SEGMENTATION-BASED URBAN LAND COVER MAPPING FROM KOMPSAT EOC IMAGES

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ABSTRACT

High resolution panchromatic satellite images collected by sensors such as IRS-1C/D and KOMPSAT-1 have a spatial resolution of approximately 6 x 6 m², making them very attractive for urban applications. However, the spectral information present in these images is very limited. In order to overcome this limitation, an object-oriented classification approach is used to identify basic land cover types in urban areas. Before an image can be classified it is segmented at different aggregation levels using a multiresolution segmentation approach. In the course of this segmentation various statistical as well as topological information is collected for each segment. Based on this information it is possible to classify image objects and to arrive at much better results than by looking only at single pixels. Using an image recorded by KOMPSAT-1 over the City of Vienna a land cover classification was carried out for two areas. One was used to set up the rules for the different land cover types. The second subset was classified based on these rules, only adjusting some of the functions governing the classification process.

1 INTRODUCTION

Satellite images provide a wealth of data at various spatial and spectral scales. With the availability of very high-resolution images as provided by IKONOS and Quickbird the gap between aerial photography and satellite imagery has narrowed significantly. While most of these developments have been driven by the United States, other countries are developing their own space programs and provide high quality data with increasing resolution. Examples for these countries are India and Korea. While their sensors may not yet provide the highest spatial resolution available, they represent a valuable data source. In this paper a panchromatic scene collected by the Electro Optical Camera (EOC) aboard KOMPSAT-1 (Korean Multi-Purpose Satellite) will be examined. Traditionally such a scene would be analysed by means of visual interpretation or a transformation using approaches such as texture analysis. The disadvantage of the former is that it is time consuming and leads to results which, as a rule, cannot be reproduced independently of the interpreter, while for the latter extensive post-processing is necessary in order to arrive at the desired classes.

The main problem for an automated approach is the lack of multivariate spectral data, forcing the user to rely on other parameters such as contrast, size, shape, neighbourhood, and so forth. Characteristics which cannot be utilised on a pixel level but rather need the presence of larger units such as image objects, for which the information described above is available. Tools, such as the object-oriented image analysis software by eCognition, allow this kind of analysis. Object-oriented classification of urban areas has already been used in a number of studies using multispectral high resolution satellite imagery (e.g. Bauer and Steinnocher, 2001, Hofmann, 2001) and airborne scanner data (e.g. Hoffmann and Van der Vegt, 2001). In this paper it will be examined how this approach may be used to perform a basic land cover classification of a panchromatic image recorded over the City of Vienna. As one important aspect is the automation of the classification procedures, a rule-set will be established for one subset. This will also be used to classify a second subset using the defined rules with only adjusting some function parameters to suit the varying test site conditions.

The results will be compared to the aggregation of an existing classification performed during the MURBANDY project (Steinnocher et al., 1999). This classification was based on the visual interpretation of a panchromatic IRS-1C image, discerning 28 classes with a minimum mapping unit of 1 ha for artificial surfaces and 3 ha for natural surfaces. As ancillary data was also used for the classification, it cannot be attempted to mimic this classification procedure using panchromatic data alone, but it can give some indication as to the quality of the results derived here and show where disagreements occur.

2 DATA AND STUDY AREA

For this study one panchromatic satellite image recorded by KOMPSAT-1 on 1st, March, 2001 was available. KOMPSAT-1, launched in December 1999 is part of a new family of satellites operated by the Korean Aerospace Research Institute (KARI). It records reflected light in the spectral region of 0.51-0.73 μm with a spatial resolution of 6.6 x 6.6 m. It is a push-broom scanner that orbits the earth in a sun-synchronous orbit at an altitude of 686 km and has a swath-width of 17 km. While the spatial resolution is comparable to IRS-1C and 1D (5.8 x 5.8 m) the radiometric resolution is much higher (8 compared to 6-bit), allowing a more detailed separation of object features.

Two study areas, located in City of Vienna (see Figure 1), were selected. In order to set up a classification system, subset A in the South in Vienna, was selected. It is a suburban areas with residential, industrial and commercial areas as well as some agricultural areas. In order to examine the generalisation capabilities of the classification system, it was tested on a different subset (B) located in the North of Vienna. As it is also located in a suburban area it has comparable features thus making a comparison feasible.

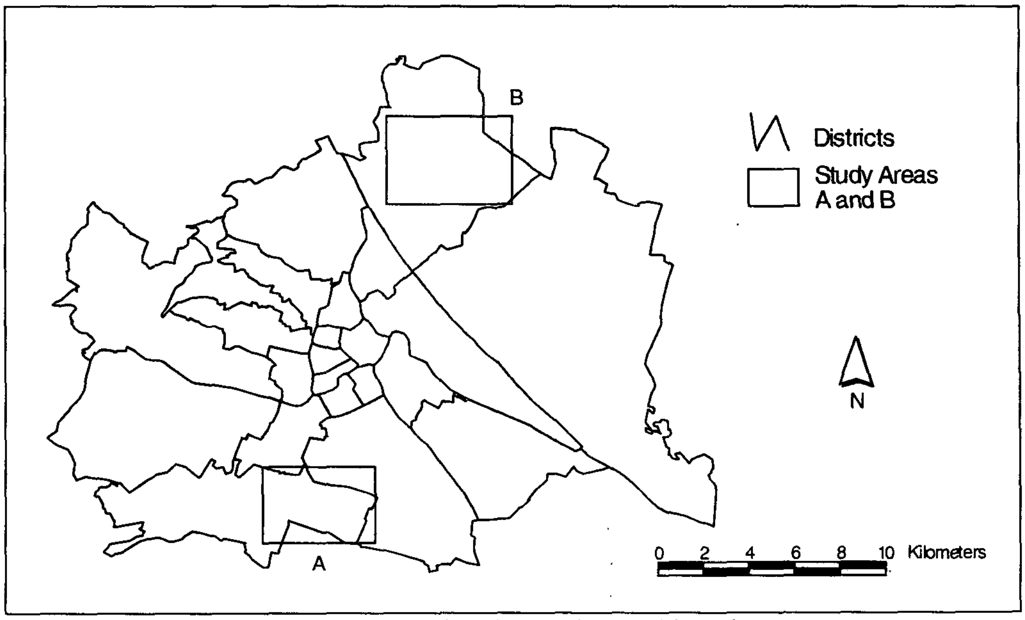

Figure 1. Districts of the City of Vienna with study areas.

The size of the subsets is 4,950 x 3,348 m or 825 x 558 pixels (A) and 5,466 x 3,876 m or 911 x 646 pixels (B). While both are located in suburban areas, the range of spectral values in each subset is quite different. The mean of all pixel values for subset A is 55.61 while that for subset B is 83.25.

Even greater is the difference in standard deviation with 12.30 for subset A and 54.29 for subset B. An attempt will be made to identify the land cover classes road, water, agriculture, industry/commerce, residential and urban open spaces. In order to verify the results, an existing classification, created during the MURBANDY project for Vienna, was used. At an aggregated level it covers six classes representing water, urban fabric, industrial/commercial/transport, green urban areas, agriculture and forest. Forest is not present in any of the selected subsets and water only in subset A.

3 IMAGE SEGMENTATION AND OBJECT-ORIENTED CLASSIFICATION

The first step of the analysis is the image segmentation. This is done by using the multiresolution approach as implemented in the software package eCognition (Baatz and Schäpe, 2000). Aim is to divide the image into homogenous objects using the parameters scale, colour, shape, smoothness and compactness. These parameters govern size, shape and spectral variation of each object. Single pixel objects are merged into bigger ones using an iterative procedure, resulting in objects with similar heterogeneity. Applying this procedure at increasing scales, building on the segmentation results of the previous scale, larger objects are created, whose borders are defined by those of the smaller objects. For each image objects parameters such as mean and standard deviation derived from the spectral values as well as shape parameters such as area, length, width, and so forth are known. In addition each object not only "knows" its direct neighbours but also those that are above and below it, irrespective of the segmentation level. Table 1 shows the number of objects and their average size at different scales for the test sites A and B. In total seven levels were defined, using the same shape, colour, smoothness and compactness parameters (0.5 for each), but different values for scale.

Table 1. Parameters derived for multiresolution segmentation of subset A and B.

		Subset A		Subset B	
Level	Scale	Number of Objects	Average Size	Number of Objects	Average Size
1	3	21,285	21.63	148,166	3.97
2	5	9,851	48.05	50,444	11.67
3	10	5,020	91.70	14,330	41.07
4	15	4,001	115.06	7,145	82.37
5	20	3,821	120.48	4,388	134.12
6	25	3,764	122.30	2,908	202.37
7	50	3,643	126.37	837	703.11

As the scale increases the number of object decreases, as more and more objects are merged together. In subset A the average object size is considerable higher at a smaller scale (levels 1-4), but decreases relatively to subset B in levels 5-7. On the other hand the number of objects is considerably higher in levels 1-5 but lower in levels 1-7. This is an indication that the segmentation algorithm considers subset A to be less complex than subset B by the segmentation algorithm. This is also indicated by the lower standard deviation.

The next step is to assign each object to its most likely class. As the spectral information is very limited, additional indicators will be used. For each of the six classes a set of rules was defined. Care was taken to limit the number of rules in order to allow an easy adaptation to other scenes and to improve the interpretation of the results. For some classes a single rule proved to be sufficient while for other classes a number of rules as well as a number of classification steps at different segmentation levels were necessary. Rules are established in the form of fuzzy membership functions. Using an iterative approach each object is classified according to these functions. For some classes an approach is beneficial where object are first identified by one parameter (e.g. spectral value). Afterwards the classification is further refined by using the output of the first classification by using other parameters (e.g. relative border to another class). Table 2 shows an overview of the different classification steps for each class together with the segmentation level at which the operation is performed. Letters next to a number indicate that these classification steps refer to the same class but are carried out one after the other.

Table 2. Classification steps with associated functions.

Step	Level	Class	Functions
1	3	Agriculture	Standard deviation
1a	3		Relative border to agriculture
1b	7		Relative area of agriculture sub-object
2	4	Water	Mean
3	4	Road	Length, symmetry, not existence of agriculture sub-object
3a	4		Existence of road neighbour
4	7	Industry/commerce	Mean
4a	7		Relative border of industry neighbour object
5	4	Residential	Not existence of agriculture, industry super-object or water sub-object Standard deviation
6	7	Urban Green	Objects not classified as agriculture, industry, road, suburban or water

Agriculture was classified on level three using a fuzzy function to assign all objects that have a standard deviation below a certain level to be more likely to be agriculture. This is based on the fact that agricultural areas at this scale are very homogenous and thus have a very low standard deviation. After this assignment, another fuzzy function was used to assign all objects, which have a large share of border with agriculture also to agriculture. This makes it possible fill holes within agricultural areas, not picked up on the basis of standard deviation. At the same time single agriculture objects are eliminated as well.

Water was classified on level four. A fuzzy function was defined that all objects with a very low mean value are more likely to be water. Care has to be taken not to assign shadows as well and if necessary an additional rule to avoid this would have to be introduced

Roads were also defined on level four. Here a two-step approach was taken. First two fuzzy functions were defined based on length and symmetry. In addition the object must not already have been classified as agriculture. The next step is to remove all isolated road objects, as they are more likely to represent misclassification, based on the assumption that roads do not appear isolated but rather as part of a larger network.

Industry/commerce were classified on level seven, based on very high mean values, as they represent buildings normally associated with large industrial and commercial complexes. Their flat roofs are strong reflectors and thus have high spectral values. In a second step all those areas which have a large share of border with industrial objects were also assigned to this class. This allows the identification of larger industrial/commercial complexes in addition to individual industrial/commercial buildings.

In order to identify **residential areas**, only those objects were examined which had not yet been classified as agriculture, industry, road or water. Suburban residential areas are normally a mixture of houses as well as vegetation and thus have high spectral variations. This leads to the fuzzy rule that all remaining objects that have a high standard deviation are more likely to be residential areas. All objects which were not classified by one of the above rules were assigned to the class of **urban green**.

4 RESULTS

Subset A was used to set up the classification rules. The same rules were applied to subset B, with only adjusting the values used by each fuzzy function to meet the image characteristics. For subset A six classes were defined. They are water, road, residential, industry/commercial, agriculture and urban green. In subset B water is not present and thus not classified. Figure 2 shows subset A of the satellite image. Using the rules described above this subset was classified into the six land cover classes(see figure 3). Water is in shown in black and while most small ponds are correctly classified, although sometimes underestimated, shadows can also show up as water. Industry/commerce (lines) and residential areas (dots) are can be discerned as well as agricultural areas (light grey). Roads are not represented very well, although major thoroughfares are shown. Open spaces (dark grey) are sometimes confused with agricultural areas and vice versa. Here a clear differentiation would only be possible by including ancillary data, as a panchromatic image alone does not contain enough information for reliable identification. If however, aim is to identify open spaces in urban areas, irrespective of their use, the results are very promising.

Figure 4 shows a comparison between the object-oriented classification and the MURBANDY results. White are those areas where the classifications agree, black those where they disagree. As roads were not part of the MURBANDY data base but rather assigned to the class for industry/commerce, major disagreements occur along roads. Also a problem exists in the differentiation of green urban areas and agricultural land. As some misclassified areas can only be correctly identified by using ancillary data, these disagreements cannot be avoided when only using panchromatic data. In total 61.37 % of the total area were correctly classified on the basis of the MURBANDY classification.

Subset B can be seen in figure 5. It has a very similar land cover composition to that of subset A. Water is not present in the scene and was thus not included in the classification. Figure 6 shows the classification results and figure 7 the comparison to the MURBANDY classification. As can be seen in the classification results, the major regions have been identified, either agriculture, industry/commerce or residential. The overall agreement is 68.24 % higher than that for subset A. Again major differences occur along roads as well as in some agricultural areas.

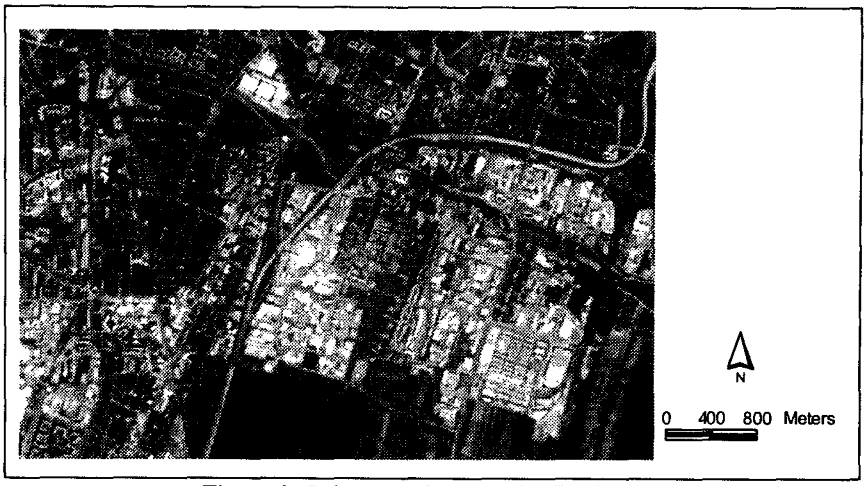

Figure 2. Subset A of KOMPSAT-1 image.

Figure 3. Classification results for subset A.

Figure 4. Comparison of classification to MURBANDY classification.

Figure 5. Subset B of KOMPSAT-1 image.

Figure 6. Classification results for subset B.

Figure 7. Comparison of classification to MURBANDY classification.

5 CONCLUSION AND OUTLOOK

In this paper an object-oriented classification approach is used to classify two subsets of a panchromatic scene recorded by KOMPSAT-1 over the City of Vienna. The disadvantage of only having very limited spectral information is to some extent compensated by the use of contextual information in the classification process. Using a multiresolution segmentation approach as implemented in eCognition, the image was first segmented into image objects at different scales. The next step was to identify a set of classification rules, both on a spectral as well as contextual level, to identify the classes for water, industry/commerce, road, residential, agriculture and green urban areas. The second subset was also classified using these rules with only adjusting some values governing the classification functions. While for some classes spectral information in the form of either object mean or spectral variation within objects was used, others could be identified alone one the basis of information referring to shape characteristics and neighbourhood.

The results were compared to an existing aggregated land use classification created in the course of the MURBANDY project. As the classes are not completely comparable and certain restrictions applied to the MURBANDY classification (i.e. minimum mapping unit) it cannot be used as a benchmark but rather as an indication of the classification accuracy. The agreement between the classifications is about 61 % for subset A and 68 % for subset B. While this may seem low the major land cover regions could be successfully identified, with the main differences between classes which can only be correctly assigned when using ancillary data. In addition the absence of roads in the reference data base lowered the overall accuracy. The higher agreement in subset B compared to subset A indicates high generalisation capabilities of the proposed classification scheme. Further improvements are necessary for the detection of roads and rules for urban features, not present in the subsets, must be developed, in order to arrive at a system that can be applied to a larger data set. Once these rules can be used satisfactorily another step is to determine whether parameters can be derived from the images to determine, how different functions must be updated to suit each particular image. Care must be taken to ensure that the rules are as simple as possible to allow an interpretation of the results and to make them adaptable to different scenes.

REFERENCES

Baatz, M. and Schäpe, A., 2000. Multiresolution Segmentation – an optimisation approach for high quality multi-scale image segmentation. In Strobl, J. and Blaschke, T. (Eds.): Angewandte Geographische Informationsverarbeitung XII. Beiträge zum AGIT-Symposium Salzburg 2000. Karhlsruhe. Herbert Wichmann Verlag, pp. 12-23.

Bauer, T. and Steinnocher, K., 2001 Per-parcel land use classification in urban areas applying a rule-based technique. GeoBIT/GIS, pp. 24-27.

Hoffmann, A. and Van der Vegt, J.W., 2001, New sensor systems and new classification methods: laser- and digital camera-data meet object-oriented strategies. GeoBIT/GIS, pp. 18-23.

Hofmann, P., 2001. Detecting building and roads from IKONOS data using additional elevation information. GeoBIT/GIS, pp. 28-33.

Steinnocher K., Ries C., Köstl M., Ehrlich D., and Lavalle C, 1999. Monitoring Urban Dynamics by Earth Observation - The Vienna Case Study. In Strobl J. and Blaschke, T. (Eds.): Angewandte Geographische Informationsverarbeitung XI, Wichmann Verlag, Heidelberg, 1999, pp. 502-509.