AUTOMATIC VEHICLE DETECTION IN SPACE IMAGES SUPPORTED BY DIGITAL MAP DATA

J. Leitloff [1], S. Hinz[2], U. Stilla[1]

[1] Photogrammetry and Remote Sensing, [2] Remote Sensing Technology
Technische Universitaet Muenchen, Arcisstrasse 21, 80333 Muenchen, Germany
{jens.leitloff, stefan.hinz, stilla}@bv.tum.de

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ABSTRACT:
Due to increasing traffic there is high demand in traffic monitoring of densely populated urban areas. In our approach we focus on the detection of vehicle queues and use a priori information of roads location and direction. In high resolution satellite imagery single vehicles can hardly be separated since they are merged to either dark or bright ribbons. Initial hypotheses for the queues can be extracted as lines in scale space which represent the centres of the queues. We exploit the fact that vehicle queues are composed of repetitive patterns. For discrimination of single vehicles a width function of the queues is calculated in the gradient image and the variations of the width function are analyzed. We show intermediate and final results of processing a panchromatic QuickBird image covering a part of an inner city area.

1. INTRODUCTION

1.1 Motivation

There is an increasing demand in traffic monitoring of densely populated areas. The traffic flow on main roads can partially be acquired by fixed installed sensors like induction loops, bridge sensors and stationary cameras. Usually traffic on smaller roads – which represent the main part of urban road networks – is rarely collected and information about on-road parked vehicles is not captured. Wide-area images of the entire road network can complement these selectively acquired data. The launch of new optical satellite systems with 1-meter resolution or higher, e.g. Ikonos and QuickBird, make this kind of imagery available. Hence new applications like vehicle detection and traffic monitoring for these images gain more scientific interest. We intend to use satellite imagery to extract vehicle queues and separate single vehicles in complex urban scenes.

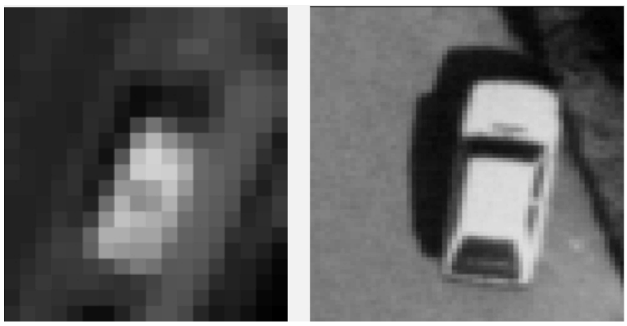
1.2 Related work

Depending on the used sensors and the resolution of the imagery different approaches have been developed in the past [Stilla et al., 2004] .
The extraction of vehicles from images with resolution about 0.15 m is widely tested and delivers good results in many situations. These approaches either use implicit or explicit vehicle models [Hinz, 2004]. The appearance-based, implicit model uses example images of vehicles to derive gray-value or texture features and their statistics assembled in vectors. These vectors are used as reference to test computed feature vectors from image regions. Since the implicit model classification uses example images the extraction results depend strongly on the choice of representative images.

Approaches using an explicit model describe vehicles in 2D or 3D by filter or wire-frame representations. The model is then matched "top-down" to the image or extracted image features are grouped "bottom-up" to create structures similar to the model. A vehicle is declared as detected, if there is sufficient support of the model in the image. These attempts show better results than approaches using implicit models but are hardly applicable to satellite imagery since there vehicles only appear as blobs without any prominent sub-structures (see Figure 1).

In Michaelsen & Stilla [2001] vehicle hypotheses extracted by a ”spot detector” are collinearly grouped into queues. Vehicle hypotheses are constrained to lie along the road boundary taken from a digital map and isolated vehicle hypotheses are rejected. Since the queues are not further used to search for missed vehicles, this strategy implies that the vehicle detector delivers a highly oversegmented result, so that grouping is able to separate correct and wrong hypotheses.

Three methods for vehicle detection from simulated satellite imagery of simple highway scenes are tested in Sharma [2000]. The gradient based method of this approach only achieves deficient results. For more promising results using the Principal Component Analysis (PCA) and Bayesian Background Transformation (BBT) in that work, a manually created background image was used. Since this requires a high effort of interactive work, the approach can hardly be generalized and is limited to single images.



a b

Figure 1. Appearance of single vehicle. a) satellite imagery* (resolution 0.6 m) b) airborne imagery (resolution 0.15 m)

An encouraging approach for single vehicle detection is presented in Jin & Davis [2004]. They use morphological filtering to distinguish between vehicle pixels and non-target

pixels similar to vehicles. Then a morphological shared-weight neural network is used for extraction. The approach achieves high completeness and correctness but is not especially designed to extract of vehicles in queues or parking lots.
The latter approaches are designed for a resolution coarser than 0.5 m and limit their search space to roads and parking lots using GIS information. By this, the number of false alarms is significantly decreased.

1.3 Overview

Figure 2 shows the overall design of our approach which is separated into three processing stages. In the pre-processing (red) a simulated GIS is used to determine Regions of Interest (ROI) in the panchromatic satellite imagery. Afterwards we use a differential geometric approach to extract initial hypotheses of the queues as lines (green). From these hypotheses we try to determine single vehicles trough analyzing the width profile of the queues calculated from the gradient image (blue). Please note that the procedure is similar to human interpretation. This means that the hypotheses generation is based on coarse and global information while for verification and refinement use details and context information is utilized.

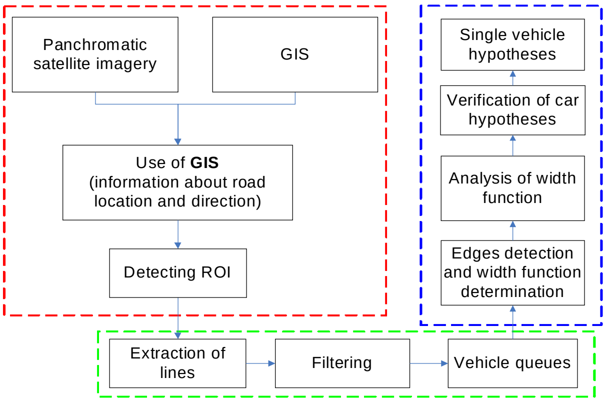


Figure 2. Overall structure

We show the results on a panchromatic QuickBird image covering a part of an inner city area (Figure 3). This work presented here is only the first implementation of a more comprehensive vehicle detection approach for complex urban scenes, which will combine global and local vehicle features for extraction. Hence, the primary objective of this work is to implement and test robust algorithms with high correctness, while less emphasis is put on the achieved completeness.

2. QUEUE DETECTION

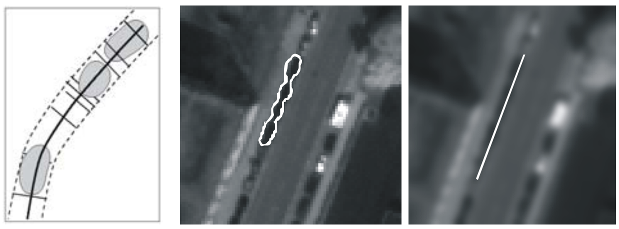
In this section the steps implemented so far are described. In section 2.1 the used model will be presented. Section 2.2 describes the extraction of vehicle queues using sophisticated line extraction. Then a number of attributes are calculated (section 2.3). Finally, the attributes are analyzed and checked for consistency to verify or falsify single vehicle hypotheses (section 2.4).

Figure 3. Urban satellite scene of the inner city of Munich*

2.1 Model of vehicle queues

The used model is similar to Hinz [2004]. But since this model is designed for aerial images with higher resolution we use less features. In our model a vehicle queue is defined as ribbon with following features:

- It must have sufficient length, almost constant width and low curvature (Figure 4a).
- It shows repetitive pattern (Figure 4b), which are also recognizable in the width behaviour.
- It is represented as line in scale space (Figure 4c).



a) model b) original image c) smoothed image
Figure 4. Vehicle queue model

2.2 Differential geometric line extraction

Since many of the involved image processing algorithms depend on the contrast of the queues, image enhancement seems to be useful. In our case the gray value ranges which contain less information (e.g. overexposed areas) are cut off. In doing so the image is scaled from the originally 11bit to 10bit.

To make use of a priori road information Regions of Interest (RoI) are derived from GIS data (shown in Figure 5 as white lines). In this case they are generated from a simulated GIS and

Figure 5. Regions of Interest*

correspond to the road axes (black lines). Only in these areas, the vehicle detection is performed.

The line extraction uses the differential geometric approach of Steger [1998]. Parameters for the line detection are roughly chosen corresponding to vehicles geometry (vehicle width) and radiometry (expected contrast to road). Furthermore, the extraction is done for different scales of the image to allow varying vehicle widths. To support the line extraction algorithm we use the given road direction and filter the image morphologically with a directional rectangular structuring element. In doing so the queues are enhanced and substructures in bright cars are almost completely removed. We choose quite relaxed parameter values for line extraction thereby allowing for an oversegmentation, which leads to a huge number of false hypotheses but also nearly all promising hypotheses for vehicle queues. Figure 6 shows results for the extraction of bright (white) and dark (cyan) lines.

With this scheme queues consisting mainly of dark vehicles can be extracted better than bright ones since they shown better contrast to roads surfaces. Small gaps can be closed through union of collinear lines. A first filtering is done by testing the extracted line directions against the given road direction. Gray vehicles can not be extracted because they hardly emerge from their surroundings. Line extraction seems unsuitable for this special task.

Figure 6. Results of line extraction*

2.3 Determining queue width in the gradient image

The width determination is done through detection of vehicle sides in the gradient image. The algorithm starts at the first point of a line and processes consecutively all following points of the line. A profile perpendicular to the line direction is spanned in each point. Afterwards the gray value in the gradient image is calculated by bilinear interpolation, thus, deriving the gradient amplitude function of the profile. The maximum value on either side of the vehicle queue is supposed to correspond with the vehicle boundary. The distance between the two maximum values is calculated with sub-pixel accuracy and gives the queue width. If no maximum is found the gaps are closed by linear interpolation after width determination. Figure 7 illustrates the algorithm for width calculation and Figure 8 shows the result of width extraction (white) after a first filtering of the lines showing in Figure 6 (cyan).

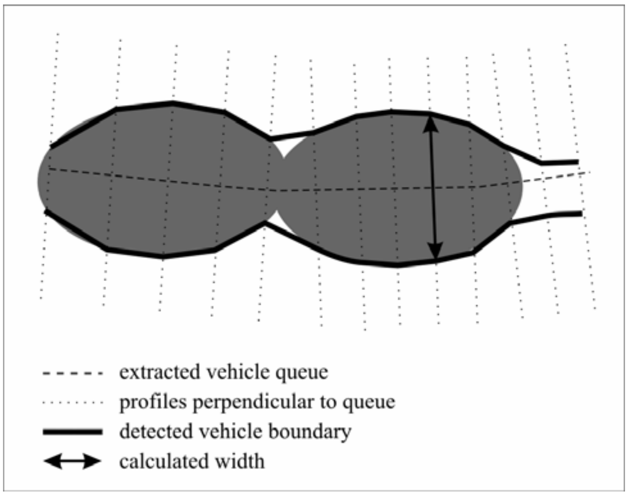


Figure 7. Concept of queue width determination

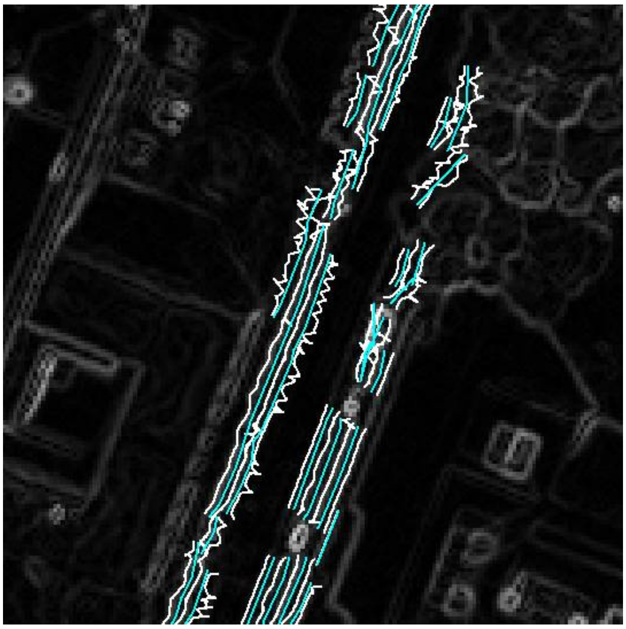


Figure 8. Width extracted from gradient image*

One can see that most edges correspond to vehicle sides. However, since the gradient image has quite weak contrast, edges extraction delivers also some irregularities, i.e. noisy boundaries. Therefore smoothing of the extracted edges is useful to reduce the number of outliers.

Usually the irregularities are caused by other strong edges nearby the vehicle queue. In future implementations we intend to detect such outliers by a more sophisticated shape analysis of the boundary functions.

2.4 Separating queues into single vehicles

To find single vehicles, we use the knowledge that vehicle queues are characterized by significant repetitive patterns caused by gaps between single vehicles. This means that the extracted width function also shows significant variations (Figure 9). Maximum values in this function approximately are assumed to represent the centres of single vehicles and minimum values represent gaps between two vehicles in the queue.

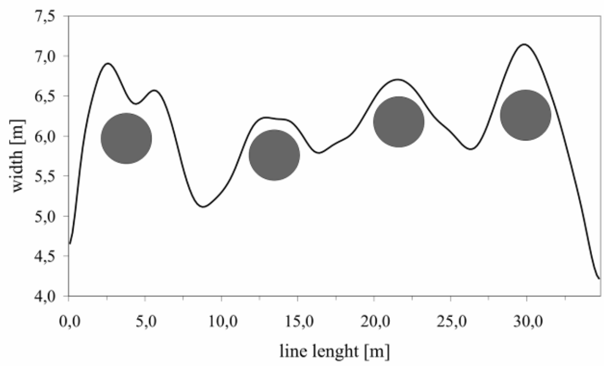


Figure 9. Width function and single car hypotheses (circles)

We define the following parameters:

v_{min} ... minimum length of a single vehicle and search interval
v_{max} ... maximum length of a single vehicle and search interval
l_{min} ... position of the minimum width within search interval
l_{max} ... position of the maximum width within search interval
d ... distance between l_{min} and l_{max}

A vehicle hypothesis is generated if the following condition is fulfilled:

$$\frac{v_{min}}{2} \leq d \leq \frac{v_{max}}{2}$$

Summarizing this algorithm, the task is to find local maxima and minima in the noisy width function and place the vehicle positions in such a way that vehicle hypotheses do not overlap. Figure 10 shows the principal concept of the width analysis.

The analysis starts at the first point of the width function and is completed if the last point is included in the current search interval.

It is possible that more than one hypothesis is found for a vehicle. This is caused by two or more maxima in the width function within the vehicle. Therefore we control the space between two hypotheses not to fall below a certain minimum distance. If more than one hypothesis is found we verify the hypothesis with the highest maxima in the width function.

After a hypothesis has been generated we use the contrast of the vehicle and the adjacent road surface for a simple verification (Figure 11). Here the difference of the median gray values of the inner and the outer region is calculated.

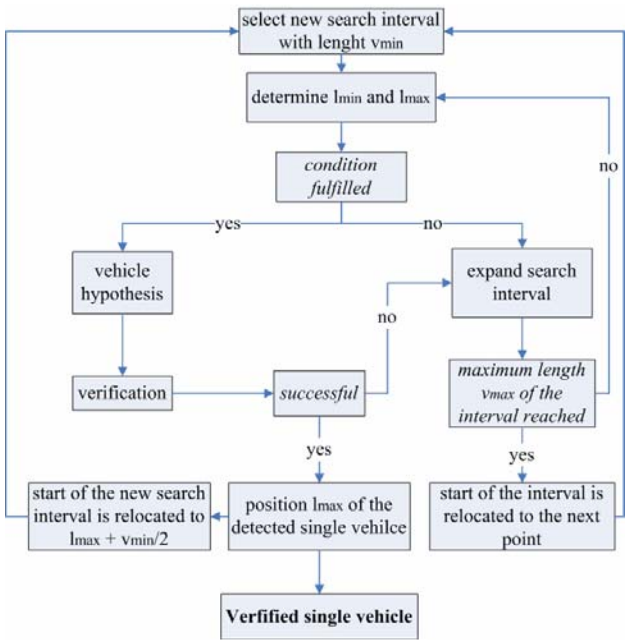


Figure 10. Concept of width function analysis

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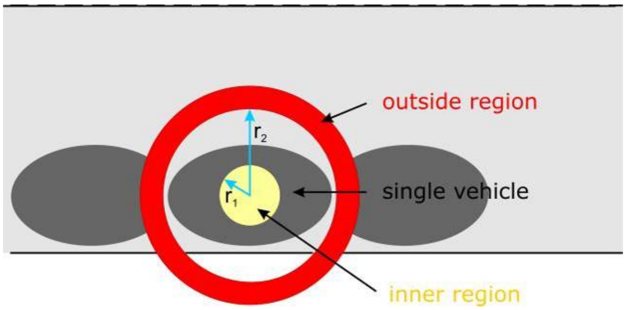

Figure 11. Verification

3. RESULTS

The performance of our implementation up to now has been tested on panchromatic QuickBird data with approximately 60 cm ground sampling distance. We evaluate the results of our approach using the well-known criteria "correctness" and "completeness". They are defined as follows:

$$\text{correctness} = \frac{TP}{TP + FP}$$

$$\text{completeness} = \frac{TP}{TP + FN}$$

with TP true positives
FP false positives
FN false negatives

With respect to a manually created reference, true positives are correct extracted single vehicles. False positives are misdetections and false negatives are vehicles which could not be extracted. Figure 12 shows examples of extracted vehicles. The cyan crosses are verified detected vehicles (TP) and the white crosses are misdetections (FP).

Table 1 shows the achieved completeness and correctness for bright and dark vehicles. In our reference data gray vehicles are also included. But as the line extraction is hardly suitable for theses vehicles, they are excluded from the evaluation.

vehicle type	TP	FP	FN	correctness	completeness
dark	49	9	34	84,5 %	59,0 %
bright	9	2	27	81,8 %	25,0 %
both	58	11	61	84,1 %	48,7 %

Table 1. Evaluation of line extraction and width analysis

Figure 12. Extracted single vehicles*

As mentioned above we are focussing on high correctness rather than completeness, since we want to test the algorithms' reliability. Hence, the correctness of about 82% is a promising result and underlines the importance of the analysis of the width functions – especially if we consider that only a very simple verification method is used at the moment. Concerning the completeness we obtain varying result. As supposed the line extraction and the verification works much better for dark vehicles, since they show higher contrast to the road surface. Despite of the promising correctness values, a maximum completeness of 59% underlines the necessity of further improvements.

Figure 13, 14 and 15 illustrate another example that shows the reason for the resulting high correctness and low completeness. In figure 13 it can be seen that nearly all vehicle are detected by the line extraction.

Due to the weak amplitudes in the gradient image not all vehicle edges could be extracted correctly (Figure 14). This strongly reduces the ability of the width function analysis to find correct hypotheses.

Figure 15 visualizes the final result for this image part. As anticipated the verification algorithm was able to reject all objects similar to vehicles. On the other hand it can also be seen that the completeness is quite low.

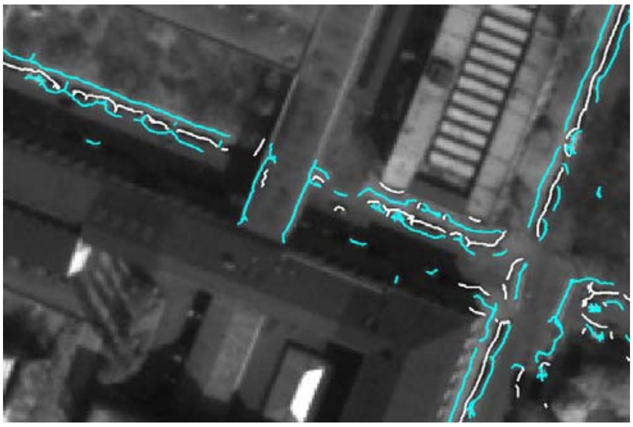

Figure 13. Results of line extraction*

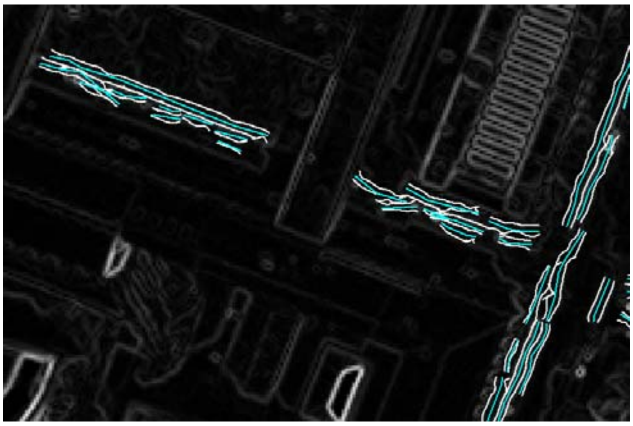

Figure 14. Width extraction from the gradient image*

Figure 15. Extracted single vehicles**

Especially from Figure 14 it comes clear that the width function can not be used as the only means for analyzing the initial hypotheses. Hence, we plan to extend the queue model to capture also the local contrast along a hypothesis. First investigations have shown that the contrast function thus derived substantially supports the verification, since it adds complementary radiometric information to the (geometric) width analysis.

4. SUMMARY

We presented an approach for vehicle queue detection from a panchromatic QuickBird image of a complex urban scene. For this purpose we use differential geometric line extraction applied in ROIs selected from a GIS and extract the width of the detected vehicle queues. Through analysis algorithms of these width functions we were able to extract single vehicles with high correctness. As dark vehicles grouped in queues show better contrast the results for completeness and correctness are better than the results for bright vehicles. Gray vehicles have not been extracted. Nonetheless, the approach implemented so far has to be seen as a first step of a more complex system for spaceborne vehicle detection. However, the fast computation makes the approach even now applicable as additional verification for other prior detection.
A reference database for several images is already set-up. In future works the parameters for line extraction as well as the verification will be obtained from the statistical analysis of this database. Furthermore the simulated GIS is supposed to be replaced by a NavTech MySQL database.

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