VEHICLE QUEUE DETECTION IN SATELLITE IMAGES OF URBAN AREAS

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ABSTRACT:

There is an increasing demand in traffic monitoring of densely populated urban areas. In our approach we use a priori information of roads location and focus on vehicle queues detection. In this imagery single vehicles are merged to either dark or bright ribbons and therefore can hardly be separated. The queues can be extracted as lines in scale space using a differential geometric approach. We exploit the fact that vehicle queues show repetitive pattern. This pattern is also observably in width profile of the queues derived from the gradient image. For discrimination of single vehicles the variations of the width profile will be analyzed. The results of processing a panchromatic QuickBird image covering a part of an inner city area are shown.

1. INTRODUCTION

1.1 Motivation

Due to increasing traffic there is high demand in traffic monitoring of densely populated urban areas. Fixed installed sensors like induction loops, bridge sensors and stationary cameras partially acquire the traffic flow on main roads. Yet traffic on smaller roads – which represent the main part of urban road networks – is rarely collected. Furthermore, information about on-road parked vehicle is not captured. Hence, area-wide images of the entire road network are required to complement these selectively acquired data. Since the launch of new optical satellite systems, e.g. Ikonos and QuickBird, this kind of imagery is available with 1-meter resolution or higher. Hence new applications like vehicle detection and traffic monitoring are opened up. We intend to use these satellite images to extract vehicle queues in complex urban scenes.

1.2 Related work

The extraction of vehicles from images with resolution of about 0.15 m is widely tested and partly delivers good results. 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 strongly depend 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).

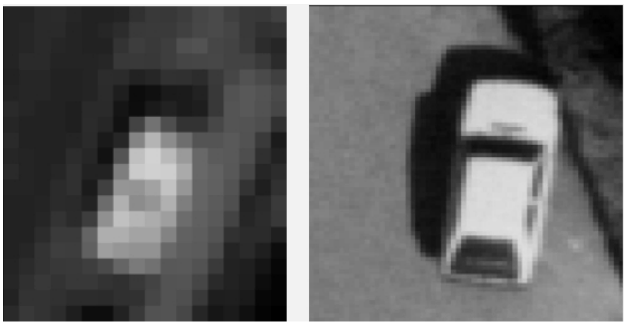

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Figure 1. Appearance of single vehicle. a) satellite imagery* (resolution 0.6 m) b) airborne imagery (resolution 0.15 m)

Depending on the used sensors and the resolution of the imagery different approaches have been developed in the past [Stilla et al., 2004]

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.

An encouraging approach for single vehicle detection is shown 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 able to extract vehicles in queues or parking lots.
All mentioned 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

In our approach we also use a priori information of roads but we focus on vehicle queues, where single vehicles are merged to either dark or bright ribbons and therefore can hardly be separated. Initial hypotheses for these queues can be extracted as lines in scale space which represent the centres of the queues. Then we exploit the fact that vehicle queues are composed of repetitive patterns. For discrimination of single vehicles a width profile of the queues is calculated from the gradient image and the variations of the width profile are analyzed. We show the results on a panchromatic QuickBird image covering a part of an inner city area (Figure 2). This work presented here is only the first implementation of a 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 stable algorithms with high correctness regardless of the achieved completeness.

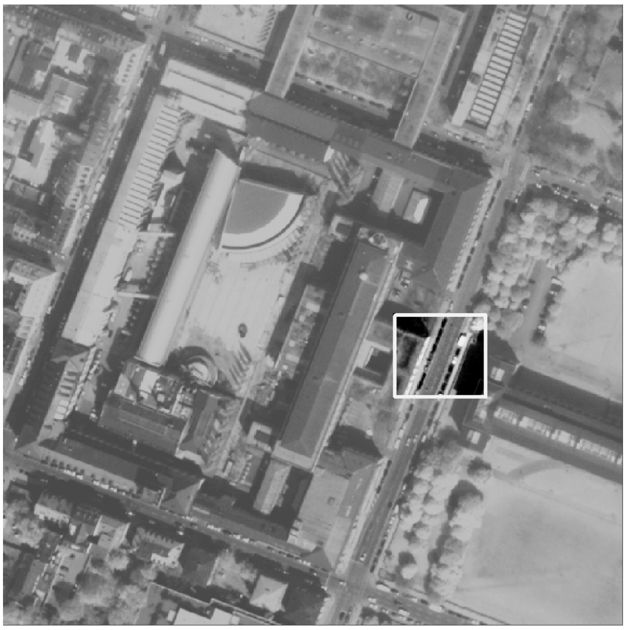

Figure 2. Urban satellite scene of the inner city of Munich*

2. QUEUE DETECTION

In this section the currently implemented steps are described. In section 2.1 vehicle queues are detected using sophisticated line extraction. Then a number of attributes are calculated (section 2.2). Finally, the attributes are analyzed and checked for consistency to verify or falsify single vehicle hypotheses (section 2.3).

2.1 Line extraction

To make use of a priori road information Regions of Interest (RoI) are derived from GIS data (shown in Figure 3 as white lines). In this case they are generated from a GIS and correspond to the road axes (black lines). Only in these areas the vehicle detection is carried out.

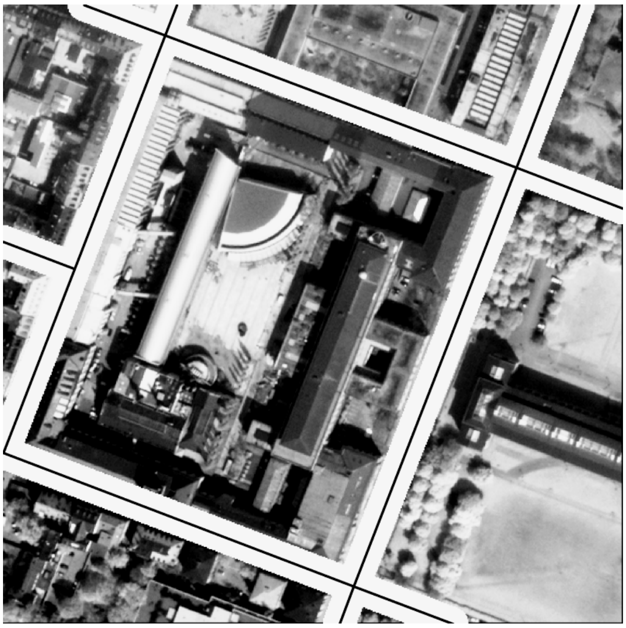

Figure 3. Regions of Interest*

The line extraction uses the differential geometric approach of Steger [1998]. Parameters for the line detection are chosen corresponding to vehicles geometry (vehicle width) and radiometry (expected contrast to road). At the moment only queues with at least two dark vehicles in a row can be extracted. Small gaps can be closed through union of collinear lines. First filtering is done by testing the extracted line directions against the given road direction. Figure 4 shows results of the line extraction including collinear merging and filtering.

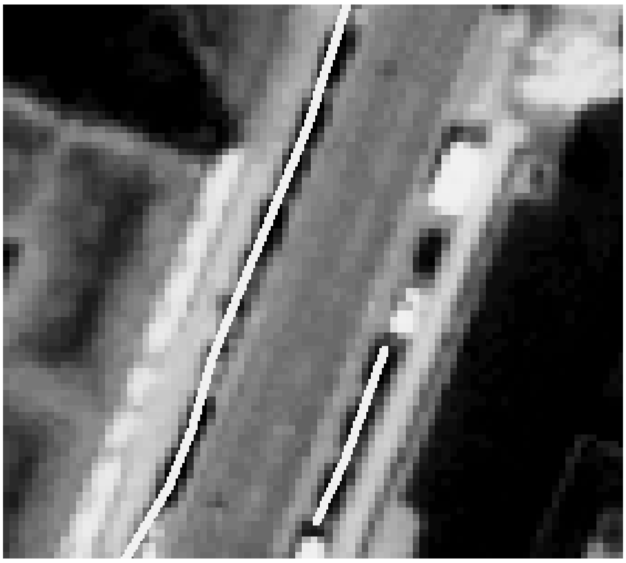

Figure 4. Extracted lines by differential geometry*

Since the line extraction strongly depends on the contrast of the queues, image enhancement seems to be useful. In our case a histogram linearization was used, with the disadvantage that the gray value range was scaled down from the originally 11bit to 8bit. Further research will include better enhancement techniques especially with respect to the line extraction in shady image regions.

2.2 Edge detection and queue width determination

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. We span a profile perpendicular to the line direction in each point and calculate the gray value in the gradient image using 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. Figure 5 illustrates the algorithm for width calculation.

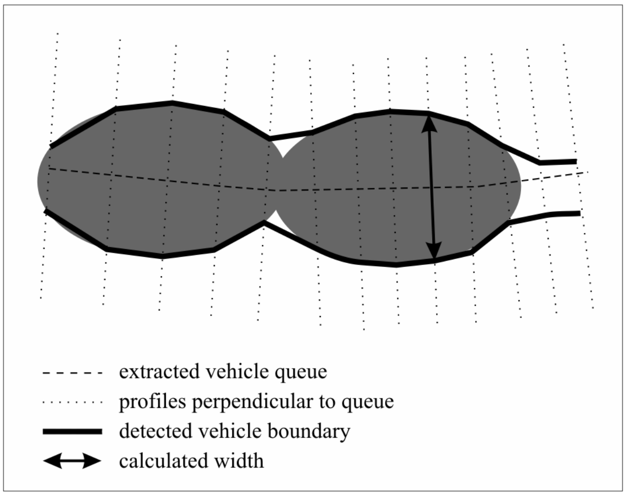

Figure 5. Concept of queue width determination

Figure 6 shows the result of width extraction. As can be seen, 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.

The irregularities are mainly caused by other strong edges nearby vehicle. One example is shown in Figure 7. In this case the border of a neighbouring shadow region was found and supposed to be the vehicle's boundary. Consequently this hypothesis was rejected by the later verification steps. Integrating knowledge about presence of shadow areas in the image seems to be useful for overcoming this limitation.

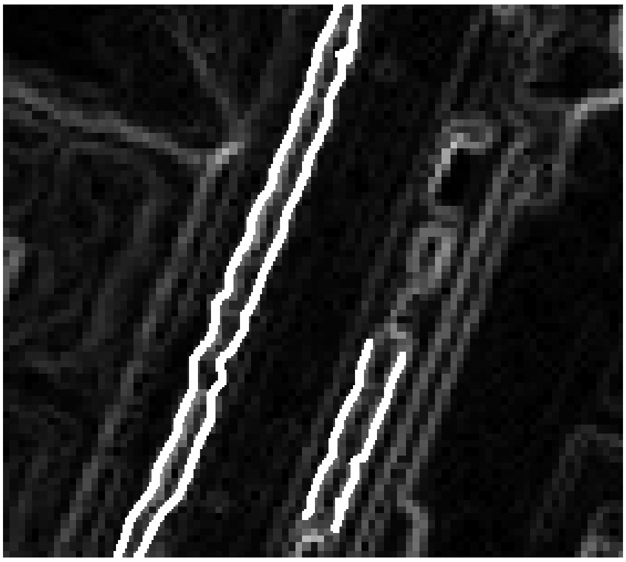

Figure 6. Width extracted from gradient image*

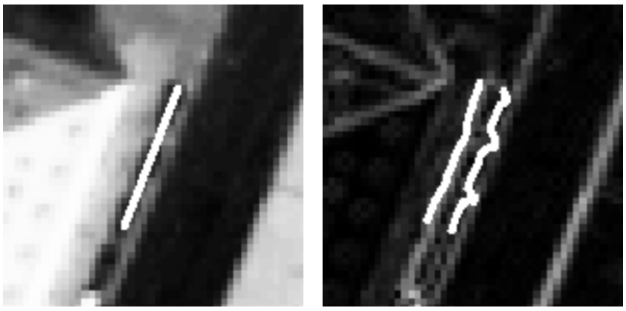

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Figure 7. False extraction of width*

2.3 Analysis of width function and vehicle counting

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 8). We assume that maximum values in this function approximately represent the centres of single vehicles and minimum value gaps between two vehicles in the queue.

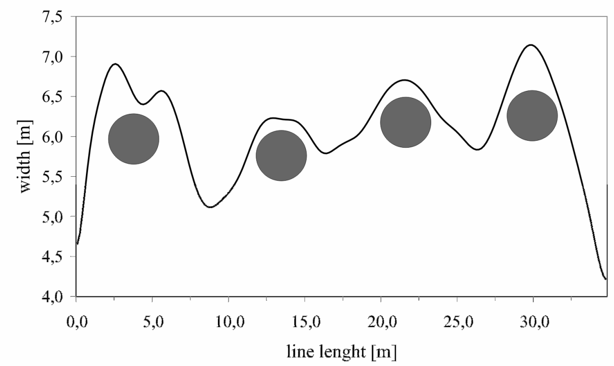

Figure 8. Width function and single car hypotheses (circles)

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}

Figure 9 shows the principal concept of the width analysis. There a vehicle hypothesis is generated if the following condition is fulfilled:

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

If a hypothesis is generated we calculate mean and deviation of gray values of the surrounding pixels in the image and use threshold operation for vehicle verification.
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.

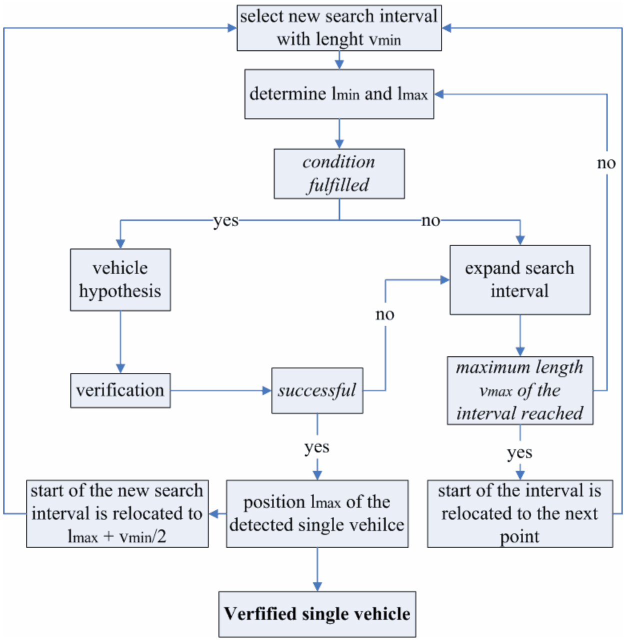

Figure 9. Concept of width function analysis

3. RESULTS

We evaluate the results of our approach using correctness and completeness, there are defined as follows:

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

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

where TP are true positives
FP are false positives
FN are false negatives

Evaluating the line extraction, true positives present the number of single vehicles in correct extracted queues. False negative are extracted lines which are not vehicle queues but similar objects.

All dark vehicles which were not extracted by the line detection are false negative.

If we evaluate the width analysis true positives are correct extracted single vehicles. False positives are misdetections and false negative are vehicles which could not be extracted through analysis of the width function.
Table 1 shows the achieved completeness and correctness for both algorithms.

algorithm	TP	FP	FN	correctness	completeness
line extraction	51	4	27	93 %	65 %
width analysis	37	4	14	90 %	73 %

Table 1. Evaluation of line extraction and width analysis

As mentioned above we are focussing on high correctness rather than completeness

Hence, the correctness of 90% 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 reach 73% for the analysis of the width function, i.e. the line extraction delivers 51 dark vehicle grouped in queues of which 37 were correctly extracted.

For evaluation of the line extraction we compare the total number of 78 dark vehicles in the image with the previous mentioned 51 vehicle grouped in queues. This is equivalent to a completeness of 65%. Since this quotient also takes single vehicles into account, we can expect an improvement if the approach is extended to these objects. The correctness of 93% shows that the algorithm is appropriate to the extraction of vehicle queues. Figure 10 shows examples of extracted vehicles.

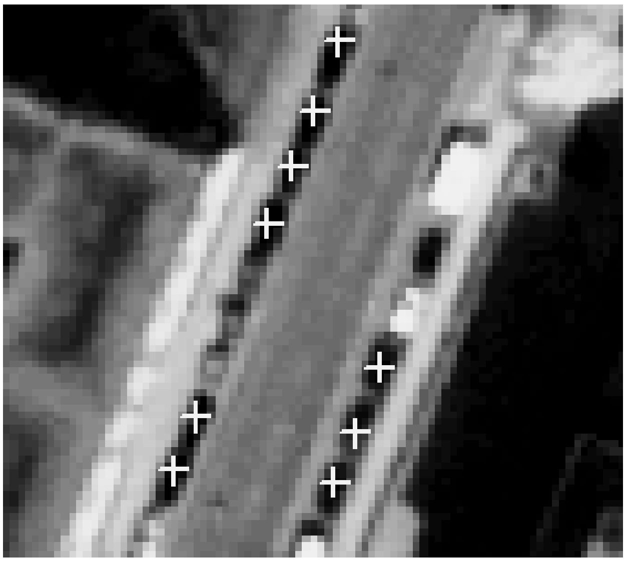

Figure 10. Extracted single vehicles*

CONCLUSION

We presented an approach for vehicle queue detection from a panchromatic QuickBird image of a complex urban scene. For this purpose we used differential geometric line extraction 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. The fast computation makes the approach even now applicable as additional verification for other prior detection. As only dark vehicles grouped in queues were taken into account, the completeness is sufficient at the moment. The next step is the extension of the approach to bright vehicles.

Further investigation and improvement will include the use of morphological filter to support the line extraction. Better verification algorithm will be implemented. Especially the knowledge of road evidence should be used. Current attempt is to build a vehicle example database for automatic derivation of the required parameters for line extraction and hypothesis verification. Finally the simulated GIS is supposed to be replaced by a NavTech MySQL Database.

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