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Detection of Vehicle Queues in QuickBird Imagery of City Areas

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Summary: There is an increasing demand in traffic monitoring of densely populated urban areas. Fixed installed sensors like induction loops, bridge sensors and cameras only acquire traffic flow in a limited area. To complement these systems, our approach uses satellite images for detecting vehicle queues on the entire road network.

In satellite imagery single vehicles are merged to either dark or bright ribbons if they stand in a row. Therefore they can hardly be separated, since they show no detectable features like windshields or shadows. To decrease the number of misdetections it is necessary to use a priori information of road location and direction from GIS to exclude non-relevant areas for the queue detection algorithm.

Initial hypotheses for the queues can be extracted as lines which represent the centers of the queues. We then exploit the fact that vehicle queues show a repetitive pattern. This pattern is also observably in the width profile of queues which can be derived from the gradient amplitude image. Variations of the width profile are analyzed for discrimination of single vehicles within a queue and an algorithm to robustly estimate the contrast of single vehicles is used for verification. We show results obtained from panchromatic QuickBird imagery covering a part of a complex inner city area and discuss the numerical evaluation of the results.

Zusammenfassung: *Erkennung von Fahrzeugreihen in QuickBird-Bildern von Stadtgebieten.* Durch das weiterhin wachsende Verkehrsaufkommen in urbanen Gebieten besteht ein verstärkter Bedarf nach intelligenter Verkehrsüberwachung und -beeinflussung. Die Erfassung der dafür benötigten Daten erfolgt hauptsächlich durch fest installierte Sensoren, wie Induktionsschleifen oder Brückenkameras. Da diese Systeme nur einen Teil des Straßennetzes abdecken, wird in der vorliegenden Arbeit ein Ansatz zur Erkennung von Fahrzeugreihen aus optischen Satellitenbildern vorgestellt. Die dadurch flächendeckend gewonnenen Daten können als Ergänzung zu vorhandenen Verkehrsmodellen genutzt werden.

Um eine möglichst geringe Fehlerrate bei der Fahrzeugerkennung zu erhalten, werden GIS Daten als zusätzliche Information verwendet. Nicht relevante Bildregionen können hierdurch ausgeschlossen werden.

Da Fahrzeugenreihen in Satellitenbildern aufgrund der geringen Auflösung als zusammenhängende Linien abgebildet werden, erfolgt als erster Schritt deren Erfassung durch Linienextraktion. Im Anschluss wird die Breite der extrahierten Linien im Gradientenbild bestimmt. Durch Analyse der Variation der Breite, welche sich wiederholende Muster zeigt, können anschließend Hypothesen für einzelne Fahrzeuge extrahiert werden. Zur Verifikation der gefundenen Hypothesen wird deren Kontrast zur Straßenoberfläche verwendet.

Es werden Ergebnisse aus der Prozessierung eines innerstädtischen QuickBird Bildes und deren Evaluierung gezeigt.

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 informa-

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tion about on-road parked vehicles is not captured. Wide-area images of the entire road network can complement these selectively acquired data. New optical sensor systems on satellites provide images with 1-meter resolution or better, e. g. Ikonos and QuickBird, make this kind of imagery available. Hence new applications like traffic monitoring and vehicle detection from these images have achieved considerable attention on international conferences, e. g. (Bamler & Chiu 2005, Heipke et al. 2005, Stilla et al. 2005). The presented approach focuses on the detection of single vehicles by extraction of vehicle queues from satellite imagery.

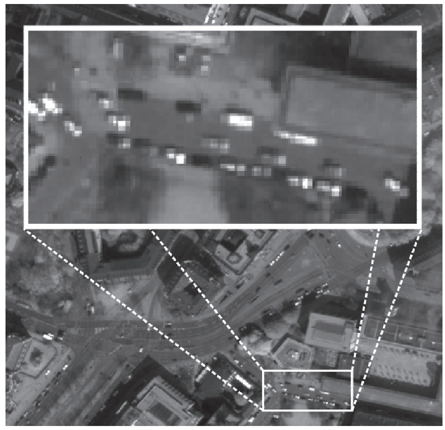


Fig. 1: Vehicles in satellite imagery (Quick-Bird). GSD = 0.6 m.

1.2 *Related work*

Depending on the used sensors and the resolution of the imagery different approaches (Stilla et al. 2004) have been developed in the past. 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 2003). 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 will be declared as detected, if there is sufficient support of the model found in the image. These attempts deliver comparable or even better results than approaches using implicit models but are hardly applicable to satellite imagery where vehicles appear as blobs without any prominent sub-structures (see Fig. 1).

Three different methods for vehicle detection from simulated satellite imagery of highway scenes are tested in (Sharma 2002). The gradient based method and the method using Bayesian Background Transformation (BBT) deliver the best number of vehicle counts compared to ground truth. Since the number of false detections is lower using BBT, this method is more reliable. A third method using Principal Component Analysis (PCA) gives inconsistent performance depending on the noise level of the image. Furthermore, the method gives the lowest vehicle count. A manually created background image is mandatory for the PCA and BBT method, which requires extensive interactive work. Consequently, the approach can hardly be generalized and is limited to images of the same scene. Gerhardinger et al. (2005) use the commercial software *Features Analyst®* to implement an iterative learning approach by analyzing the spectral signature and the spatial context. The authors report that good results can be achieved using a very accurate road GIS, which was only available through manual digitalization. An encouraging approach for single vehicle detection is presented in (Jin & Davis 2004). First, they use morphologic filtering for a rough distinction between vehicle pixels and non-target pixels, though being similar to vehicles. Then a morphological shared-weight neural network is used for extraction. The approach achieves good performance values under the condition that vehicles appear isolated. The approach is not designed for vehicle queues or traffic jams (Jin & Davis 2004).

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.

In dense traffic situations, traffic jams or parking lots, car groupings show quite evident regularities (see e. g. Fig. 1). Exploiting the knowledge about these repeating occurrences and the fact that cars rarely occur isolated is also referred to as global modeling in the field of vehicle detection. Vehicle hypotheses extracted by a neural network classifier (Ruskoné et al. 1996) or a "spot detector" (Michaelsen & Stilla 2001) are collinearly grouped into queues while isolated vehicle hypotheses are rejected. Hinz & Stilla (2006) use a differential geometric blob detector for initial extraction followed by a modified Hough transform for accumulating global evidence for car hypotheses. Since these grouping schemes select hypotheses but do not add new hypotheses, these approaches need an over-segmentation as initial result. They are designed for medium resolution images of approximately 0.5 m GSD.

When high resolution imagery is available a more promising strategy is to focus on reliable hypotheses for single vehicles first and complete the extraction afterwards by searching for missing vehicles in gaps of a queue using a less constrained vehicle model (Hinz 2003). By this, not only queues but also isolated cars can be extracted as long as they belong to the set of reliable hypotheses.

One of the few approaches focusing directly on vehicle queues – in particular military convoys – is presented in Burlina et al. (1997). They extract repetitive, regular object configurations based on their spectral signature. The search space is limited to roads and parking lots using accurate GIS-information in their approach. This seems necessary since the spectrum will be heavily distorted, if adjacent objects gain much in

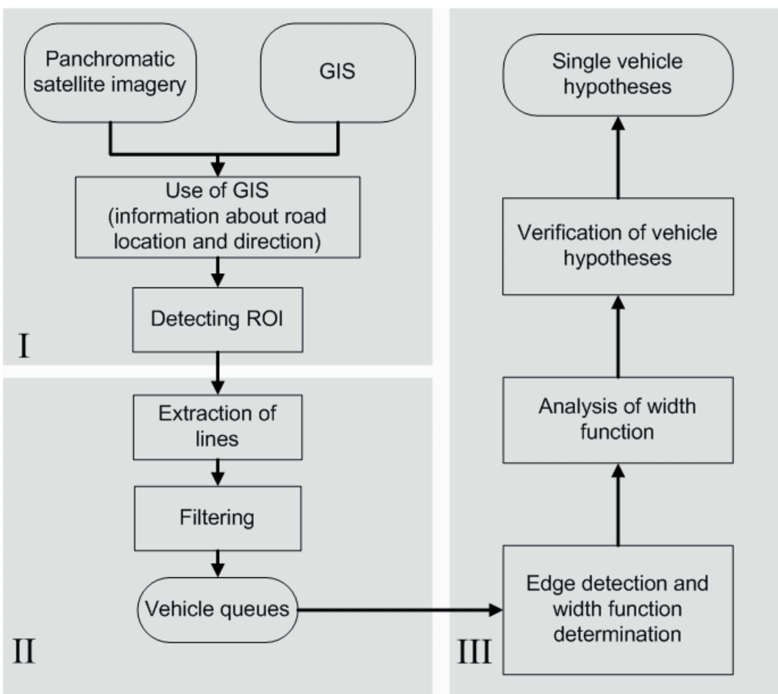


Fig. 2: Processing steps.

influence – even if the spectrum is computed for quite small image patches.

1.3 *System Overview*

Fig. 2 shows the overall design of the presented approach which is separated into three processing stages. In the pre-processing stage (Fig. 2 I) data from a GIS are 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 (Fig. 2 II). From these hypotheses "single vehicles" (Fig. 2 III) are determined by analyzing the width profile of the queues calculated from the gradient image. The analysis strategy is "coarse-to-fine", i. e. hypotheses generation is based on coarse and global information while for verification and refinement details and context information is utilized.

For testing we have selected a section of a complex inner city area captured by panchromatic QuickBird imagery. This presented work is just the first implementation of a module from 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 test robust algorithms with high correctness, while less emphasis is put on the achieved completeness.

2 Detection

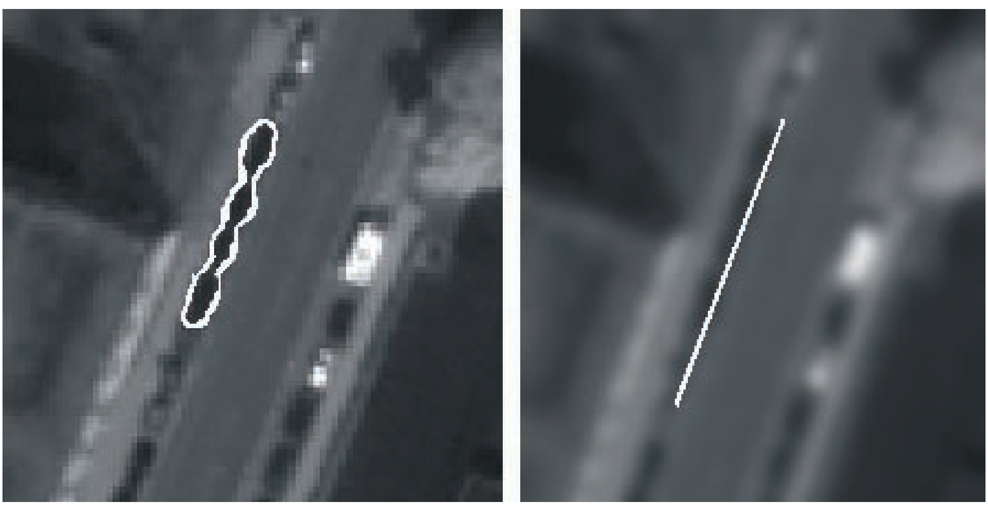
In section 2.1 the used model will be presented. Section 2.2 describes the extraction of vehicle queues using sophisticated line extraction. Then a number of attributes are calculated (section 2.3). Finally, the attributes are analyzed and checked for consistency to verify or falsify single vehicle hypotheses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

2.1 *Vehicle Queue Model*

Generally, a vehicle queue is defined as ribbon with distinct symmetries along and across its local orientation. Basically, the model is similar to that defined in (Hinz 2003); though, since this model is originally designed for aerial images, a number of modifications regarding the significance of different features have been applied.

A vehicle queue

- must have sufficient length, bounded width and low curvature;



(a) (b)

Fig. 3: Queue model. a) original image, b) smoothed image.

- shows a repetitive pattern along the medial axis, both in contrast and width (Fig. 3a), while length and width of the individual replica correspond to vehicle dimensions;
- collapses to a line in Gaussian scale space, i. e. when smoothing the image accordingly (Fig. 3b).

Please, note that this queue model differs from the above mentioned approaches in a way that – in particular through the scale-space description – the queue is modeled as a unique structure and not just as a composite of its underlying, smaller elements. At first glance, this seems of less importance. Still, it provides the basis for detecting a queue hypothesis as a whole (even though at a coarser scale) rather than constructing it from smaller elements. Thereby global knowledge can be incorporated from the very beginning of extraction.

2.2 *Vehicle Queue Hypotheses*

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 11 bit to 10 bit.

For exploitation of a-priori road information, Regions of Interest (RoI) are derived from road axes of GIS data. Within these areas the vehicle detection is performed. Please notice that the assumption about the road width is vague, because the accuracy of road map data is approx. 2 m.

For generating first hypotheses, line extraction is carried out by applying the differential geometric approach of Steger (1998). This algorithm is primarily based on the computation of the second image derivatives, i. e. the local curvatures of the image function. Parameters for the line extraction are chosen corresponding to vehicle geometry (vehicle width: w) and radiometry (expected contrast to road), i. e. the corresponding scale parameter for line extraction has to be chosen as

$$\sigma = \frac{w}{2\sqrt{3}}$$

where σ defines the smoothing factor, calculated from the maximum expected width (e. g. $w = 2.5$ meter).

In addition, the line extraction algorithm is supported by morphologic filtering with a directional rectangular structuring element oriented along the particular road segment. In doing so the queues are enhanced and substructures in bright cars are almost completely removed. The relaxed parameter settings lead to a huge number of false hypotheses but also return nearly all promising hypotheses for vehicle queues. Fig. 5 shows results for the extraction of bright (cyan) and dark (white) lines. However, since the line extraction requires a minimum amount of contrast between vehicles and the road surface, gray vehicles cannot be extracted reliably, because they hardly emerge from their surroundings.

Bright and dark lines are extracted separately. They are connected if they fulfill distance and collinearity criteria. In the given data a maximum distance of one vehicle length must not be exceeded. Furthermore, the merging of parallel lines would lead to significant positional errors and is therefore prevented. The final processing steps consist of geometric smoothing by polygonal approximation and resampling (Ramer 1972), and testing all resulting lines against a minimum length threshold and a maximum direction difference to the road.

2.3 *Determination of Vehicle Queues' Width*

The width determination is done by 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

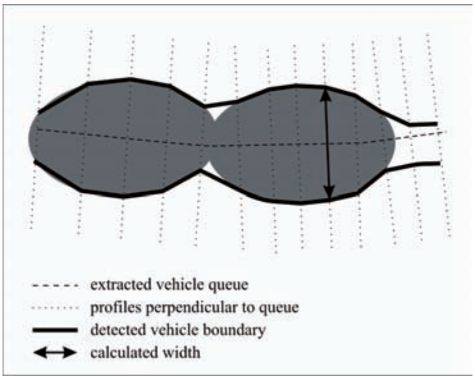


Fig. 4: Concept of queue width determination.

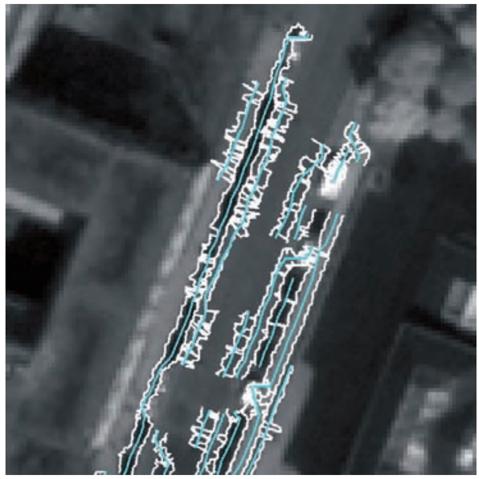


Fig. 5: Width extracted from gradient image: Extracted edges (white), queues' contrelines (cyan).

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. Fig. 4 illustrates the algorithm for width calculation and Fig. 5 shows the result of width extraction.

One can see that most edges correspond to vehicle sides. However, since the gradient image has quite weak contrast, edge 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 (Fig. 6). 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.

The following parameters are used:

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:

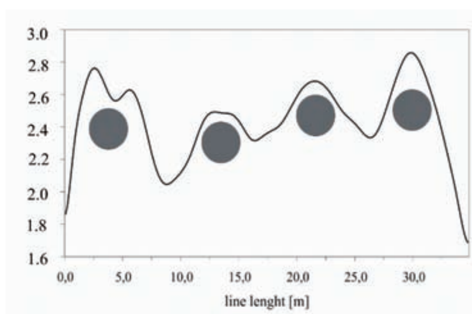


Fig. 6: Width function and single car hypotheses (cricles).

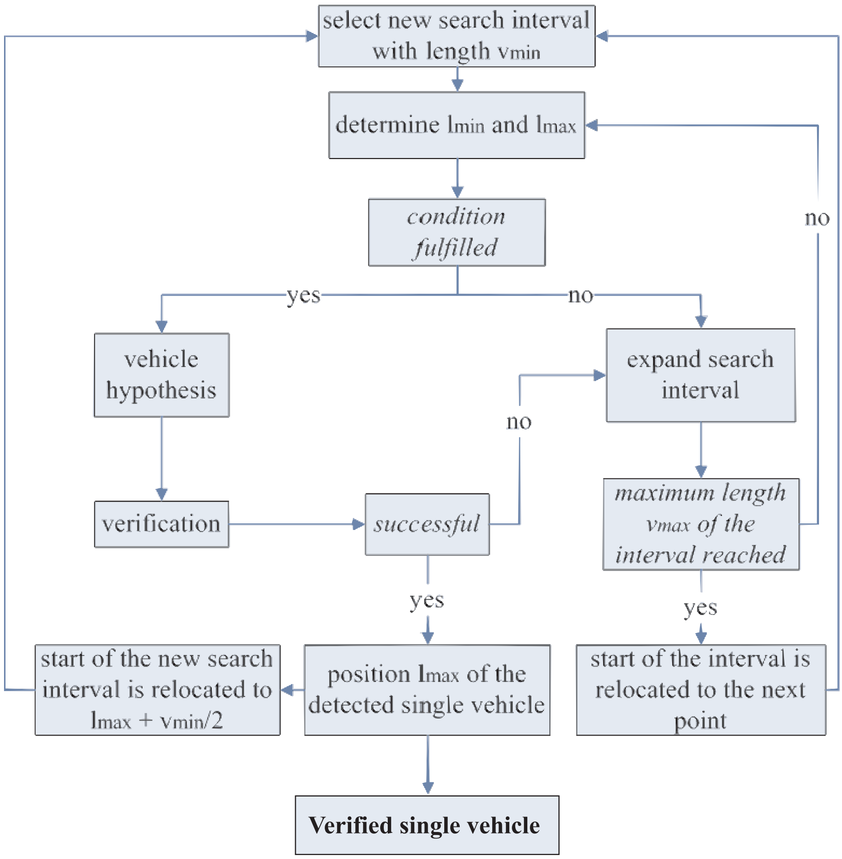


Fig. 7: Concepts of width functions' analysis.

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

Fig. 7 shows the flow chart of the width analysis scheme. Essentially, this algorithm tries 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.

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, the hypothesis with the highest maxima in the width function will be verified.

After a hypothesis has been generated we use the contrast of the vehicle and the adjacent road surface for a simple verification. Here the difference of the median gray values of the inner and the outer region is calculated (see Fig. 8).

3 Results

The performance of the implemented approach has been tested on panchromatic QuickBird data with approx. 60 cm GSD. The results of the approach were evaluated concerning the criteria "correctness" and "completeness". They are defined as follows:

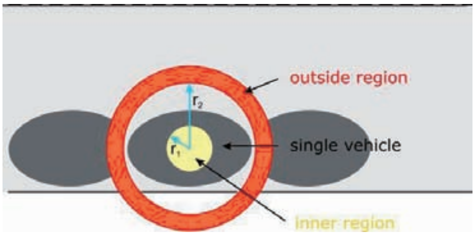


Fig. 8: Verification.

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

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

with TP true positives
FP false positives
FN false negatives

The measures refer to single vehicles, i. e. true positives are correctly extracted vehicles, false positives are misdetections, and false negatives are missed vehicles with respect to the reference data. Fig. 9 shows examples of extracted vehicles. The cyan crosses are verified detected vehicles (TP) and the white crosses are misdetections (FP). Tab. 1 summarizes the evaluation depending on the four types of reference data included:

a) all vehicles
b) only bright and dark vehicles, i. e. without gray vehicles
c) only bright vehicles
d) only dark vehicles

Gray vehicles have been excluded from the reference in b) since they almost show no contrast to their surroundings. It has to be mentioned that the acquisition of reference data for some vehicles is certainly not free of errors. Even a human observer is sometimes not able to identify all vehicles in an image scene with high confidence. Therefore our reference data can only be treated as a very good approximation of real "groundtruth".

As mentioned in the beginning we are focussing on high correctness rather than completeness, since we want to test the algorithms' reliability in terms of providing seed points for completing the result. Hence, the correctness of about 76% 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 results. As supposed the line extraction and the verification works much better for dark vehicles, since more dark vehicles are grouped in queues. Despite of these promising correctness values, a maximum completeness of 48.2% underlines the necessity of further improvements.

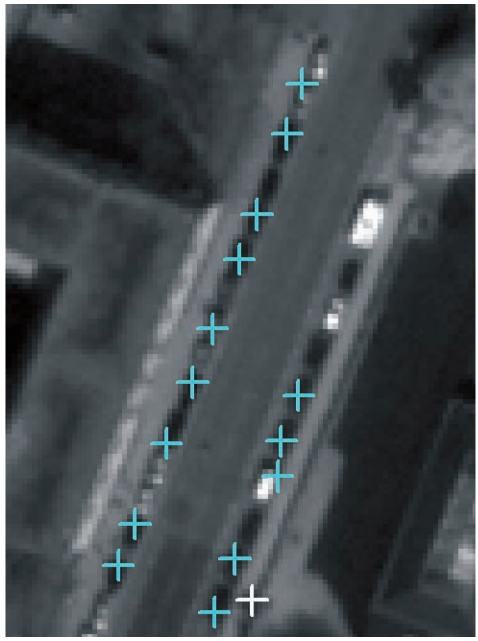


Fig. 9: Extracted single vehicles: Correct extractions (cyan), misdetections (white).

Tab. 1: Evaluation of the line and width analysis.

	Reference data			
	(a)	(b)	(c)	(d)
Completeness [%]	34.1	40.3	22.2	48.2
Correctness [%]	76.0	72.3	71.1	73.1

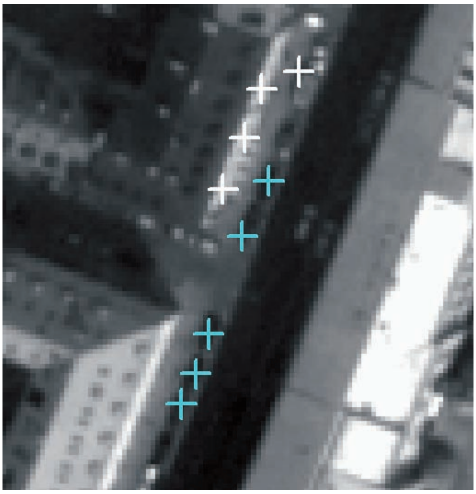


Fig. 10: Extracted single vehicles: Correct extraction (cyan), misdetections (white).

Concerning this weak completeness, one has to keep in mind that not all vehicles are contained in queues and, furthermore, that the line extraction does not extract all existing queues.

There are also a number of misdetections, in particular when objects similar to vehicles are at side-walks (see e. g. Fig. 10). Such failures could be overcome, for instance, when analysing neighbourhood relations of extracted vehicles more in-depth. A constellation as achieved for the right queue in Fig. 9 is very unlikely to happen; five vehicles are almost perfectly aligned in a row while one isolated vehicle is located on the "wrong" side of this row. Incorporating this kind of reasoning into the approach would allow furthering reducing the misdetection rate.

The numerical assessment of the results obtained when applying the approach to a large, complex urban scene confirms the discussion above (see Fig. 11). Despite the weak completeness, the good correctness of the eventually extracted vehicles allows to serve as starting point for searching additional vehicles. Therefore the next steps of implementation will include the search for isolated vehicles using the information from the previously queue detection. Preliminary investigations using a differential blob detector (HINZ 2005) for accomplishing this task have already been undertaken.

Concluding the discussion, vehicles with good or even medium contrast to the road surface can be extracted very accurate. Furthermore, the results show that the analysis of width is able to extract single vehicles from queues with high correctness. Still, the completeness of the overall extraction is relatively low, since only queues can be extracted but no isolated vehicles. The results clearly show that the approach is promising but further improvements are necessary.

4 Summary

We presented an approach for vehicle queue detection from panchromatic QuickBird imagery of urban scenes. 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. The analysis of these width functions allows to extracting 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 space-borne 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 manually digitized road data of the GIS are supposed to be replaced by a national core database (ATKIS).

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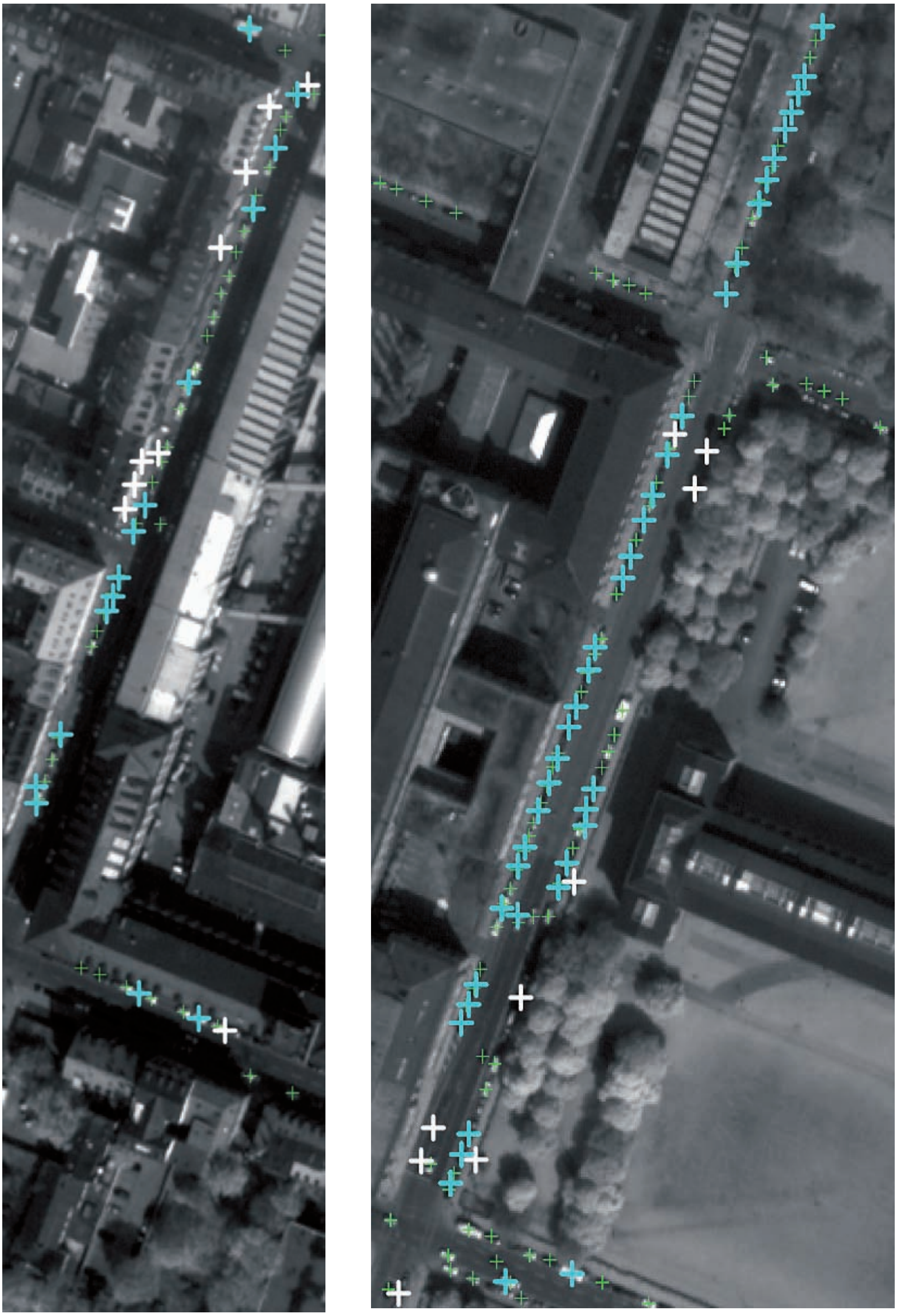

Fig. 11: Results for a large urban area: Correct extractions (cyan), misdetections (white), missing extractions (green).

www.ipk.bv.tum.de/jrl] which is funded by Helmholtz Gemeinschaft.

References

BAMLER, R. & CHIU, S., 2005: Spaceborne traffic monitoring from SAR and optical data (Jointly Organized with ISPRS WG III/5). – Session at IGARSS'05 (on CD)

BURLINA, P., CHELLAPPA, R. & LIN, C., 1997: A Spectral attentional mechanism tuned to object configurations. – IEEE Transactions on Image Processing **6**: 1117–1128.

GERHARDINGER, A., EHRLICH, D. & PESARESI, M., 2005: Vehicle detection from very high resolution satellite imagery. – In: STILLA, U., ROTTENSTEINER F. & HINZ. S. (Eds.): CMRT05, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **36** (Part 3/W24): 83–88.

HEIPKE, C., JACOBSEN, K. & GERKE, M. (Eds.), 2005: High-resolution earth imaging for geospatial information. – International Archives of Photogrammetry and Remote Sensing **36**, Part 1 W3 (on CD).

HINZ, S., 2003: Integrating local and global features for vehicle detection in high resolution aerial imagery. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **34** (Part 3/W8): 119–124.

HINZ, S., 2005: Fast and subpixel precise blob detection and attribution. – Proceedings of ICIP 05, Sept. 11–14, 2005, Genua.

HINZ, S. & STILLA, U., 2006: Car detection in aerial thermal images by local and global evidence accumulation. – Pattern Recognition Letters **27:** 308–315.

JIN, X. & DAVIS, C.H., 2004: Vector-guided vehicle detection from high-resolution satellite imagery. – Proc. IEEE International Geoscience and Remote Sensing Symposium (IGARSS '04), Vol. **2**: 1095–1098.

MICHAELSEN, E. & STILLA, U., 2001: Estimating urban activity on high-resolution thermal image sequences aided by large scale vector maps. – Proc. IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion over Urban Areas, 25–29.

RAMER, U., (1972): An iterative procedure for the polygonal approximation of plane curves. – Computer Graphics and Image Processing **1**: 244–256.

RUSKONÉ, R., GUIGES, L., AIRAULT, S. & JAMET, O., 1996: Vehicle detection on aerial images: A structural approach. – In: KROPATSCH, G. (Eds.): Proc. 13th International Conference on Pattern Recognition (ICPR'96), Vol. 3, IEEE Computer Society Press, 900–903.

SHARMA, G., 2002: Vehicle detection and classification in 1-m resolution imagery. – MSc Thesis, Ohio State University, Columbus, USA-OH.

STEGER, C., 1998: An Unbiased Detector of Curvilinear Structures. – IEEE Transactions on Pattern Analysis and Machine Intelligence **20** (2): 113–125.

STILLA, U., MICHAELSEN, E., SOERGEL, U., HINZ, S. & ENDER, J., 2004: Airborne monitoring of vehicle activity in urban areas. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **35** (Part B3): 973–979.

STILLA, U., ROTTENSTEINER, F. & HINZ. S. (Eds.), 2005: Object Extraction for 3D City Models, Road Databases, and Traffic Monitoring – Concepts, Algorithms, and Evaluation (CMRT05). – Int. Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **36** (Part 3/W24).

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