

AUTOMATIC DISCRIMINATION OF FARMLAND TYPES USING IKONOS IMAGERY

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ABSTRACT:

The aim of this paper is to introduce an approach for the discrimination between the farmland types cropland and grassland from single satellite images by estimating the main direction of cultivation in cropland. The approach uses structural features caused by the cultivation, in particular straight lines caused by agriculture machines. The core of the approach is the transformation of an edge image into Hough space, and a following interpretation of the results to determine the main direction. The new approach is presented in detail and is illustrated with the help of examples. The examples and the evaluation demonstrate the potential and the limits of this approach.

1. INTRODUCTION

An immense amount of decisions in private and public life relies on geospatial information. The automatic management of spatial data is performed in geoinformation systems. The usefulness and acceptance of such geoinformation systems mainly depend on the quality of the underlying geodata. The availability of high resolution optical satellite imagery appears to be interesting for geospatial database applications, namely for the capture and maintenance of geodata. Among others, Büyüksalih and Jacobsen (2005) show that the geometry of IKONOS and Quickbird imagery is accurate enough for topographic mapping.

The main topic of this paper is the automated verification of existing topographic data using high resolution satellite imagery. For this task we have set up an interdisciplinary project called WiPKA-QS^{**}. One of the main tasks in WiPKA-QS is to extend the approach regarding the discrimination between deciduous and coniferous forests and between cropland and grassland. For the verification of these object classes we use explicit radiometric features as well as structural features (Busch et al., 2006).

The object classes cropland/grassland cover a large area in many countries and are therefore of prime relevance. Hence, we focus on the discrimination of these classes at first. A main differentiation between grassland and cropland is the exploitation of structures caused by the cultivation, which is conducted more frequently in crop fields compared to grassland. The agricultural machines normally cause parallel

straight lines which are observable in the image. Our approach for the detection of these parallel straight lines is divided into three steps; we detect edges which then are transformed into Hough space, and finally the orientation is estimated.

In this paper, we present at first related work and discuss briefly the applicability of this work to our problem of discrimination between cropland and grassland. After an introduction to the project WiPKA-QS, we describe our Hough-based approach, and we give four examples. The last section concludes the paper.

2. RELATED WORK

In this selection we briefly review approaches for extracting different vegetation types based on structural and radiometric features. A more complete review of extracting vegetation objects, e.g. based on hyperspectral information or multi-temporal imagery, is beyond the scope of this paper.

The idea to use structural features is also pursued in (Trias-Sanz, 2006) who uses structural properties to discriminate objects with similar radiometric and textural properties (e.g. forest and plantation) in high resolution satellite images. These object classes can be distinguished only by precise orientation characteristics e.g. forest and untilled fields have none, tilled fields have one, and orchards and vineyard have two main structure directions. All computations are carried out within a pre-selected window called texton, whose shape and size can be arbitrary. The starting point is the calculation of a variogram which is similar to autocorrelation. After the transformation of the variogram into a special accumulation space, a histogram of this space is derived. The maximum of the function in this histogram corresponds to the primary direction in image space. A disadvantage of this approach is that the appearance of the structural features like cultivation structures and field crop has

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to be homogeneous. This approach can be used to discriminate a large number of object classes by properly choosing the texton, but can yield wrong results if the texton parameters are selected inappropriately. In contrast, we focus on the discrimination of only two object classes (grassland and cropland).

Additional methods for the determination of structural features are the Fourier and Radon transformation. Chanussot et al. (2005) estimate the orientation of vineyard rows automatically using the Fourier spectrum of a pre-processed image and its Radon transformation. However, the authors apply their method to high resolution aerial data only, and furthermore, a very important assumption is a regular spacing between the rows. This assumption is usually satisfied for vineyards, but not necessarily for cropland. In cropland the distance between rows can vary from one field to the next, depending on the culture of vegetation, and the kind of machine which was used, and furthermore, the visibility of the structures in the image of one field.

A huge number of publications deals with various approaches of orientation estimation.. Le Pouliquen et al. (2002) use convolution masks for a scale-adaptive orientation estimation which is divided into a gradient based and valleyiness operator. Compared to this approach, De Costa et al. (2002) use orientation difference histograms. The focus of the approach of De Costa et al. is not the quantitative estimation of the direction, instead only the existence of a direction is of interest. This idea is also sufficient to characterize cropland. However, both approaches were tested for synthetic images only.

Warner and Steinmaus (2005) identify orchards and vineyards in IKONOS panchromatic imagery. In this approach the classes are detected using autocorrelation. After the definition of a square kernel and the normalization of each pixel of this kernel the autocorrelation for the cardinal directions and both diagonals is determined. For each autocorrelation calculation (called autocorrelogram) each pixel is analyzed separately to identify orchards. An orchard pixel is detected if an orchard pattern is identified in more than one autocorrelogram centered on the same pixel. However, the trees have to be approximately equally spaced. Similar to the aforementioned approach of Chanussot et al. (2005) this assumption is usually not met in cropland.

Radiometric features were used by Itzerott and Kaden (2006 and 2007) to discriminate between various farmland types. They analysed typical economic plants and grassland in the German federal state of Brandenburg. It was shown that grassland possesses a non-zero NDVI (Normalised Difference Vegetation Index) in all seasons, whereas during the winter season several agricultural plants have a very low NDVI which is significantly different from the NDVI of grassland.

The literature review shows that some work on the classification of farmland types using structural and radiometric features has been done. However, either the approaches rely on training samples or on precise knowledge on the structure or radiometric properties of the field class, i.e. they are model-driven. For our approach we want to be independent of such conditions and therefore pursue a more data-driven approach.

3. AUTOMATIC DISCRIMINATION OF FARMLAND TYPES

3.1 Workflow of WiPKA-QS

The aim of the project WiPKA-QS is the automated verification of the German topographic reference dataset ATKIS^{***} or in general GIS. The main components of ATKIS are the object based digital landscape models (DLM) encompassing several resolutions with a geometric accuracy of up to +/-3m.

The core of the automated procedure is the knowledge-based image interpretation system GeoAIDA (Bückner et al., 2002). GeoAIDA uses a semantic network that represents the scene to be analyzed. First, in a top-down or so called model-driven step, the system searches for evidence for the object to be verified in the orthoimage. Evidence can be the existence of a main direction of cultivation. Thereby, the system focuses only on objects of interest. Afterwards, in the bottom-up or so called data-driven step, the system derives an acceptance or rejection decision assessing the evidence. Hence, discrepancies between objects and the image features can be detected. Is the verification of an object successful the system labels this object as accepted (green); otherwise the object is labelled as rejected (red). For the rejected objects, a final decision is made by a human operator. Further details of the system are available in (Busch et al, 2004) and furthermore in (Müller and Zaum, 2005), its workflow is sketched in Figure 1.

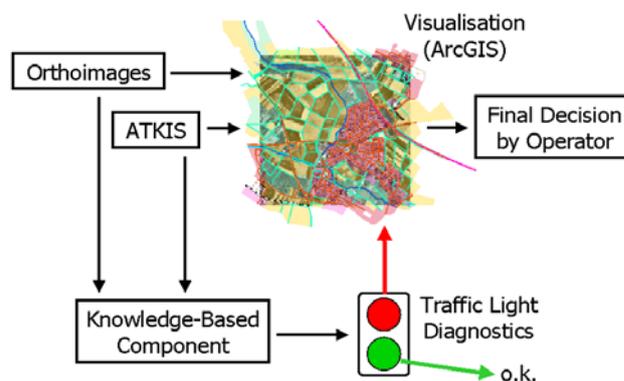


Figure 1: Workflow WiPKA-QS

3.2 Strategy

The underlying semantic model of the approach is shown in Figure 2. The first level of the semantic net describes the *Real World*: farmland can contain cropland and grassland, and furthermore cropland consists of untilled or tilled cropland. The second level *Geometry/Material* explains the geometrical and material characteristic of the objects. Finally, the *Imagery* level shows the characteristics which are visible in the image.

*** Amtlich topographisch-kartographisches
Informationssystem (Authoritative Topographic
Cartographic Information System)

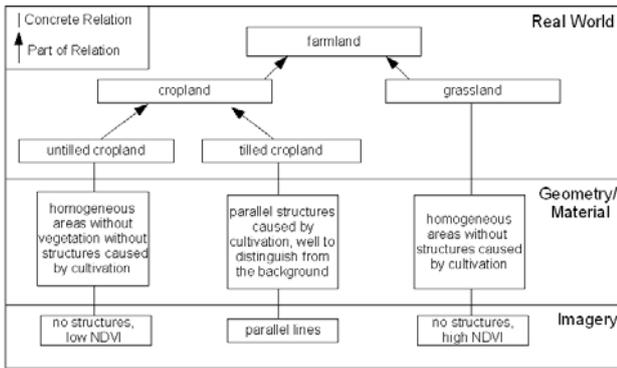


Figure 2: Knowledge Presentation using Semantic Net

Untilled cropland shows no structural features, at least in the image resolution we are dealing with. The discrimination between untilled crop fields and grassland in which structural line features are not visible is achieved using radiometric features like in this case the NDVI. Untilled cropland has a low NDVI, whereas the NDVI of grassland is usually rather high. If we detect no vegetation, grassland can be ruled out (Itzerott and Kaden, 2006 and 2007).

Furthermore, three issues must be considered. First, due to disturbances in the object border area, e.g. structures caused by turning agricultural machines, the approach is restricted to the interior object area. The reduction is done using simple erosion.

Second, in ATKIS or other GIS, inside one object the existence of more than one land cover class are tolerated if a size threshold is not exceeded. Furthermore, several objects of the same land cover type are permitted. For example, in an ATKIS object "cropland" the existence of a small area of grassland is allowed and it is possible that several crop fields with different cultivation directions are present. Therefore, a verification of one object is performed subdividing the objects into segments of radiometrically homogeneous regions; or alternatively, tiles as shown in Figure 3 before further processing. In the top-down step our approach searches for evidence for the existence of a main direction in each segment or tile. In the bottom-up step adjacent segments or tiles with the same main direction are merged, and subsequently, the object is assessed.

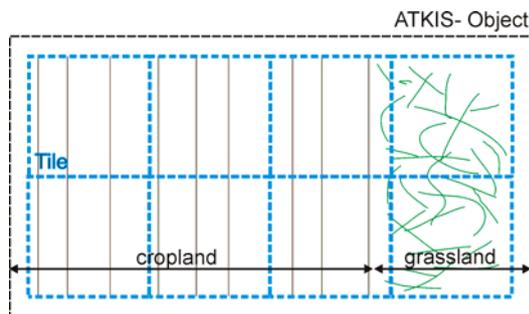


Figure 3. Schematic sketch for tiling a GISObject

In this paper we focus on the image analysis step – the top-down step where we discriminate cropland and grassland using structural as well as radiometric features in one segment or tile.

3.3 Approach to the estimation of structural features

3.3.1 Edge detection

We work with pansharpened four-channel (RGB and Near Infrared) images with a spatial resolution of 1m. An example of a cropland object is shown in Figure 4. Currently, we compute an average grey value for each pixel from the four channels (termed 'intensity channel' in the following).



Figure 4: Image of a cropland object represented in RGB

In a pre-processing step the images are enhanced such that the contrast is optimized and further an edge-preserving smoothing limits the impact of noise to edge extraction. Then, a pre-processing an edge image is computed using the Canny operator (Canny, 1986). Compared to other edge detection operators, the Canny operator permits a better detection of edges, especially under noise conditions (Sharifi et al., 2002). Due to the described pre- processing step only little attention needs to be paid to the trimming of parameters for the edge extraction. The edge image of the cropland object depicted in Figure 4 is shown on the left side of Figure 5.

An alternative to edge extraction would be to extract lines (bar edges), e.g. using the sophisticated line extraction operator proposed by Steger (1998). However, not all structures in the field appear as lines with a distinct and constant width. Therefore, to extract edges is the more general approach here.

3.3.2 Hough space

An analysis of the structure inside the field is carried out by transformation of the edge image (image space) to a proper accumulation space (Hough space). The line parameters in image space are the angle between the normal vector of the line and the x-axis (ϕ), the distance of the line from the origin (d). Figure 5, right side, shows an illustration of a cropland object in image space and in Hough space.

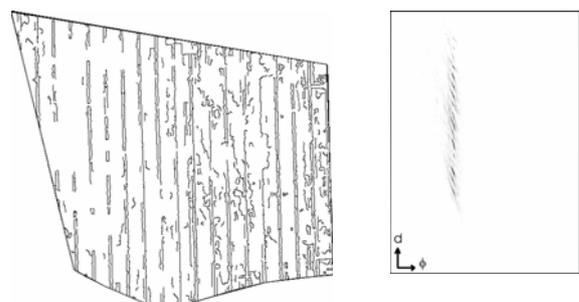


Figure 5: Edge image (left) and its Hough space representation (right) of the cropland object shown in Figure 4

Thus, parallel lines are mapped into points situated vertically above each other, assuming the ϕ -parameter is mapped to the horizontal axis in Hough space. Furthermore, if the space between lines in image space is constant, a periodicity of the point positions in Hough space is observable.

By extracting these points in the Hough image we focus on salient lines in image space. Points are extracted using the Förstner operator (Förstner and Gülch, 1987) and are called points of interest (POI).

3.3.3 Orientation Estimation

In the next step, a histogram of the extracted points along the ϕ -axis in Hough space is derived. The histogram of the previous cropland object is shown in Figure 6. The unit for ϕ on the x-axis is grad, the y-axis shows the number of occurrences of the angles.

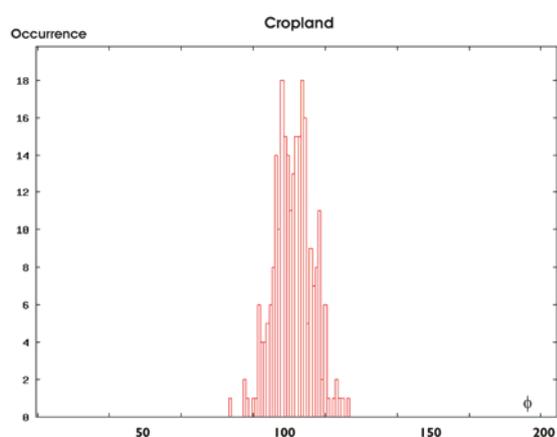


Figure 6: Histogram of angles in Hough Space of Figure 5 (right)

3.3.4 Assessment

As a final step we investigate the in the histogram probable direction of cultivation by computing the largest peak in the histogram, and in addition the standard deviation σ for this peak. For cropland σ must lie below a pre-defined threshold t , whereas for grassland σ is assumed to be larger than t . In addition, a number of at least s lines with the same direction must have been detected. The parameters s and t are defined heuristically. In Figure 6 σ amounts to approximately 5grad and at least 5 lines with the same direction are detectable. Finally, the object depicted in Figure 4 is accepted as a cropland object.

3.4 Examples and Evaluation

The described approach was implemented and tested on a number of IKONOS images. Here, we show results obtained from a scene acquired on June-24m, 2003 in the area of Weiterstadt, Hessen. In addition, we present results from a scene close to Rostock, Mecklenburg- Vorpommern acquired on July-27, 2006.

Examples of images, edge images, and derived histograms of ATKIS grassland and croplands objects are shown in Figure 9- Figure 11. In the histogram of grassland of Figure 9 a significant edge direction is not detectable, and the object is accepted by the verification system.

The results presented in Figure 10 indicate that object can be accepted as cropland. Although, the edge image is not as clear as the one in Figure 6, a main direction can still be detected unambiguously.

In contrast to the preceding example, in Figure 11 a successful verification of the cropland object is not possible. The cultivation lines are not separable from the background as can also be seen in the edge image. In the histogram a significant peak can not be detected. The verification system rejects the object – a false negative decision.

For the second scene depicting an area close to Rostock the approach was tested on the whole image compared to the few shown examples of the scene Weiterstadt. An example of a cropland object in this scene is shown in Figure 12. The peak of the main direction is at 12grad. The standard deviation is 3.6grad. In the histogram three peaks are visible. The first peak has the highest occurrence and is the main direction of cultivation. The second peak has an occurrence of less than five and lies below the threshold. This peak is noise in the image caused by disturbances, i.e. in this case the trees inside the field. The third peak is a part of the first one, appearing at approximately 200grad due to the periodicity of the edge direction.

The results of the scene Rostock are investigated using a confusion matrix (Figure 7). The percentage of corresponding acceptance indicates the efficiency of the approach. There will also be undetected errors if objects which have been accepted by the automatic procedure, are rejected by the human operator. The percentage of undetected errors has to be as small as possible.

	Automatic	Green	Red
Human Operator			
	Green	Efficiency	Interactive Final Check
	Red	Undetected Errors	Interactive Final Check

Figure 7: Confusion Matrix

In Figure 8 the confusion matrix for the scene Rostock is shown. At this scene 77 cropland objects are checked by a human operator and by our approach. Objects rejected by automatic system need to be checked by the human operator interactively. The threshold t for σ is 5grad, for s a value of 5 is chosen. As shown in Figure 8 the efficiency of our approach is around 55%, the false alarms are 31%. 11 objects (14%) which were wrong in the GIS are detected by the system automatically. Undetected errors are not present.

	Automatic	Green	Red
Human Operator			
	Green	55%	31%
	Red	0%	14%

Figure 8: Confusion Matrix of the scene Rostock

3.5 Discussion

The examples show the potential of the approach. In general the presented approach is rather robust, because given all the edge pixels we are only interested in two single value, namely the

number of occurrences in the highest peak of the angle histogram and its standard deviation. Therefore, gaps in the edge image have little influence on the determination of the main direction.

It should be noted that rather than transforming the edge image into Hough space followed by projection to the ϕ -axis, we could have derived the edge direction histogram directly from the edge image. However, the resulting histograms are much noisier, if no operation analogous to the POI selection in Hough space is carried out.

The whole strategy of this approach fails if

- line structures caused by cultivation are not observable (e.g. maize close to harvest, untilled crop fields)
- lines in crop fields are not straight respectively parallel to each other (e.g. on hillsides),
- grassland possesses parallel lines

Regarding the first point, we already described the verification of untilled cropland at the beginning in section 3.2 using NDVI. The last two aforementioned cases are not very common in Germany. However, the influence of these problems is to be investigated, and if necessary the strategy is to be modified.

4. CONCLUSIONS

We describe a strategy for the automatic discrimination of the farmland types grassland and cropland using IKONOS imagery by detecting parallel lines caused by cultivation.

Concentrating on the interior object area, first, we check the NDVI to rule out untilled fields. The core of the structure based approach is the detection of edges using the Canny operator. The edge image is then transformed into Hough space. After the determination of points of interest (POI) in Hough space, a histogram is calculated. This histogram represents the number of occurrences of POI depending on the angles. The assessment which land cover object is present is conducted by using a statistical interpretation of the histogram.

An advantage of our approach is the fact that periodic rows or a minimum distance between rows are not required. Furthermore, since we are using edge detection in contrast to texture a training of parameters is not necessary. Therefore, an intervention of a human operator is only necessary to check rejected objects. First results for cropland objects have shown the efficiency of our approach to be around 55%.

We conclude the paper with a brief outlook to the next steps which are the segmentation of fields and the definition of tiles in every GIS object. Additionally, a final assessment step of the respective GIS object in the bottom-up step by merging the results of every segment/ tile, and the results of other operators of WiPKA will be developed. In addition the approach will be tested on more scenes for cropland and grassland objects.

5. ACKNOWLEDGMENT

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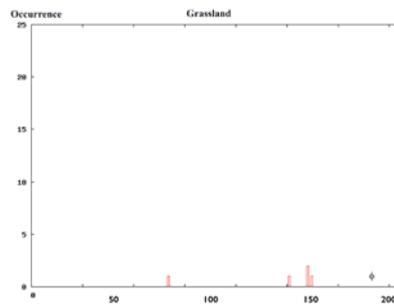
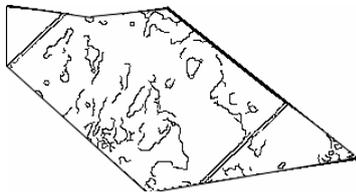


Figure 9: Image space, edge image and histogram of a grassland example (from left to right)

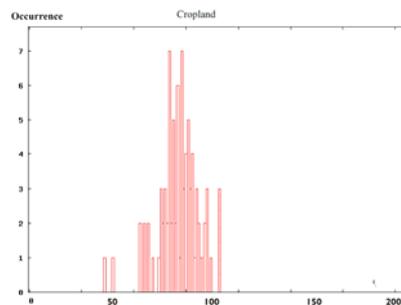
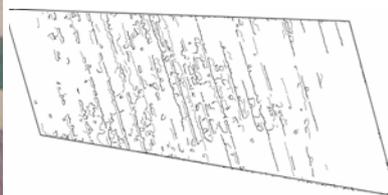


Figure 10: Image space, edge image and histogram of a cropland example (from left to right)

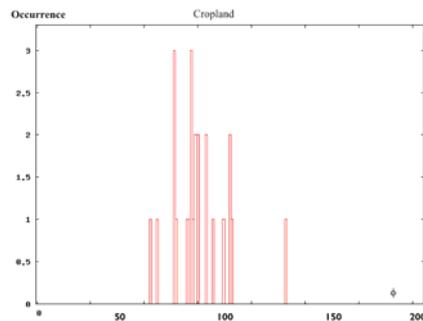
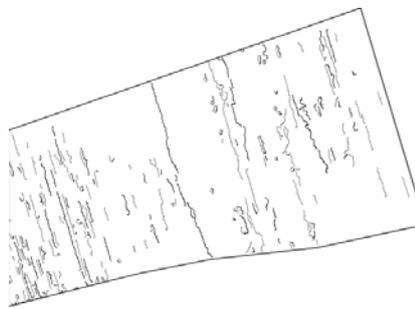


Figure 11: Image space, edge image and histogram of a cropland example (from left to right)

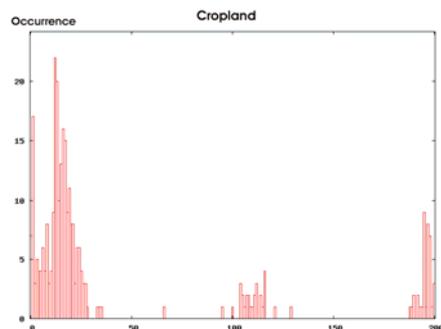
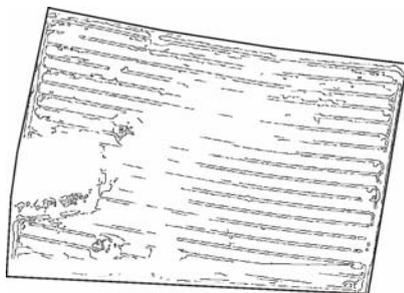


Figure 12: Image space, edge image and histogram of a cropland example (from left to right)