

## DETECTION OF DOMINANT ORTHOGONAL ROAD STRUCTURES IN SMALL SCALE IMAGERY

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### ABSTRACT

The objective of the presented work is the automatic segmentation of urban areas from high resolution satellite images, such as MOMS-02 images or from aerial images taken from high altitude flights. The structure of urban areas, as seen from satellites or aeroplanes, is mainly characterized by three elements: the road network, the morphology of the built up areas and the distribution of the vegetation. There exist many types of road structures in large cities, which govern the local topology and geometry of the individual roads. Typical examples are orthogonal networks, star type networks or irregular networks. Seen world wide, orthogonal networks appear to be the most common ones, as e. g. to be found in Mannheim, Barcelona, New York or Canberra. The paper presents an approach for segmentation of *dominant orthogonal road structures* from high resolution satellite images, like MOMS-02, or aerial images.

### 1 INTRODUCTION

The structure of urban areas, as seen from satellites or aeroplanes, is mainly characterized by three elements: the road network, the morphology of the built up areas and the distribution of the vegetation. The road network immediately attracts one's special attention for its geometrical arrangement which reveals its man made origin. The morphology of the building areas can be described in two levels: one is complementary to the road network and shows the overall structure of the settlement, the other is the local arrangement of the buildings within building blocks. Road network and building areas are in a particular way injected by vegetation. Roads may be partially or totally bounded by trees, e. g. when forming allees. Built up areas show irregularly structured vegetation, especially in gardens. Moreover, parks or cemeteries often form larger closed areas within cities, either at the boundary of a town or completely surrounded by built up areas. Though all three components are closely related we start with the analysis of the road structure as it appears to be recovered most easily and gives the most essential information about the overall city structure. Due to their diversity in structure and in appearance vegetation and built up areas are less significant for identifying city structures.

### 2 MOTIVATION

There exist many types of road structures in large cities, which govern the local topology and geometry of the individual roads. Typical examples are orthogonal networks, star type networks or irregular networks. Seen world wide, orthogonal networks appear to be the most common ones, as e. g. to be found in Mannheim, Barcelona, New York or Canberra. Hippodamos called the grid network the "Rationality civilized behavior" [(Sennet, 1991), S. 70].

There exist early works on the extraction the road structure from low resolution images, but mainly of rural road (Barzohar and Cooper, 1996, Fischler et al., 1981, Fischler and Heller, 1998). These approaches ignore the intersections of roads and so they lose the topology of the road network. In contrast to it (Baumgartner, 1998, Hinz et al., 1999, Steger et al., 1995, Steger et al., 1997) focus on the generation of descriptions of the road grid with topology intact, but only focus on rural roads too. Price (Price, 1999) is the only one he extract road networks in cities and with consideration the topology. For modeling he needs to interactively provide three points that give the location, direction and spacings of the road network. This step could be replaced by an automatic method to find dominant directions, as we will present it in the following sections.

Our task is the automatic segmentation of urban areas from high resolution satellite images, like MOMS-02 images, based on road structures. The segmentation should lead to a partitioning of the city area into regions with a dominant orientation of the roads within a region and different orientation of the roads in neighboring regions. Such a segmentation can then be used to ease the extraction of individual road segments in each region, as their orientation is known. Moreover, roads

with super regional function which cross the regions in an arbitrary orientation can be identified. This allows to perform a classification of the roads with respect to their role in the city, thus discriminating local and regional or global road connections. Such a situation can be clearly seen in the city map of New York (cf. Fig. 5(a)). Our task may be divided into two parts:

- (1) modeling the generic structure of the expected road network and its appearance using the sensor model
- (2) analyzing the image for establishing a description of the road structure.

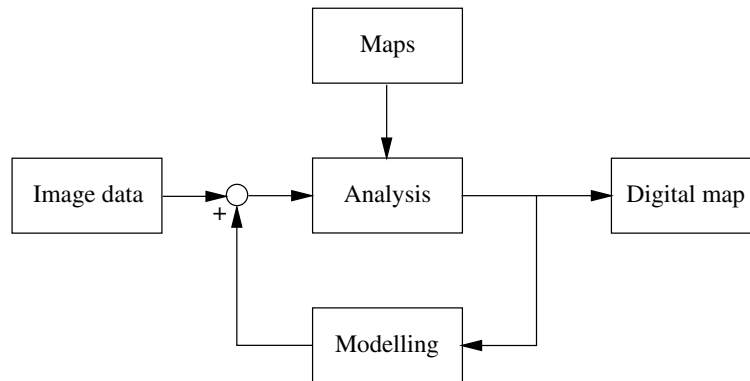


Figure 1: Concept of the task

The model is used for controlling the analysis, whereas the results of the analysis are used to improve the assumed models for increasing performance in subsequent analysis steps (Fig. 1). Initialization of the model may be done by hand or using existing maps. This is the reason why we will test our procedure on existing city maps.

### 3 MODELING

Let us describe the model, first in general, then for our special segmentation task. Following our previous discussion (Förstner, 1993, Förstner, 1994), our model consists of three parts: the object model, the sensor model and the image model. We will describe this in the next subsections.

#### 3.1 Object model

The object model describes the object, which we intend to extract from the image data. In our case the object *city* would have three elements: the road network, the morphology of the built up areas and the distribution of the vegetation. The attributes of the elements and their relations could be topological, geometrical, physical or biological. Our special model describes *dominant orthogonal road structures*. The *ideal map*  $\mathcal{S}$  consists of a partitioning

$$\mathcal{S} = \bigcup_{i=1}^n \mathcal{S}_i$$

$$\mathcal{S}_i \cap \mathcal{S}_j = \emptyset \quad \forall i, j$$

Each area  $\mathcal{S}_i$  contains two kinds of roads  $r_{ij}(\phi_{ij})$ :

- roads, which belong to the network, their orientation angle is

$$\phi_{ij} = \phi_i + k_j \frac{\pi}{2} \quad k_j \in \{0, 1, 2, 3\}, \phi_i \in [0, \frac{\pi}{2}), j = 1, \dots, J \quad (1)$$

Thus, to each area  $\mathcal{S}_i$  is assigned an orientation  $\phi_i$  which is the smallest orientation angle for one of its roads, belonging to the orthogonal road network. The orientation of the roads differs by the angle of  $\frac{\pi}{2}$ .

- roads, which are not part of the orthogonal network. Their orientation angle  $\phi_{ij}$  is random. We assume uniform distribution

$$\phi_{ij} \sim U(0, 2\pi) \quad (2)$$

The regions  $\mathcal{S}_i, i = 1, 2, 3, \dots$  are assumed to have piecewise smooth boundaries, i. e. have a maximum curvature except at corners which need to have a minimum distance. This guarantees observability of the boundary, as too high curvature parts or too dense corners can not be recovered due to the limited density of the roads within the region. This implicitly excludes too small regions.

### 3.2 Sensor model

The sensor model describes the sensor, which is used to get input data, specifically its geometrical and radiometrical properties.

In our project images of the MOMS-02 camera are used. As the flying height is large compared with surface undulations and the viewing angle is small we can expect small geometric differences between object and image. The resolution of 5–6 m in the panchromatic channel limits the detectability of individual objects. This is the reason why we modeled roads as linear objects not as area objects. The multispectral channels of the MOMS-02 camera with a resolution less than 10 m pixel size do not appear sufficient for road extraction in urban areas.

### 3.3 Image model

The image model describes the expected appearance of the object in the image. It formally may be derived from the object and the sensor model.

In our case the partitioning of the map into map regions can be used directly except for the detailed geometry. We assume the road elements to appear as bright or dark lines. The width of the lines is expected between a half and one pixel. They can be expected to be disturbed by traffic or trees and of course sensor noise. Therefore no complete network can be reconstructed. This is the reason why we did not require connectivity of the road elements in the object model.

The image model therefore consists of the same partitioning of the map as describe above. However, the road segments will partially be lost, additional segments may appear, e. g. due to linear structures in building areas. All segments will show errors in length, usually being too short, and orientation which depends on their extracted length. The statistics of the line segments may be learned from example segmentations.

At the moment we assume the number of disturbing line segments to be less than 25 % of the good line segments. For simplicity, we also assume the orientation errors to be independent on the length of the extracted line segment.

## 4 ANALYSIS

### 4.1 Aspects and Assumptions

The analysis has to cope with a set of problems. The following Tabular (Tab. 1) will describe and give possibilities to solve these problems.

| Problem   | Solution   |
|---|--|
| <ul style="list-style-type: none"> <li>Roads within a region with the same dominant orientation have directions which differ by multiples of <math>90^\circ</math>. The <i>unknown multiplicity</i> needs to be eliminated to come to a unique estimated direction <math>\hat{\phi}_i</math> for each region <math>\mathcal{S}_i</math> (Fig. 3).</li> <li><i>Roads not belonging to a region</i>, i. e. roads which cross the region at an arbitrary angle, should not influence the estimate of the direction of that regions.</li> <li><i>Orientation of roads is not available between the roads</i>. In order to obtain closed boundaries orientation values should be made available for all positions in the map.</li> </ul> | <ul style="list-style-type: none"> <li>The representation of directions should map the orientation <math>\phi_{ij}</math> of each road segment belonging to the same region to the same value. To eliminate the multiplicity of the angle we use the 4 fold angle <math>\alpha_{ij} = 4\phi_{ij}</math>. Thus <math>4\phi_{ij} \bmod 2\pi = (4\phi_i + k_j)\pi/2 \bmod 2\pi = 4\phi_i</math>.</li> <li>We use a robust estimate for the fourfold orientation angle, allowing up to 25 % outliers.</li> </ul> |
| <ul style="list-style-type: none"> <li>The analysis should be robust with respect to <i>variations in the density of the road network</i>.</li> </ul>   | <ul style="list-style-type: none"> <li>We use an iconic description of the map, i. e. we work on a raster image of the map. For each pixel of this map we robustly estimate the mean orientation of all roads in a certain neighborhood. For this purpose we perform a vector-raster transformation of the extracted line segments.</li> <li>Up to now, we assume approximately homogeneous density of the roads, which is reasonable in densely populated areas.</li> </ul>                                 |

Table 1: Problems of analysis and their solution

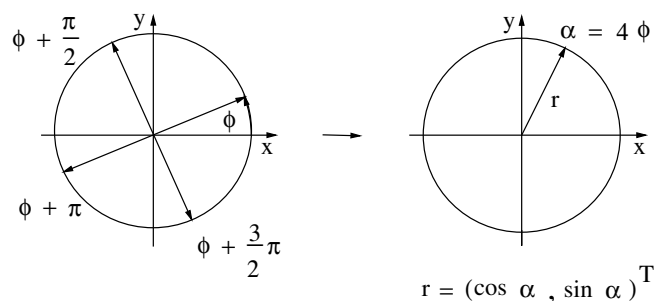


Figure 3: Mapping of the orientation angles of orthogonal edges to the same value

The idea of our algorithm is to estimate the dominant orientation of extracted line segments in a moving window and build connected components of centers of windows with similar orientation.

The analysis of images regarding to a dominant orthogonal road structure requires two main steps: the Preprocessing in connection with the line representation and the Segmentation. This steps we will describe in the next subsections and are show in Fig. 2.

## 4.2 Preprocessing and line representation

The Preprocessing of the images and the representation of the roads as lines we realized by:

**Line extraction** When using the image data of the MOMS-02 camera, we magnified them by a factor of four using bicubic interpolation. This lead to a pixel size of appr. 1.25 m on the ground.

We use the program for line extraction from C. Steger (Steger, 1996) which is specialized for extracting roads in digital images. Output of this algorithm are vectorized line data.

**Evaluation of orientation** The orientation  $\phi_{ij}$  of extracted line segments is determined and mapped to the unique four fold angle  $\alpha_{ij}$ .

**Coding of lines corresponding to the orientation** To simplify the procedure we go back to the raster representation. Each pixel of a line segment will be set to its fourfold angle.

## 4.3 Segmentation

The segmentation process described in this section is divided in (1) the evaluation of a histogram of the orientations, (2) the determination of an estimated dominant orientation and (3) the partitioning. The first two steps are working in a moving window covering the complete map. The size of the window has to be adapted to the average density of the road network, which up to now is done manually.

**Determination of histogram of orientation** Within each window we evaluate the grey value histogram without consideration of the background value.

**Determination of an estimated dominant orientation** The middle of the smallest interval which contains  $p\%$  of all of the grey values now describes the estimated dominant orientation (Meer et al., 1990). It is a robust estimate allowing at least 50% outliers, when assuming the other data to be uniformly distributed. For  $p = 50\%$  we will get the least median square estimation. We actually use the  $p = 25\%$ , allowing 25% outliers. The robust estimation is done for all positions  $r, c$  of the window and so we obtain for all these positions a vector representation  $\mathbf{f} = (\cos\alpha(r, c), \sin\alpha(r, c))^T$ . We represent the fourfold angle  $\alpha$  in order to cope with discontinuities at  $2\pi$ .

This way we get an image which contains nearly homogeneous regions describing the estimation of orientation into the regions of interest. Within the searched regions the estimated orientation will be quite good. At the borders there might be a bias if the density of the roads in the neighboring regions is different.

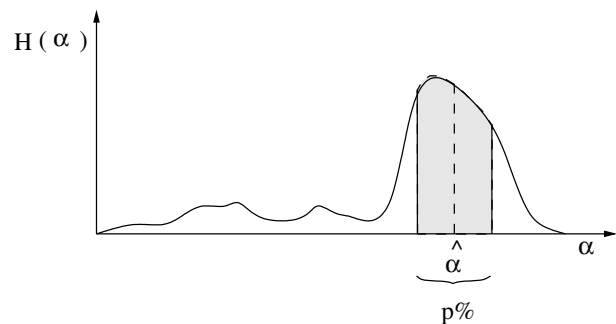


Figure 4: Histogram of the orientation angles  $\alpha$ . The robust estimation will be obtained as the middle of the shortest interval containing  $p\%$  of the values. For  $p = 0.5$  it leads to the *least-median-square-estimation*.

**Partitioning** To find homogeneous regions corresponding to the dominant orientation of the area in the road network we use our feature extraction program FEX(Fuchs, 1998). The homogeneity measure, essentially the gradient magnitude of the planar orientation, is used to decide whether a pixel will be interpreted as belonging to the region or not. The value in the homogeneous regions represents the mean direction in this regions. We extract the homogeneous regions at this two channel image only. The exoskelett we use as region boundaries.

## 5 RESULTS

Now we will describe results of the presented segmentation algorithm for two examples. The first example uses a piece of a printed map of New York (Fig. 5(a)), the second a piece of an original MOMS-02 (Fig. 5(a)) image of Ballarat (Australia), taken during the D2-mission.

- City map of New York: Fig. 6(a) shows the result of line extraction, Fig. 6(c) the homogeneous regions as result of segmentation and Fig. 6(c) the original image overlapped with the border lines of segments. We can observe, that the main segments are clearly visible and correctly found by the algorithms. The boundaries are somewhat irregular. The boundaries of the small region above the center of the map is found quite well. The other regions are contaminated by border effects of the segmentation procedures due to the large window size of appr. 15% of the complete map.
- MOMS-02 image of Ballarat (Australia): Fig. 7(a) shows the result of line extraction, Fig. 7(c) the homogeneous regions as result of segmentation and Fig. 7(c) the original image overlapped with the border lines of segments. In this image exist only two larger regions with different orientations: the main region, extending over the whole image nearly, and a smaller one at the left image margin. These two regions were clearly segmented. Additionally some small regions inside the main region were missed segmented, because there are any errors in the detected lines. The result for the MOMS-02 image is not so clear as the result of city map of New York. The main reason is the irregularity of the density of the road network.

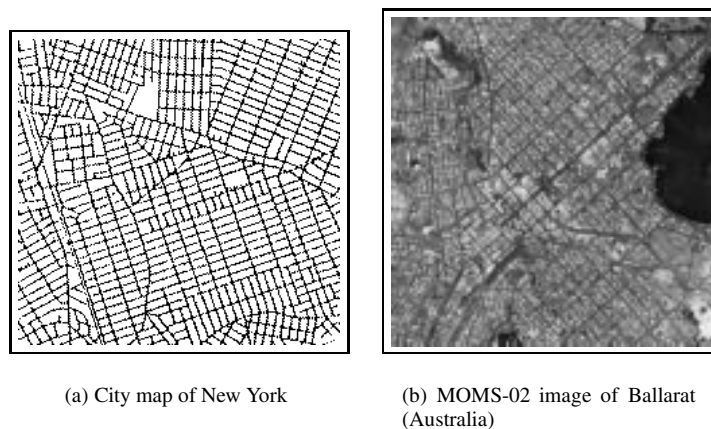


Figure 5: Example data sets

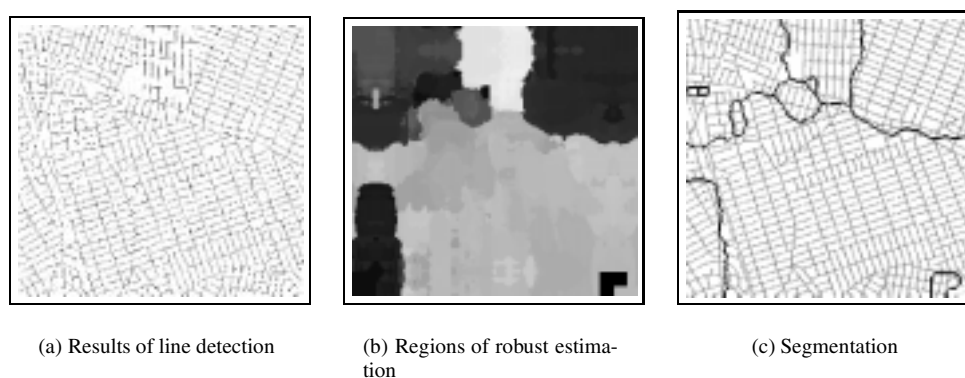


Figure 6: Results for the city map of New York

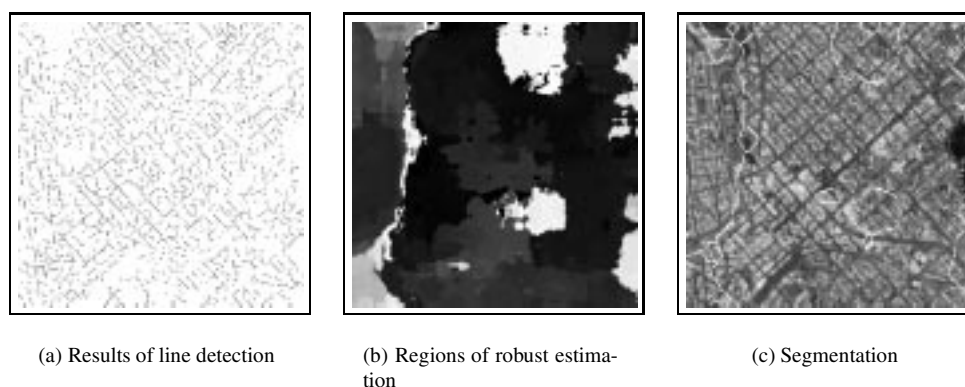


Figure 7: Results for the MOMS-02 image

## 6 CONCLUSION

One may proceed in two directions to improve the results of the algorithm:

- Regarding to the results described above, as a first step we have to investigate into the automation the choice of an adaptive size of the window depending of the density of the road network.
- Replace the algorithm for transferring the orientation data from the roads to the building blocks by a distance transform carrying the orientations into the neighborhood. This will significantly increase the robustness of the procedure with respect to variations in density.

- We will use the estimated orientations for improving the feature extraction, thus decreasing the orientation errors of the extracted road segments.

The grouping of the road segments will then lead to a first description of the road network. By using the hough transform inside the segmented regions we can obtain a more exactly description of the road network alternatively. Further work will be done in integrating multispectral information to presegment the scene with respect to vegetation, in order to focus on the urban area alone.

## 7 ACKNOWLEDGMENTS

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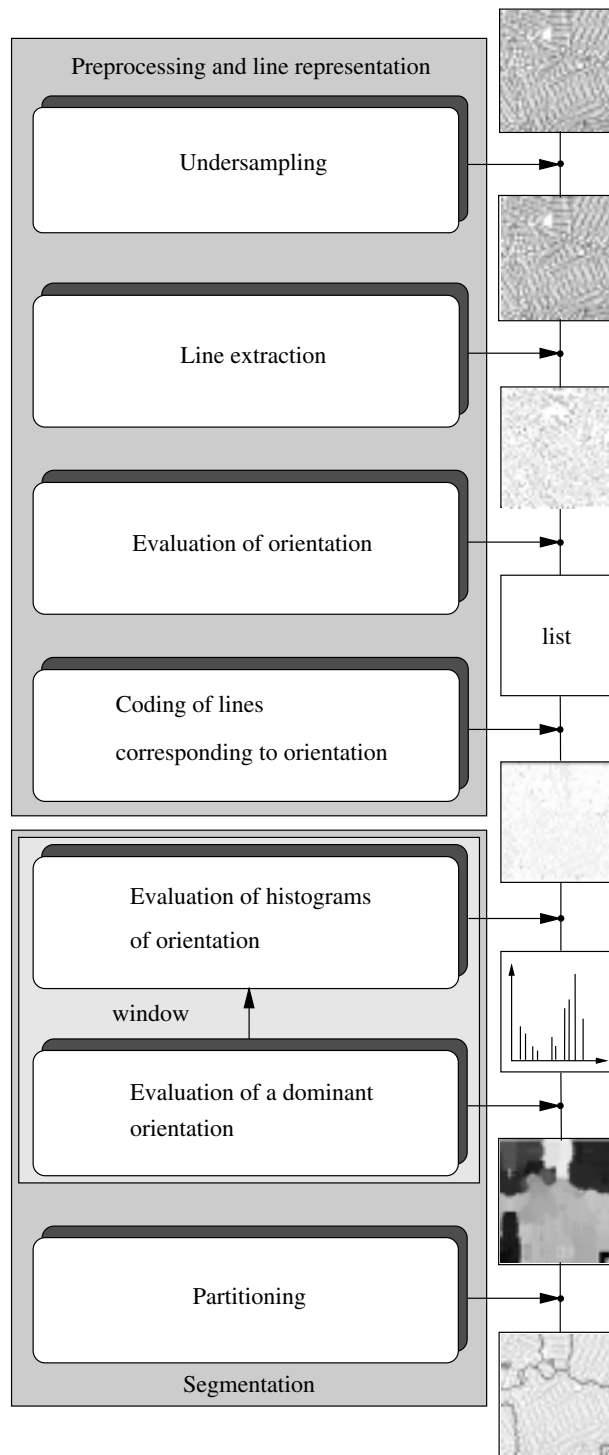


Figure 2: Algorithm for detection a dominant orthogonal road structure