

DECISION BASED DATA FUSION TECHNIQUES FOR THE ANALYSIS OF SETTLEMENT AREAS FROM MULTISENSOR SATELLITE DATA

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ABSTRACT

Despite the population stagnation in many industrialized countries, we experience a steady sprawl of urban/suburban space. This fact is based on the migration out of the inner cities, increasing demands on living space, and set-aside of land for commercial developments. In developing countries, this urban growth occurs at dramatic speeds and costs to the environment. Often, planning offices have no or only outdated information about new settlements and their composition in their jurisdiction. The University of Osnabrueck's Institute for Geoinformatics and Remote Sensing has developed a hierarchical method for decision based fusion to automate the delineation of new residential and commercial built-up area. The procedure is based on fusion techniques at the decision level using differently weighted parameters for texture, shape, and spectral characteristics. It was applied to multisensor satellite images from sensors such as SPOT-5, Kompsat 1, Landsat ETM, and Aster. Using this method, accuracies exceeding 90% could be achieved.

INTRODUCTION

Despite rigid laws for environmental protection, the transformation of Germany's agricultural and natural areas into residential and commercial developments has increased to about 130 hectares per day over the last years. To reduce this trend, adequate planning and policy implementations are needed, which in turn depend on the availability of reliable and current spatial information. For this reason, the Institute for Geoinformatics and Remote-Sensing (IGF) at the University of Osnabrueck developed a decision based data fusion technique for settlement area detection from multisensor remote sensing data. A number of high and medium spatial resolution satellites were selected as a basis for a semi-automated detection of settlement areas. The high resolution satellite datasets were comprised of panchromatic images from SPOT-5 with 5 m ground sampling distance (GSD) and KOMPSAT-1 with 6.6 m GSD. Medium resolution multispectral data were obtained from Landsat ETM and Aster datasets with 30 and 15 m resolution, respectively (table 1). The aim was to produce a binary mask with the classes "settlement" and "non-settlement". Settlement is understood as a sum of real estates, traffic surfaces, commercial areas, sport and recreation facilities as well as parks and cemeteries (Apel & Henckel, 1995).

Table 1. Selected satellite datasets

System	Landsat 7	SPOT 5	Terra	KOMPSAT 1
Sensor	HRG	ETM+	Aster	EOC
Recording date	6/26/2001	3/16/2003	8/3/2003	5/20/2004
Geometric resolution in m	30 m	5 m	15 m	6.6 m
Spectral resolution	multispectral (6 bands)	panchromatic	multispectral (4 bands)	panchromatic
Scene size in km ²	180 x 180	60 x 60	60 x 60	17 x 17
Approximate cost in €	600	2750	45	110

METHODOLOGY

Decision Based Fusion

The advantages of iconic image fusion (i.e. pixel based fusion) are that a rich theoretical background exists to discuss appropriate techniques and their associated characteristics (see, for example, Pohl and van Genderen, 1998; and Ehlers, 2005). Also, pansharpened images produce a better visual appearance by combining the high resolution panchromatic image with the multispectral information from the lower resolution image. Unfortunately, for many fusion techniques we experience more or less significant color shifts which, in most cases, impede a subsequent automated analysis (Zhang, 2002; Ehlers & Klonus, 2004). Even with a fusion technique that preserves the original spectral characteristics, automated techniques do not produce the desired results because of the high resolution of the fused datasets. For this purpose, feature based or decision based fusion techniques are employed that are usually based on empirical or heuristic rules. Because a general theory is lacking, fusion algorithms are usually developed for certain applications and datasets.

Contrary to the iconic image fusion techniques, the images we used were rectified to ground coordinates but otherwise left in their original format. Parameters such as texture and shape are extracted from the high resolution panchromatic data, vegetation information from the multispectral images (see figure 1). Using an adaptive threshold procedure, the information from the image datasets is fused and forms a binary mask for the areas “settlement candidates” and “definitely no settlements”. This process is repeated at a hierarchy of differently sized segments ranging from coarse to fine with a set of different threshold parameters at each level (see figure 2). At each step, the next level analysis is only performed in areas that were identified as settlement candidates. More details can be found in Tomowski et al. (2006).

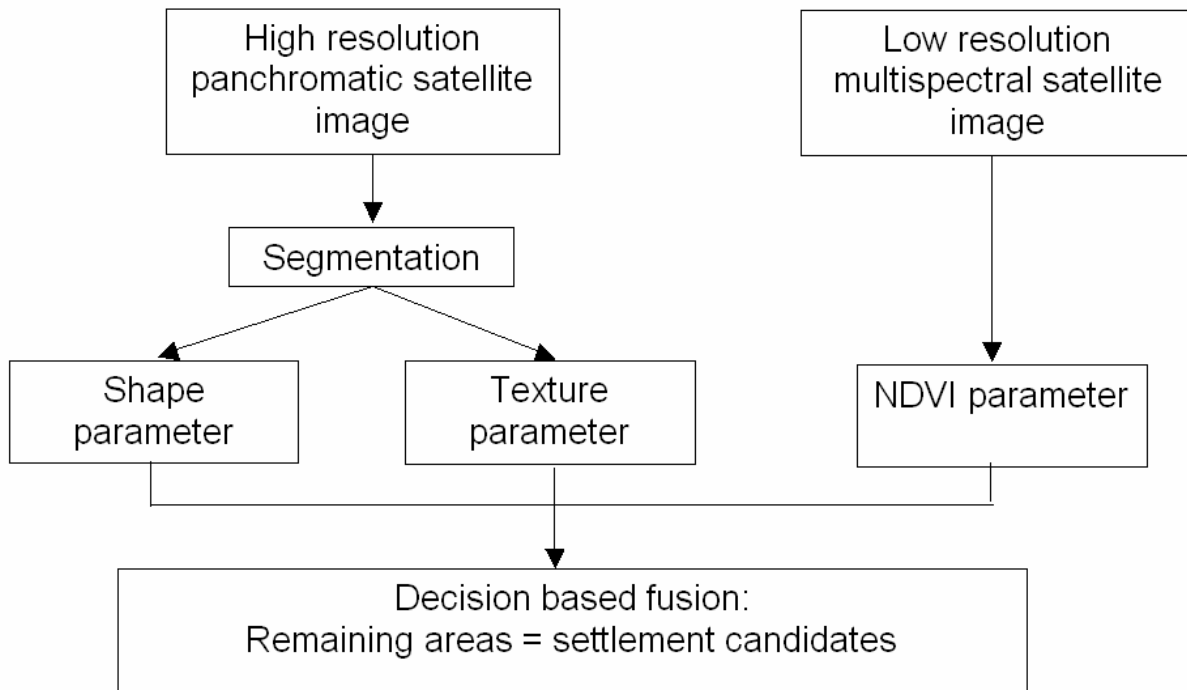


Figure 1. Decision based fusion process. Texture and shape parameters are calculated from the high resolution panchromatic data, whereas the multispectral data are used to calculate vegetation indices.

Hierarchical Segmentation

Our method was applied to two randomly selected test areas (25 km² each), using panchromatic and multispectral satellite data. For the first area, data from SPOT and Landsat were used, and for the second, KOMPSAT and Aster data. The procedure is based on a hierarchical network of segments (Batz & Schaepe, 2000), which consists of three levels. The size of the segments decreases from level 3 (coarse) to level 1 (fine) (table 2). The aim of this subdivision is the

gradual isolation of settlement areas with the help of the hierarchical network (figure 2). The segmentation was applied solely to the panchromatic data.

Table 2. Segmentation parameters for the hierarchical network

	Scale	Color	Shape	Compactness	Smoothness
Level 3	48	0,7	0,3	1,0	0,0
Level 2	24	0,7	0,3	1,0	0,0
Level 1	12	0,7	0,3	1,0	0,0

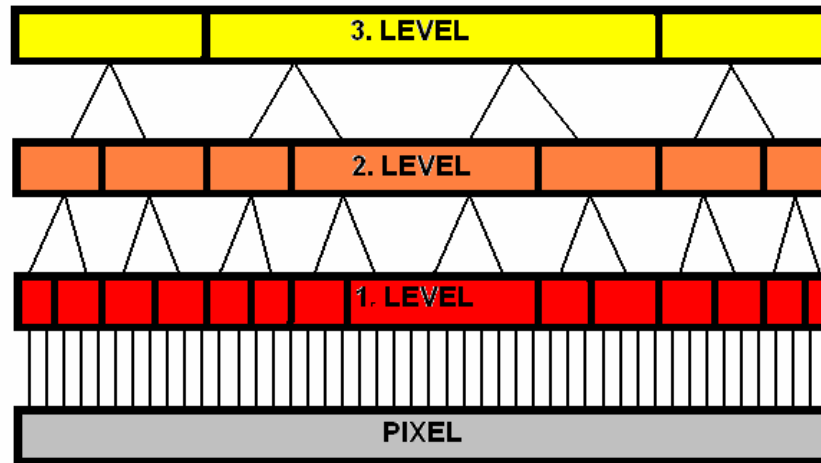


Figure 2. Hierarchical network of segments for the decision based fusion.

The classification algorithm starts at the third (coarsest) level. For each segment of the newly generated class „settlement“, texture and form parameters as well as an average NDVI were calculated. The "gray level co-occurrence" (GLC) matrices (Haralick et al., 1973) that examine the spectral as well as the spatial distribution of gray values in the image form the basis for the texture calculation. A GLC matrix describes the likelihood of the transition of the gray value i to the gray value j of two neighboring pixels. For the differentiation of "settlement" and "not-settlement" we used the inverse distance moment (IDM) derivative from the GLC-Matrix:

$$IDM = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i - j)^2}$$

with

N = row or column number,

i, j = gray value combination in row i and column j of the GLC-matrix,

$P_{i,j}$ = appearance probability of a gray value pair.

With the application of the IDM, it is possible to distinguish between heterogeneous and partially homogeneous non-settlement areas. However, since agricultural surfaces can show texture values similar to settlement surfaces, the use of the IDM alone during the classification may not be sufficient. A solution for the elimination of agricultural surfaces using texture is presented by Steinnocher (1997). He distinguishes three texture qualities to describe surfaces in images:

1. direction dependent inhomogeneous surfaces
2. direction independent inhomogeneous surfaces

3. homogeneous surfaces

If the IDM is calculated for four possible directions in each case (horizontal, vertical, right-diagonal and left-diagonal), it appears that directional-dependent components of the IDM are approximately identical between settlement and forest areas. At agricultural surfaces, however, the IDM values for the vertical direction are higher than in the other directions (Steinnocher, 1997).

This fact can be used for further differentiation. The difference between the values of two texture directions produces results that are significantly larger than zero. The magnitude of the difference between texture values is calculated between horizontal and vertical alignment, and between left-diagonal and right-diagonal alignment of the IDM. As a result, previously unidentified non-settlement areas can be excluded from the settlement candidates area.

At the third level of the segment hierarchy, the form parameter "length/width" (Definiens, 2003) is introduced. After a series of iterative tests it was possible to eliminate rivers and/or highways (i.e. long segments) using this criterion. Finally, further non-settlement areas, such as forests and vegetated areas, are excluded using the average NDVI (normalized difference vegetation index) values, which were calculated for the multispectral satellite data.

The next step of the method starts at the second segmentation level, in which the threshold values for the classification characteristics (texture, form and NDVI) are increased. Additionally, the classification characteristics are only calculated for the settlement areas (so-called filial segments (Ehlers et al., 2005)) that are part of a non-excluding area at the third level. Beside the classification characteristics already known, a new parameter, the compactness degree (C), is introduced:

$$C = \frac{\text{segmentlength} * \text{segmentwidth}}{\text{pixel}}$$

The idea with the implementation of C is that, theoretically, man-made structures (e.g., houses) usually show more compact forms than natural structures (e.g., rivers). This seems to be a reasonable assumption which could be substantiated by a number of tests.

The increase of the threshold values for the second level leads to a successful identification of the settlement areas but also to an elimination of some settlement surfaces within settlement areas (areas with high NDVI or low texture values). The reason for this result is the hierarchical classification based approach, which can lead to undesirable sliver polygons (yellow circles in figure 2) or even missing segments (Schiewe et al., 2001).

In order to integrate these wrongly excluded segments a new class "enclosed segments in level 2" is added to the mother class "settlement". The classification rules for the new class are:

1. Segments must have a slightly stronger texture than that of the class "settlement" to ensure that agricultural surfaces are not assigned to settlement areas in border regions.
2. Segments must be surrounded by at least 50 % of segments of the class "settlement".

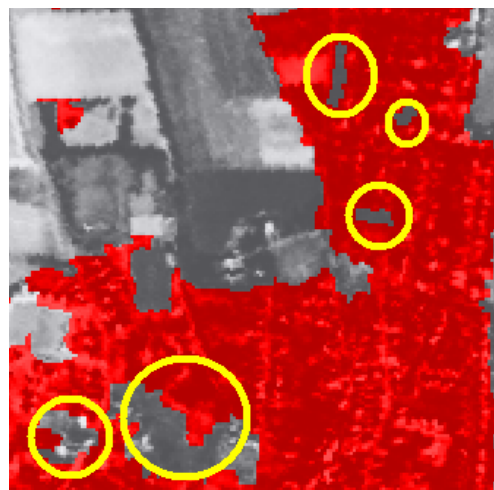


Figure 3. Examples of sliver polygons (yellow circles) within settlement areas (red color).

After the classification of the second segmentation level, the settlement segments are merged and classified with changed segment borders. The idea of this additional step is to assign possible sliver polygons through the fusion of the settlement segments to the class "settlement".

At the segmentation level 1 (finest granularity), the classification rules are again applied but with higher restriction parameters. Through the increase of the threshold values, final non-settlement areas are eliminated. However, also new sliver polygons can be generated. Therefore, the principle to assign these surfaces via a "daughter class" to the class "settlement" is applied again, and a new daughter class "enclosed segments in level 1" is created. In order to retain the assigned sliver polygons of the second level (enclosed segments in level 2) we use the advantages of the hierarchical classification network. Using the definition of a relationship to the super objects (sliver polygons from the second level), we assign these areas to the mother class "settlement" of the level 1. After the classification of this segmentation level, the settlement segments are also merged and classified based on the changed segment borders.

Fine Tuning

Further processing steps to improve the quality of the classification are introduced at the fine tuning step. A classification criterion to identify incorrectly assigned agricultural surfaces (such as surfaces without vegetation and high texture values), has to be found. Usually, agricultural surfaces show a low gray value variance, while settlement surfaces show a high gray value variance (Jürgens, 1997). To take advantage of this fact, the segmentation levels 2 and 3 are deleted. In the next step, the settlement segments of the level 1 are merged to larger segments and the gray value variance is calculated for each segment. The merging of the segments has the particular advantage that the settlement areas are no longer modifiable (no sliver segments appear) and merged settlement areas always have a high gray value variance (while small agricultural surfaces have a low gray value variance). As a result, further non-settlement areas are excluded.

Since the goal of this study is the identification of settlement area, and not the identification of impervious areas, inner-urban regions such as parks, water bodies or cemeteries with low texture values have to be integrated as a last step. For this purpose, the settlement segments are recoded and saved as a 1-bit image.

After a new gray value weighted segmentation of the image, it is possible to differentiate between settlement segments and sliver polygons; because settlement surfaces and sliver polygons have gray values of 1 and 0, respectively. The inner-urban surfaces without texture represent individual segments that are completely surrounded by settlement areas with a gray value of 1. The classification produces the desired binary settlement mask.

The procedure described above was applied to both datasets. Since KOMPSAT data have a lower spatial resolution (6.6 m) than the SPOT data, the threshold values for the texture parameters received a lower weighting factor.

RESULTS

For the first test area (figure 4, left), the borders between "settlement" (red) and "non settlement" (no color) are represented with a low level of generalization (borders are not smooth). A few vegetated areas such as playgrounds or parks (green circles) are missing and small houses or farms outside the kernel settlements (yellow circles) are not completely included. In general, however, the decision based fusion method produces excellent results for both datasets and test areas.

Despite the differences between the datasets, the results were very similar (see figure 4, right). Contiguous settlement areas (high density areas) were certainly detected. For an analysis of the final accuracy, settlement areas were manually digitized and compared to the ones selected by the automated hierarchical processing at each level (table 3).

Table 3. Users' accuracy for the detection of settlement areas

Hierarchical Level	SPOT-5/Landsat ETM Fusion	KOMPSAT/Aster Fusion
3	19.79%	45.28%
2	76.31%	84.18%
1	92.06%	95.03%
Final	93.51%	97.26%

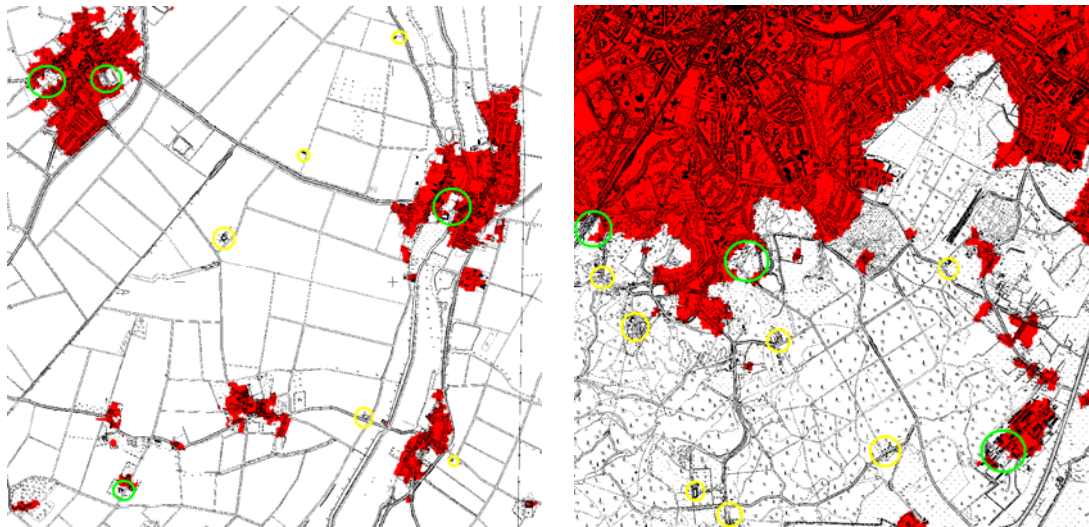


Figure 4. Final result of the decision based fusion: Results of the SPOT/Landsat fusion (left) and the KOMPSAT/Aster fusion (right).

For both combinations, results are almost identical and exceed 93% users' accuracy (see Congalton & Green, 1993) at the final level. Kappa values (see Cohen, 1960) are 0.8427 and 0.8968 for the first and the second test area, respectively. Based on an evaluation scale proposed by Ortiz et al. (1997), which ranges from "very bad" to "excellent", both test area classifications are rated as "excellent".

CONCLUSIONS

We have developed an efficient and accurate semiautomatic decision based data fusion for the detection of settlement areas. This procedure works equally well with different multisensor satellite data and classification results can be successively improved at each classification step (see table 3).

Some limitations were observed when trying to identify smaller settlement areas (farms or individual houses) or areas with high vegetation within settlements (sports grounds and parks). The reason for this is the generalization that takes place during the segmentation steps (see also Koch et al., 2003). A possibility to reduce this problem is to combine the generated binary mask with the result of a pixel-based classification method. The time required to find optimal segmentation parameters and thresholds for the classification characteristics was higher than desired (see also Schiewe et al., 2001). Another disadvantage was the impossibility to use the segmentation software (eCognition) to completely automate the procedure, or to plan additional alterations to the segmentation process with a programming interface (Tomowski, 2006). Also, for the accuracy analyses one should consider that different interpreters may produce different ground truth masks for comparison. This means that we would always have a certain amount of background noise for our analysis and an accuracy of 100% cannot be achieved at all.

In the comparison to the pixel based classification procedures, it is, however, evident that the introduced object and decision based procedure leads to better results because no salt-and-pepper effects appear (Koch et al., 2003). Settlement areas are identified as uniform regions that do not include incorrectly classified single pixels or small pixel groups. In addition, claims by Meinel et al. (2001) that the segment based classification method leads to a decrease of unclassified areas could be proven through the consistent use of exclusion areas in the binary mask. Furthermore, we showed that the procedure is transferable to different data sources (SPOT/Landsat or KOMPSAT/Aster) without altering the procedure or the employed parameters. Contiguous settlement areas were correctly detected in both test areas. Based on the definition of settlement proposed by Apel & Heckel (1995), it is possible to use the generated binary settlement mask as a basis for a landuse/landcover classification.

Improvements of our approach to allow the identification of smaller settlement areas warrant further research. We

will also investigate if other options exist to fully automate our procedure. The method will be further tested with very high spatial resolution satellite images such as Ikonos and Quickbird satellite data.

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