classification result

This simple approach already leads to good results. The reason for this is, that changes of objects mostly refer to the thematic of the object and not to geometry. However, the results show, that this matching approach also recognize most of the cases in which a geometry change happened.

6.2 Matching of line objects

Because of the problems shown above, a more extended approach is needed for the matching of line objects. The result of the classification is first converted from the pixel oriented representation into a vector oriented representation. This is done by a multy leveled process chain which is presented figure 6.

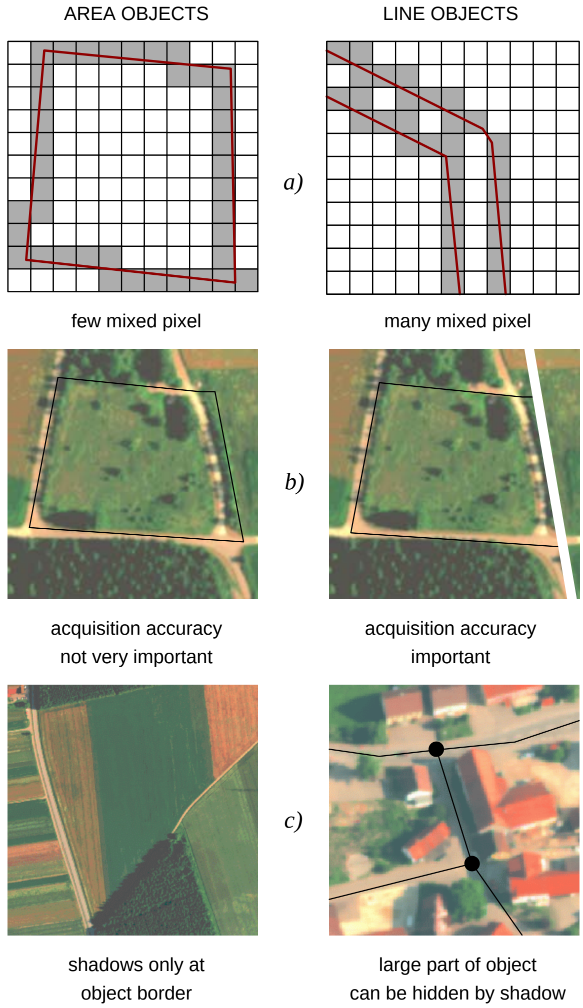

Figure 5: Matching of line and area objects

The first step is to select all pixels from the classification result which are classified as streets. This step can be further refined. For example all pixels which are located on a street which is already stored in the GIS database and which are classified as forest can be added to the selection result, so that all streets in areas which are classified as forest will be accepted by the matching procedure. Since streets are mostly hidden in forests, this strategy is reasonable for the automatic verification of streets in remote sensing data.

After the selection a raster oriented preprocessing has to be done. This includes for example the filling of small gaps or the removing of small pixel groups. Since streets are small and narrow objects, all pixel groups are removed which do not have a small and narrow shape. Than a sceletation is computed.

The pixel oriented result of the sceletation has to be converted into a vector oriented representation. Some further preprocessing steps are carried out with the vector data. For example all vectors are removed which are short and which have only at one node a topological neighbour. After all these preprocessing steps the classification result is converted into a representation which is very similar to the representation of the GIS objects and the matching can be performed.

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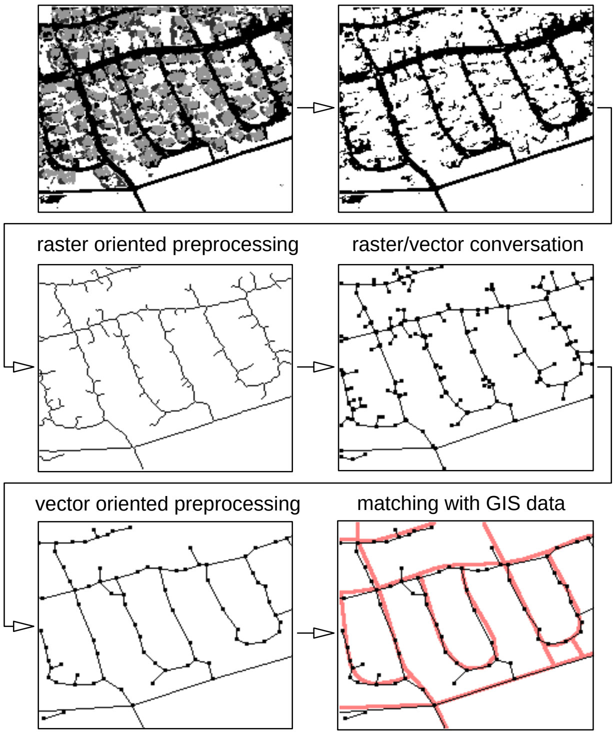

Figure 6: Processing of the classification result

The matching of line objects is done with a similar approach as the matching of area objects. All line objects are subdivided into the classes *full match* (1), *partly match* (2) and *no match* (3). The decision to which class an object belongs is made by measuring the percentage of overlap of the extracted vector elements which are located in a buffer with the width ε. Figure 7 shows this approach at an example. There are four vector elements which are located at least partly in the buffer arround the line object. The percentage of overlap is calculated by a line with an angle of 90 degrees from the line object to the starting point and respectively ending point of the vectors. This leads at paralell vectors to a high number of overlap and at vectors which have a different direction as the line object to a lower number of overlap. (the maximum overlap is 100 percent whereas the minimum is, of course, 0 percent). Then the matching is done with a quite similar rule as by the matching of area objects:

$$class(\text{object}_{\text{street}}) = \begin{cases} 1 & \text{if the object has more than 66 percent vector overlap} \\ 2 & \text{if the object has less than 66 percent and more than 33 percent vector overlap} \\ 3 & \text{else} \end{cases}$$

This approach leads to good results. More extended approaches also consider for example the topological relations in the data sets. An example for the relational matching of data sets can be found in [V. Walter 1997] or [V. Walter and D. Fritsch 1997].

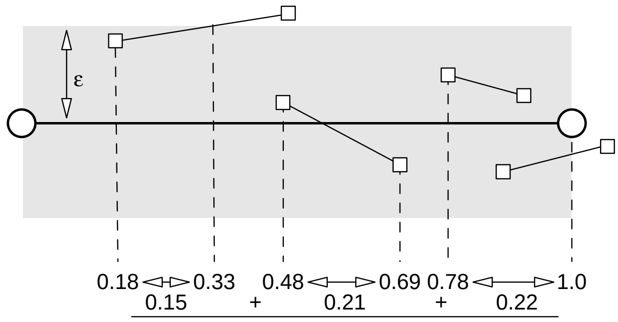

Figure 7: Matching of line objects

7 RESULTS

Some examples of classification and matching results of area objects are presented in figure 8. The results can be visualized on the screen to control the results interactively. Figure 8 a) shows two objects which are stored in ATKIS as agricultural areas but meanwhile changed to settlements. The classification result shows very clearly the structure of the buildings and the streets. The grass areas between the buildings are classified as agricultural areas. The two ATKIS objects *agricultural area* could not be detected by the matching procedure and therefore are marked as not matched. The program recognizes strong changes of the landscape without problems.

In figure 8 b) a situation is presented where also strong changes of the landscape occurred. Now an industrial area is at the location where in former times fields and forest existed. Also a new street was build, which is not stored in ATKIS. The street could be classified very clearly and also the structure of the industrial building. However, pixels of the classes *industrial area* and *street* are exchanged with each other in some cases. The reason for this is the very similar spectral characteristics of streets and buildings (especially with flat roofs). The non existence of the forest could be detected by the matching procedure without problems because no forest pixels at all were found in this part of the image. The object *agricultural area* is matched partially because large green areas can be found in the industrial area.

The DPA image of figure 8 c) shows an area which is completely captured as forest in ATKIS. However, it can be seen that a part of this forest contains only very small trees and in some parts no vegetation can be seen at all. The classification result shows homogeneous areas where the trees are dense and large. In areas with less vegetation also agricultural area pixels are detected. This leads only to a partly match of the forest objects.

In figure 8 d) a settlement object is presented which has a strange shape. The reason for this is, that ATKIS objects are not only captured from orthoimages but also from cadastral maps. Therefore the acquisition of object borders is done often according to ownership structures and not according to detectable structures in the image. A large part of the settlement object consists of forest and only a small part consists of buildings and street. This leads also to a partly match.

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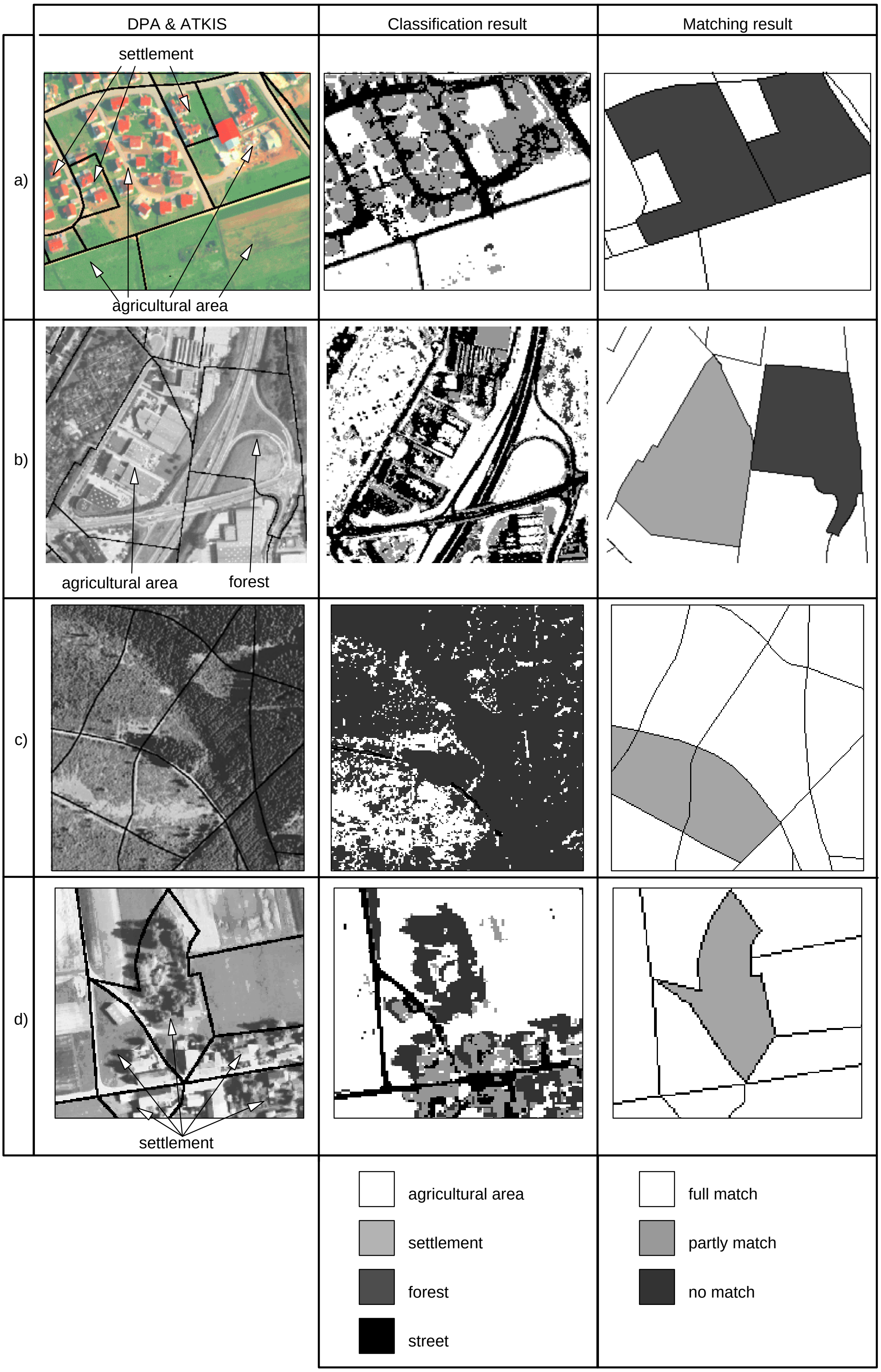

Figure 8: Classification and matching of area objects

Figure 9 shows the classification and matching results of line objects. In figure 9 a) the DPA image with the original resolution of 0.5 m is shown. The rectangles in the image show regions of interest which are discussed in the following. Figure 9 b) shows the result of the classification and figure 9 c) shows the result of the matching procedure. Streets, which are captured in ATKIS, are represented by their border lines and are fillled with different grey values dependent on the matching result. The extracted vectors from the image are represented by black lines.

Region 1 shows an area where a street can be seen in the DPA image but it is not represented in the ATKIS data. Even the street is narrow and partly hidden, it is detected by the classification procedure. Region 2 shows a similar situation.

In region 3 two ATKIS streets are captured which could not be detected by the matching procedure. But when looking in the DPA image, it could be seen that the right street is not represented in the image at all and the left street is only represented very unclear. Therefore the matching result is satisfying. Region 4 shows the inverse situation of region 3. In this situation the street can be seen in DPA image but it is not represented in ATKIS data. Again, the classification procedure detect this street. Region 5 shows a street whithin an agricultural area which has no asphalt face. This street is classified in ATKIS as a *path.* Streets of this kind very often lead to problems and can not be detected automatically. The matching procedure is not able to match this street. However, even a human operator has very often problems to detect streets of this kind. There are a lot more line structures in the DPA image which could be small streets (or paths) but are not captured in the ATKIS data set.

8 SUMMARY

In this paper a fully automatic approach for verification of GIS data using high resolution multispectral data is presented. The main idea of the approach is to use the already existing GIS information for the automatic generation of training areas for multispectral classification. The result of the classification is a pixel oriented representation of different land use classes. This result has to be compared with the GIS data in order to find inconsistencies

For each area object the percentage of pixels, which are classified in the same way as the object itself, is measured. This approach leads to promising results but it is not sufficient for the matching of objects with linear shape. Therefore we implemented also a matching strategy for the matching of line objects. In order to match line objects the pixel oriented result must at first be converted into a vector oriented representation. This is done by a multy leveled process chain. Then the percentage of overlap of the extracted vector elements which are located in a buffer is measured.

The approach was tested on ATKIS and DPA data. The results show that inconsistencies between ATKIS and DPA can be detected in most of all cases. Problems may appear by objects which are captured according to ownership structures and not to detectable structures in the image. Objects of this kind have often inhomogeneous spectral and textural characteristics. As a result, problems occur with automatic verification. However, this is not a problem of the used algorithms but it is the result of the definition of the objects in the object catalogue. Even a human operator is often not able to update the ATKIS objects only by using orthoimages without additional information.

The main focus of the further work will lie in the improvement of the matching algorithms. When matching area objects not only the number of correctly classified pixels has to be considered but also their distribution. Therefore we suggest to use not only a pixel oriented approach but also an object oriented approach. Spectral and textural characteristics has to be computed for each object and then evaluated in the same way as pixel characteristics in a 'normal' maximum likelihood classification.

The main problem of matching of streets is that street pixels are often classified as settlement pixels and vice versa. This problem can be solved by using of additional information sources. This can be for example laser range data or digital elevation models which are derived from stereo data. First tests show that the classification result can be improved when adding these information. This is especially important in inner city areas. Furthermore the preprocessing of the classification result can be improved when adding further techniques like for example snake algorithms.

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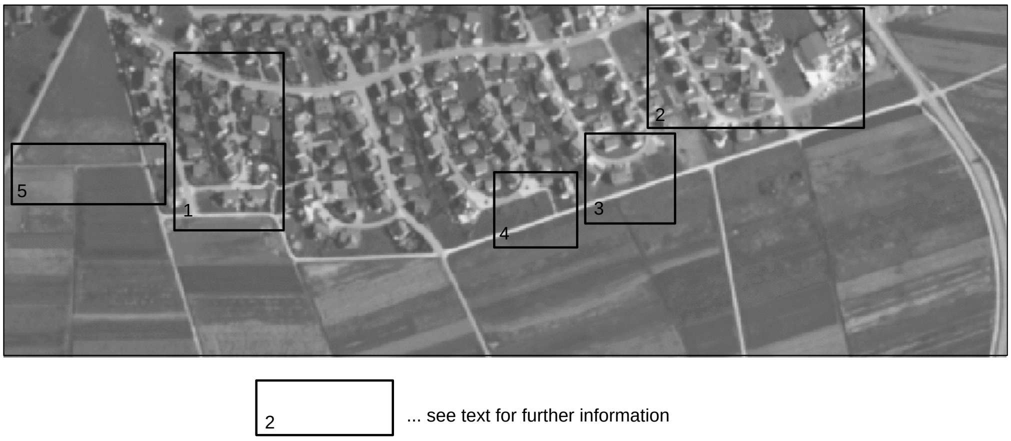
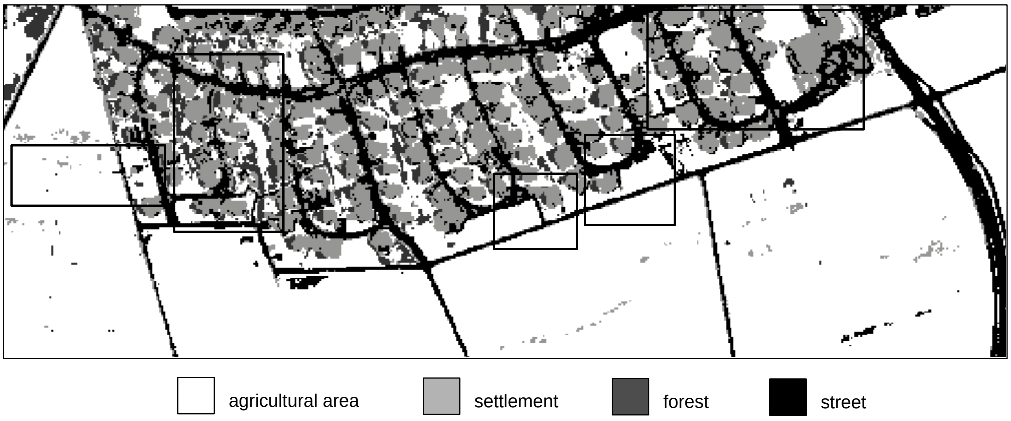
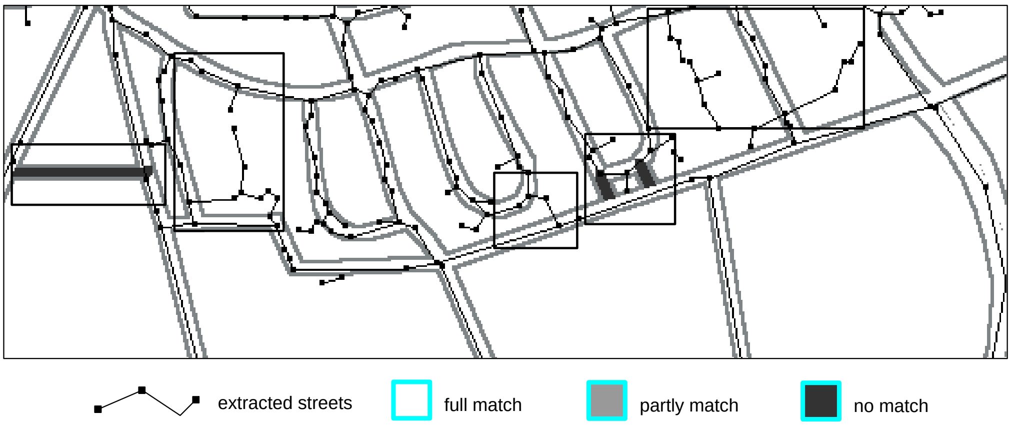


a) DPA image (original resolution 0.5 m)



b) classification result (2 m resolution)



c) matching result

Figure 9: Classification and matching of line objects

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