SEGMENTATION OF OPTICAL SATELLITE IMAGERY USING SPATIAL SUBPIXEL ANALYSIS*

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ABSTRACT

Due to low resolution of satellite imagery in relation to the size of observed objects the problem of mixed pixels arises. These pixels have spectral signatures being a combination of two or possibly more pure spectral signatures of objects (e.g. agricultural parcels, roads, etc.). In this contribution, a satellite image is segmented using standard segmentation algorithm to obtain mean pixel values of regions. The second step uses "edgel chains" to obtain region boundaries to subpixel accuracy. These two steps deliver the parameters for correcting the mean pixel values of regions by subpixel analysis.

KURZFASSUNG

Die niedrige Auflösung von Satellitenbildern in Relation zu den zu untersuchenden Objekten verursacht das Problem von Mischpixeln. Die spektralen Signaturen dieser Pixel bestehen aus einer Kombination von zwei oder mehr reinen Signaturen von Objekten (z. B. Landwirtschaftsflächen, Straßen, etc.). Dieser Beitrag behandelt dieses Problem in zwei Schritten. Das Satellitenbild wird mit herkömmlichen Segmentierungsalgorithmen segmentiert. Im zweiten Schritt werden sogenannte "edgel chains" verwendet, um Objektgrenzen in Subpixelgenauigkeit zu erhalten. Die Kombination dieser beiden Ergebnisse liefert die Parameter für die Verbesserung der mittleren Pixelwerte von Objekten durch räumliche Subpixelanalyse.

1 MOTIVATION AND INTRODUCTION

In [1], a physical model for the image acquisition process is discussed and formulated. The inversion of the model is used for remote sensing image understanding. The model transforms the reflectance values of objects (regions on the terrain surface) to pixel values in the image. It is advisable not to work on a pixel-by-pixel basis, but rather to segment the image into "region tokens" (i.e. sets of pixels belonging together in some sense) prior to the inversion process. A feature vector for each region token is produced containing necessary image parameters for the physical model. Possible parameters are mean pixel intensity, pixel variance, etc. There are at least two advantages of the segmentation approach: The amount of information to be processed in the model inversion step is reduced, and the "mixed pixel problem" can be managed if a proper subpixel segmentation procedure is employed.

New sensors with higher resolution are being developed questioning the need for spatial subpixel information. However, the following arguments speak for the usefulness of spatial subpixel analysis:

- Availability of satellite images is a problem when used operationally considering bad weather conditions or other impairments. It may thus be necessary to be able to use images from any sensor available.
- The objects to be examined can be smaller, e.g. trees, houses, etc.

In the first part of this contribution, standard segmentation algorithms well known to the computer vision community are applied to remotely sensed imagery. There is no classification involved. The segmentation is based solely on spectral homogenity properties of pixels in a region.

The second part deals with finding object borders with subpixel accuracy. Edgel chains provide the means to find those borders. Spatial subpixel analysis is applied to correct the mean pixel values of regions.

The segmentation and the production of edgel chains do not influence each other so that they can be executed in parallel to increase the speed of the process (see also figure 1).

2 STANDARD SEGMENTATION ALGORITHMS FOR SATELLITE IMAGERY

A pixel in the interior of a region has only small intensity differences to the other pixels in the region. Thus, spatial subpixel analysis of interior pixels is not practical. Even though it might be a mixed pixel, spatial subpixel analysis achieves no improvement. Segmentation of the image delivers boundary pixels neighboured to pixels with high intensity differences in their spectral signatures.

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For a start, standard segmentation algorithms are investigated. Some examples are watershed [3], zero crossing [4], and region growing [5], that deliver region tokens directly. Region growing can be performed with multiple input images so that the segmentation can be based on several bands of satellite imagery. The performance is improved further by combining these methods with pure edge detection algorithms, e.g. Canny [5], Burns, Gradient Edge, etc. It turns out that these methods are quite suitable for the segmentation task and deliver good results.

A region growing algorithm with adaptive thresholding was employed to obtain figure 2. Let t be a fixed threshold value indicating where a region stops to grow. Adaptive thresholding modifies the threshold $t_{adaptive}$ dynamically according to the mean m and standard deviation σ of the region as it is being grown. The modification equation is based on an algorithm by Levine and Shaheen [6] and is given by:

$$t_{adaptive} = t \cdot (1 - \min(0.8, \frac{\sigma}{m})) \tag{1}$$

the adaptive threshold $t_{adaptive}$ will never be larger than the value t but can be much smaller. This method prevents "bleeding" across slow image gradients (see [6],[2]).

Ultimately, "pure" spectral signatures of the region tokens have to be calculated. Region tokens consist of boundary pixels and interior pixels. Interior pixels provide pure intensity values for the acquisation of the signatures, whereas boundary pixels (4- or 8-adjacent to pixels outside the region token) are most likely mixed pixels, which falsify the spectral signatures. The problem of mixed pixels is a severe one if the average size of region tokens is not much larger than the pixel size, thus, having only few interior pixels with pure signatures. In this case, there will be a very high percentage of mixed pixels. It is therefore necessary to apply spatial subpixel analysis.

The mean pixel value of regions is determined from the interior pixels. In case of regions with few interior pixels, the boundary pixels are used to compute the mean pixel value. Additionally, a reliability index r for each region is made available.

$$r = \frac{A^{pure}}{A^{mixed}}, \tag{2}$$

where A^{pure} is the area of pure pixels and A^{mixed} the area of mixed pixels. Before spatial subpixel analysis is applied, r is equivalent to the ratio between interior pixels and boundary pixels. r is modified dynamically as mixed pixels are subpixel analysed.

3 SPATIAL SUBPIXEL ANALYSIS

There are several approaches to deal with the mixed pixel problem (see [7],[8],[9],[10],[11]). In this contribution, "edgels" are applied to obtain spatial subpixel information for digital images of scenes built up of homogenous regions delimited by edgel chains.

Edgels are tokens defined by the following features:

- point location at subpixel accuracy,
- gradient magnitude (Several kernels, e.g. Roberts, Prewitt, Sobel with dimension 3×3 or 5×5 are possible for computing the gradient.),
- gradient angle, indicating the direction of the gradient.

Edgel detection is based on the following criteria:

- high gradient magnitude, above a specified threshold,
- locally maximal gradient magnitude in the gradient direction.

Edge detection is performed at each pixel. If an edgel is found (i.e. the gradient magnitude is above a specified threshold), the location is determined to subpixel accuracy along the gradient direction.

Edgels adjacent according to some metric are then linked to "edgel chains" (i. e. open polygons, see also figure 3). Parameters such as the angle between an edgel gradient and the link to an adjacent edgel, the angle between gradients, as well as the link length of adjacent edgels are used in the chaining algorithm.

Once the edgel chains are determined, every triple of consecutive edgels in a chain (the edgels $i-1, i, i+1$ for $i = 2, \cdots n-1$, n is the number of edgels in a chain) are used to produce a least mean square error line segment fitted to these edgle triples. The error distance is measured by the normal distance from the edgels to the line. The endpoints of the line fit are the maximum extents of the projections of the edgels onto the line. The midpoint of these line segments is used to obtain the coordinates of a pixel. If this pixel is a boundary pixel of a region, it is subject to spatial subpixel analysis (see figure 4).

The mixed pixel value

$$p = f_1 p_1 + f_2 p_2 \tag{3}$$

is considered a linear combination of different signatures of two adjacent regions as separated by the edgel chain (or line segment). f_1 and f_2 are the area portions of the mixed pixel. The line segment as described above delivers the parameters to determine f_1, f_2. It is reasonable to use mean pixel values, m_1, m_2, of the two regions adjacent to the mixed pixel for computing the values p_i. If the values m_i have high reliability, i.e. the reliability index r is high, the mean intensity values cannot be corrected. If both m_i are of low reliability then the mixed pixel is marked for further processing. However, if one m_i is of low reliability, then a correction of the mean intensity values can be achieved. Let m_1 the mean pixel value of the region with higher reliability. p_1 is then replaced by m_1. p_2 is calculated according to the above mentioned relationship 3:

$$p_2 = \frac{p - f_1 m_1}{f_2} \tag{4}$$

The mean pixel value of region 2

$$m_2 = \frac{\sum_{j=1}^{n} s_j}{n} \tag{5}$$

with low reliability r_2, where n is the number of pure pixels in the region and s_j the spectral signature of pixel j, is modified as follows:

$$m_2^{new} = \frac{f_1 m_1 + \sum_{j=1}^{n} s_j}{f_1 + n} \tag{6}$$

The reliability index r_2 is also modified in the following way: Let A_2^{pure} be the area of all pure pixels, and A_2^{mixed} the area of the mixed pixels of region 2.

$$r_2^{new} = \frac{A_2^{pure} + f_2}{A_2^{mixed} - 1} \tag{7}$$

The modification of r increases the reliability of regions. The next iteration deals with marked mixed pixels. The iteration is repeated until all mixed pixels were processed or until no change occurred from one iteration step to the next. This iteration makes it possible to obtain reliable signatures of low reliability regions surrounded by low reliability regions.

Figure 5 shows boundary pixels rendered with the mean pixel values of the regions they belong to together with line segments superimposed.

4 CONCLUSION AND OUTLOOK

Standard segmentation algorithms are applied to remotely sensed imagery, delivering region tokens. Boundary pixels intersecting edgel chains are then subject to spatial subpixel analysis. This approach proves useful for obtaining radiometrically reliable signatures of region tokens, even in the case of high percentage of mixed pixels.

Of course, the result of this work represents a preprocessing step to the physical model approach as in [7] or some other kind of classification.

The edgel chain information can be used to extract lines as borders of objects with subpixel accuracy. These lines can build the basis for fusing satellite images with cadastral information, a research area becoming increasingly important. This problem is being dealt with in [12].

5 ACKNOWLEDGMENTS

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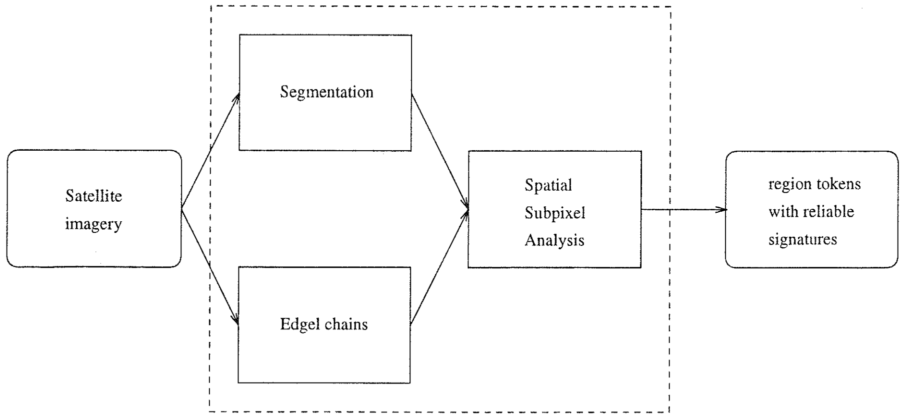

Figure 1: Diagram of proposed algorithm

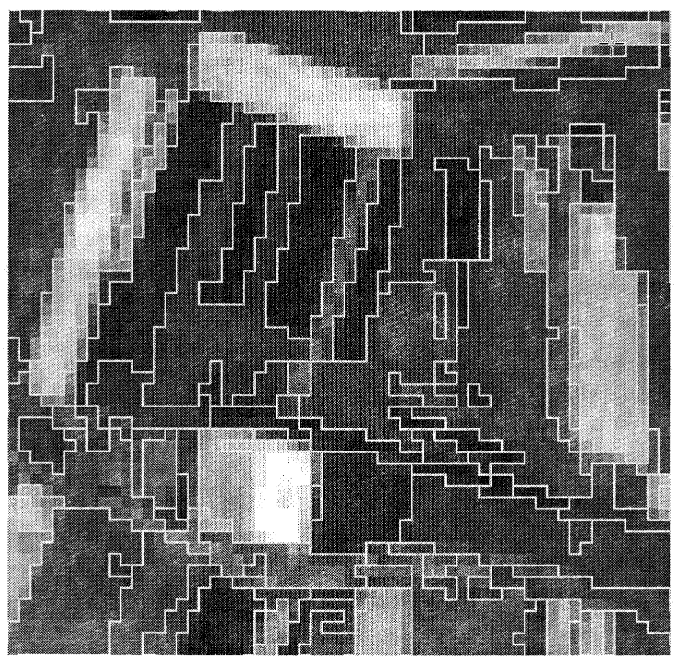

Figure 2: Band 4 (near-infrared) of Landsat TM image, region token borders superimposed

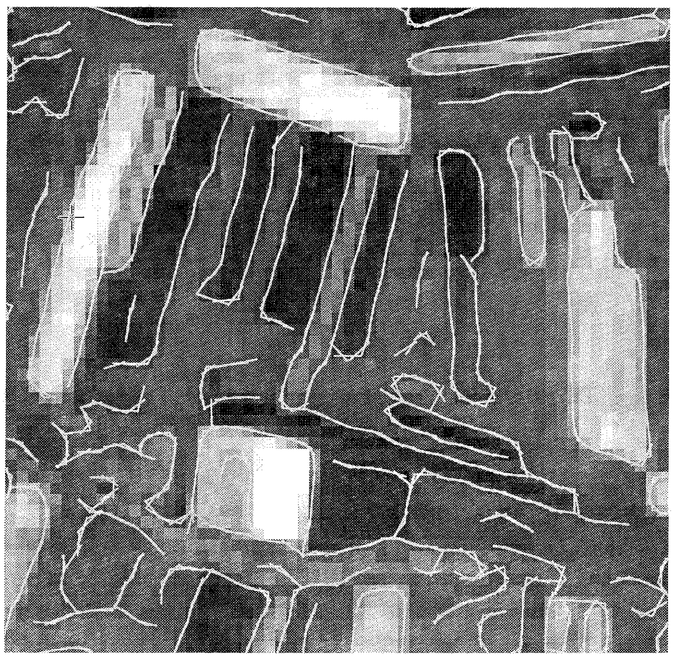

Figure 3: Band 4 of Landsat TM, edgel chains superimposed

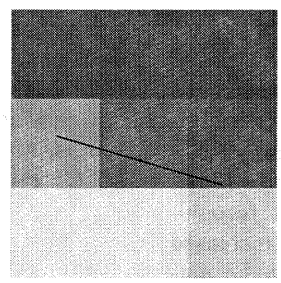

Figure 4: Line segment with midpoint passing through a mixed pixel

Figure 5: Boundary pixels rendered with mean pixel value of region (white pixels are interior pixels), edgel chains superimposed