Analysis of Image Sequences for the Detection and Monitoring of Moving Traffic

Matthias Butenuth, Peter Reinartz, Dominik Lenhart & Dominik Rosenbaum, München; Stefan Hinz, Karlsruhe

Keywords: Image Sequences, Self-calibration, Detection, Tracking, Moving Traffic

Summary: This paper focuses on the detection and tracking of vehicles from airborne image sequences to monitor moving traffic. Two different systems are described: the first one is a near real-time tracking algorithm based on normalized cross correlation. The second approach includes model knowledge about driver behavior, traffic dynamics and context to exploit svelocity and trajectory evaluation. The shown results and derived quality measures demonstrate the performance of the proposed systems, in particular the contribution of the traffic model knowledge enhances the correctness of the tracking results. Finally, concluding remarks are given to point out further research.

Zusammenfassung: *Analyse von Bildsequenzen zur Detektion und Überwachung von fließendem Verkehr.* Dieser Artikel zielt auf das Erkennen und Verfolgen von Fahrzeugen aus luftgetragenen Bildsequenzen zur Überwachung von fließendem Verkehr. Zwei unterschiedliche Systeme werden beschrieben: Das Erste ist ein echtzeitnahes Tracking-Verfahren, welches auf der normalisierten Kreuzkorrelation basiert. Das zweite Verfahren bindet Modellwissen über Fahrerverhalten, Verkehrsdynamiken und Kontext ein, um Geschwindigkeits- und Trajektorienbewertungen auszunutzen. Die Ergebnisse und die abgeleiteten Qualitätsmaße zeigen die Leistungsfähigkeit der Systeme, insbesondere der Beitrag des Verkehrsmodellwissens erhöht die Korrektheit der Trackingergebnisse. Abschließend wird ein Ausblick auf zukünftige Forschungen gegeben.

1 Introduction

The analysis and interpretation of image sequences for the detection of moving objects is an important research topic. An early overview is given, for instance, in (Cedras & Shah 1995) and more recent advances with focus on air- and spaceborne traffic data collection can be viewed in the compendium in (Hinz et al. 2006). In general, traffic monitoring is mainly based on data from conventional stationary ground measurement systems such as induction loops, radar sensors or terrestrial cameras. All ground measurement systems embedded in road infrastructure deliver precise traffic data with high temporal resolution, but their spatial distribution is still limited to selected positions along motorways and main roads. The sparse spatial sampling of these systems makes area-wide traffic monitoring difficult, since detailed traffic models are necessary to interpolate between the measurement positions. An alternative approach is to collect traffic data by means of vehicles equipped with mobile measurement units, which flow with the traffic. These so called floating car data, FCD (Schaefer et al. 2002, Busch et al. 2004), is often obtained from taxicabs and delivers very useful traffic information along specific routes within cities. Yet such systems are currently only available for a few big cities. Furthermore, the traffic information available from this source depends inherently on the routes taxicabs are taking. Taxi drivers tend to avoid busy roads during rush hours, leading to only few or even no data being available for roads burdened with commuter traffic.

DOI: 10.1127/1432-8364/2009/0030 1432-8364/09/0030 $ 2.50

The big advantage of the remote sensing techniques presented in this paper is that they complement the aforementioned techniques. The measurements can be acquired nearly everywhere except of tunnels and roads occluded by trees. The entire traffic dynamics for a given area can be recorded and analyzed, e. g., vehicle density, velocities, overtaking maneuvers, merge and exit behavior, and traffic congestions for a certain time span. Such results are highly relevant input data for traffic modeling and simulation programs, for testing the efficacy of traffic control measures and for the input into GIS systems for traffic monitoring. In addition, there are no dependencies on any third party infrastructure.

The usefulness of airborne video data from both the visible and thermal spectrum has been studied using many different approaches (Ernst et al. 2003, Stilla et al. 2004, Toth & Greijner-Brzezinska 2004, Yao et al. 2008a), and also first attempts with airborne LIDAR data have been published (Toth & Greijner-Brzezinska 2006, Yao et al. 2008b). Tests with several camera systems and various airborne platforms as well as the prototype development of an airborne traffic monitoring system and thematic image processing software for traffic parameters were done in the projects "LUMOS" and "Eye in the Sky" (Ernst et al. 2003, Börner et al. 2004). Both systems are based on video cameras mounted on aerial platforms. They meet the requirements of rapid airborne traffic data acquisition, however, the field of view is limited.

To overcome this limitation of video cameras, we develop a system for automatic derivation of traffic flow data which is based on using for commercial medium format frame cameras. These cameras enable the coverage of large areas at a reasonable ground sampling distance. Yet the frame rate is quite low (and occasionally variable) as more time is necessary for reading-out the data. These peculiarities need to be considered in the design of an airborne traffic monitoring system. There are not many investigations on optical airborne image sequences with a large field of view (Toth et al. 2004). The general suitability of image sequences taken with airborne cameras for traffic monitoring was shown in (Reinartz et al. 2006, Rosenbaum et al. 2009). An approach that can deal with these characteristics is presented in (Lenhart & Hinz 2006, Lenhart et al. 2008). Further advances of this work are introduced in this paper.

Most of the mentioned approaches utilize data from a road database as a priori information for the automatic detection of road area and vehicles. For less complex roads a geometrical refinement is possible as a preceding step, e. g., using network snakes (Butenuth 2007, Butenuth 2008). From the database, numerous attributes can be assigned to each road polygon, including the driving direction on motorways, which reduces the search space during automated tracking.

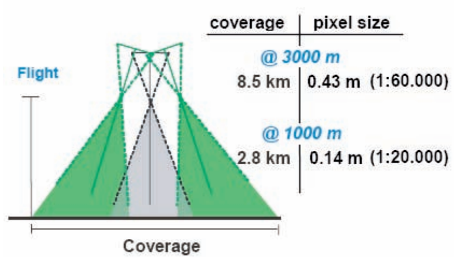
In the following, we present our research activities on airborne traffic monitoring with special emphasis on vehicle tracking. The system is designed in such a way that it fulfills following requirements:

- The camera system must support a large coverage comparable to photogrammetric aerial photographs, it must deliver a spatial resolution sufficient for vehicle detection and tracking (< 25 cm), and its frame rate must enable image acquisition in such intervals that also fast cars traveling anti-parallel to the aircraft are imaged at least twice.
- The algorithms for traffic analysis must provide the results in near real-time so that traffic management can immediately react on the current situation.

The paper thus focuses on the characteristics of the camera system first (cf. Section 2), and then outlines two approaches for the detection and tracking of vehicles to monitor moving traffic. The goal is to point out the usability of image sequences analysis with different approaches (cf. Section 3) and to compare the derived results with each other (cf. Section 4). Finally, concluding remarks are given to highlight further investigations and research opportunities.

2 3K Camera System

In this section the newly developed 3K camera system of DLR is presented to provide the image sequences for the aimed analysis. The



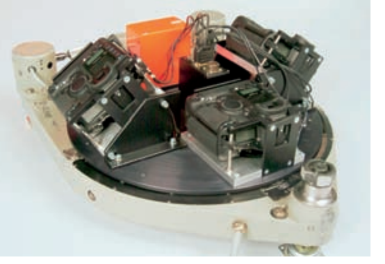


Fig. 1: Left: Illustration of the image acquisition geometry. The tilt angle of the sideward looking cameras is approx. 35°; right: DLR 3K camera system, integrated in a ZEISS aerial camera mount including the IMU of the IGI georeferencing system (orange) for attitude measurements.

camera system consists of three non-metric off-the-shelf cameras (Canon EOS 1Ds Mark II, 16 megapixels each). The cameras are aligned in an array with one camera looking in nadir direction and two in oblique direction, which leads to an increased FOV of max 110°/31° in across track/flight direction (cf. Fig. 1). The ground pixel size and swath width are depending on the flight altitude and range between 15 cm to 50 cm and 2.5 km to 8 km respectively. This camera system is operated on board the DLR research planes Dornier 228 and Cessna 208B, but an extension to other platforms may be possible in future.

The 3K camera can be used in different mapping or traffic acquisition modes and, thus, a high resolution and wide-area monitoring task even at low flight altitudes, e. g., below the clouds, is feasible. Within two minutes an area of approximately 10 km × 8 km can be monitored. The frame sensor system is coupled with a real-time GPS/IMU navigation system (IGI), which enables the direct georeferencing. The ability to acquire image sequences with up to 3 Hz allows the application to monitor moving traffic. Prerequisite is a high precision orthorectification of the data using an underlying SRTM DEM. The sequential images have to match each other (for ground pixels) with sub-pixel accuracy, which can be reached by direct georeferencing including calibration and boresight values.

Two calibrations of the 3K camera system were performed: one on a ground test field in 2006 (Kurz et al. 2007) and one in-flight in 2008. For the latter, tie points were matched and all control points were measured in 281 images from all three cameras. These tie points, control points and GPS positions were introduced into a self calibrating bundle adjustment. Altogether, a redundancy of about 10^5 was reached and five interior parameters were estimated for each camera.

3 Detection and Monitoring of Moving Traffic

In this section, the methodical aspects of traffic monitoring are described. In order to detect also non-moving vehicles, we conceptually separate the tasks of vehicle detection and vehicle tracking, thereby focusing on tracking in the following. Detection of vehicles in single images can for instance be done with the approach of (Hinz 2004) for high resolution images and (Leitloff et al. 2009) for moderately sampled images.

In the following sub-sections two different systems for vehicle tracking are outlined. The first one is simpler from a methodological point of view but works in near real-time. The second includes more knowledge about driver behavior, traffic dynamics and context, but needs more parameters to initialize and a longer execution time. Both approaches are independently from each other, but an integration in terms of an adaptive system is a possible future advancement. The first tracking algorithm may be used in distinct scenarios like motorways providing traffic data with a high actuality, whereas the second one can be applied in difficult environments like urban main and side roads.

3.1 *Near Real-Time Vehicle Tracking with Normalized Cross Correlation*

An easy to use and robust technique for vehicle tracking is based on matching image patches by normalized cross correlation (Lewis 1995). For traffic data acquisition the camera system operates in a so-called burst mode with four or five consecutive images at a high repetition rate of up to 3 fps followed by a break of several seconds. During this break the plane moves significantly over ground until the next image sequence is started. Thereby a configurable overlap of 10% to 20% between two consecutive image sequences (bursts) is obtained. This reduced the data amount produced by the camera system significantly compared to a mode where images are taken continuously with a frame rate of 3 fps. The vehicle detection is done on the first image of the burst, vehicle tracking starts with the image pair consisting of the first and second image of a sequence. For each vehicle detected in the first image, a template image is generated at the position of the vehicle detection in the first image. In the second image, a rectangular search window is opened at the vehicle position obtained from the detection in the first window. Thereby, the rectangle is aligned to the driving direction, which is obtained from the road database. The length of the search window depends on the maximum expected velocity for the road and the time difference between the two images. The normalized cross correlation is calculated between the template image and second image. The obtained values give the probability of finding the vehicle from the first image at a certain position within the search window in the second image; Fig. 2 shows an example for a correctly tracked car.

The derived score [0.0 ... 1.0] needs to exceed a certain value for keeping it as a match. A maximum correctness is reached with an acceptable completeness in tracking by setting this score threshold to a value of 0.9. The tracking is restarted within the second and third image (and with further consecutive pairs of the exposure burst in succession) in order to track the vehicles through a whole image sequence. For vehicles that disappear at image borders or below bridges during an exposure of the sequence (but have been detected or tracked in the image before) the tracking algorithm does not find a match. This means that disappeared vehicles are normally not confused with other vehicles or objects, because of the high matching threshold of 0.9. Vehicles occluded by bridges or other objects may be detected again after reappearance by a new vehicle detection performed on a further exposure sequence. However, they appear as new detections and loose their identification relation. In order to increase correctness, cross correlation is performed as matching band by band in RGB color space to exploit the varicolored object information.

For vehicle tracking on motorways, rotations of the template vehicle image are neglected, because the lane change angles at typical velocities obtained on motorway is quite low. However, for city regions, rotation of the template during correlation can be turned on, but this will result in increased computing time linearly with the number of rotation steps during correlation. In order to save computation time, matching is not performed with sub pixel accuracy. Integral images are not calculated since it is not cost efficient on small templates. We further accelerate normalized cross correlation by an estima-

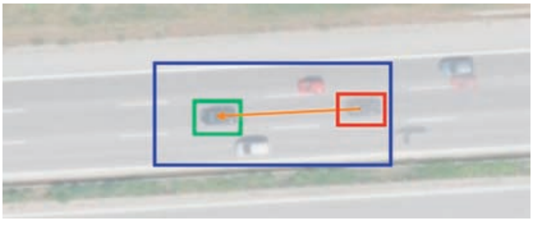


Fig. 2: Matching with normalized cross-correlation (two sequential images are superimposed).

tion of the normalization since calculating the full norm at each position in the search window takes quite a lot of calculation time. Assuming that the illumination situation does not change a lot between two images, an upper limit of the correlation score is estimated for each correlation position in the search window. Only if this upper limit exceeds the score threshold the exact normalized cross correlation is calculated at that position. For the estimation of the score only the first (blue) channel of the color image is used. We choose the first channel for the estimate, since it provides faster memory access then the second or third channels due to the definition of the program internal image data structure. These arrangements decrease computation time by a factor of at least four. These arrangements lead to computation times of less than 10 s per image burst tested on a scene containing about 100 cars using standard hardware based on Quad-Core CPU.

At high resolutions (GSD ~ 15 cm) on motorway scenarios this tracking algorithm reaches a correctness of better than 95% at a completeness of more than 90%. This high sufficiency might be due to the fact, that at such resolutions car details like car body types, the presence or absence of sunroofs and similar features can be resolved. While vehicle tracking based on normalized cross correlation in RGB color space itself works fine at high resolutions, it is sensitive to false alarms obtained in vehicle detection. As mentioned before vehicle tracking is based on vehicle detection performed in the first image of each burst. Although the vehicle detection algorithms used for this may be highly sufficient they deliver a certain percentage of false detections. Although several false vehicle detections can be eliminated during tracking as outliers in direction or velocity space, other false alarms still remain in tracking. Especially objects from the dashed lane markings that were detected as vehicles erroneously may still remain in tracking. This is due to the fact, that the object shape of the dashed markings reappears periodically within a search window and the fact that all of these markings have almost exactly the same shape and intensity.

3.2 *Advanced Vehicle Tracking Using Velocity and Trajectory Evaluation*

In this section, the approach complementing the aforementioned system uses image triplets and track evaluation is presented. Again, vehicles are assumed to be detected beforehand. The tracking of the cars is accomplished in the consecutive two images. Since time gaps between frames may get large tracking is done by matching the cars of the first image (i. e., car patches as reference patches) over the next two images. To this end, an adaptive shape-based matching algorithm is employed including internal evaluation and consistency checks (Steger 2001, Ulrich 2003). The similarity measure is invariant against noise and illumination changes but not against rotations and scale. Thus, for each image the reference patch is updated to adapt illumination and aspect variations. Fig. 3 illustrates the multiple hypotheses matching over image triplets.

The matching process delivers a number of matched positions for each vehicle where the best match is not always the correct one. In our algorithm, we use a maximum number of the six best matches for each run. Thus, we may receive up to six match positions in Image 2 (3) and 36 match positions in Image 3 (4)

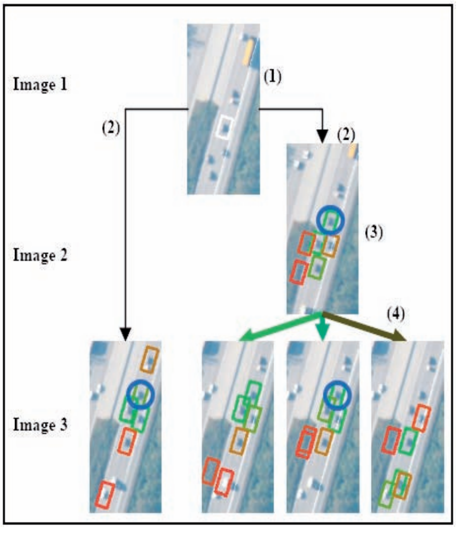


Fig. 3: Matching concept with image triplets using sequential matching between image pairs and direct matching between 1st and 3rd image.

for each vehicle detection. Also having six match positions for direct matching from Image 1 to Image 3 (2, left branch), we need to evaluate 216 possible tracking combinations for one car. At a first glance, this seems quite cost intensive. Yet, many incorrect matches can be rejected through simple thresholds and consistency criteria controlling the computational load easily.

For the evaluation of the tracks, a Bayesian maximum a posteriori probability decision rule based on a simple motion model is applied (Lenhart & Hinz 2006). The model focuses on smooth tracks and smooth velocity profiles, yet with braking and standing cars allowed. During the evaluation, a variety of intermediate weights are employed which include matching score, motion consistency and spatial identity of the results from direct and indirect matching. Finally, these weights are aggregated to an overall tracking score and the best match combination is chosen as the correct vehicle track.

In order to refine the detection and tracking results, a velocity and trajectory analysis is carried out which is independent of the preceding detection and tracking algorithms. The goal of this analysis is to eliminate false alarms from the set of detections. This allows a more precise velocity estimation for road segments since false alarms significantly influence velocity accuracy. There are mainly two ways how false alarms may be tracked:

- Collinear motion for redundant objects/features belonging to vehicles (e. g., trailer, car shadow).
- With zero velocity if objects belong to the background (e. g., road bank, shadows of trees).

A first step to eliminate false detections is to remove redundant objects from the set of detections. These are the kind of objects that belong to vehicles, such as shadows or trailers. For each pair of detections, the spatial distance is calculated. A search for very small distances delivers candidates for redundant objects, which are analyzed in terms of their trajectories. The analysis includes the speed and direction of the determined trajectories and the relative direction between the candidates. Identical trajectories and constant relative direction indicates redundant candidates while passing vehicles will have at least a slight difference in their speed or relative orientation.

For velocity analysis, we use fuzzy sets for knowledge representation (Zadeh 1965) which allows an intuitive way of describing vehicle behavior as a function of the state of traffic and the location with respect to intersections or traffic lights. For each road segment, the density is determined. In dependence of the density D and the distance d to road node points, possibilities for the range of velocities are defined (cf. Fig. 4). By linear interpolation along the axes of density D and distance d, a cubic membership function can be derived (cf. Fig. 5).

According to the fuzzy membership function, a weight μ_A is assigned to each of the detections. The weight contributes to the calculation of a weighted mean velocity $\bar{v}$ per road section:

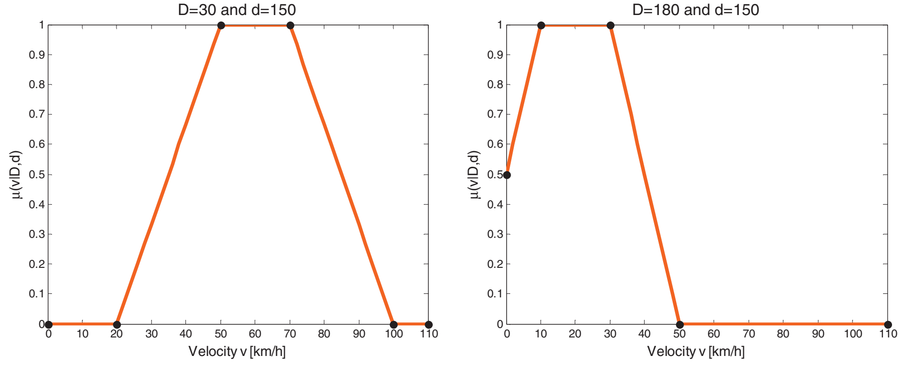


Fig. 4: 1D membership functions given a traffic density $D = 0$ and $D = 180$, respectively, and distance $d = 150$ with support points (black dots).

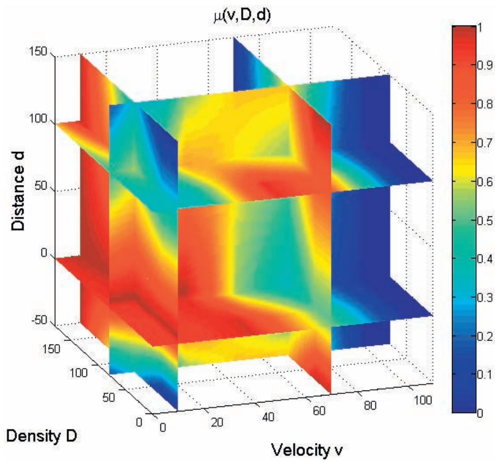


Fig. 5: 3D membership function with slices at $v = 10$, $v = 70$, $D = 80$, $d = 0$ and $d = 100$.

$$\bar{v} = \frac{\sum_i v_i \cdot \mu_A(v_i, D_i, d_i)}{\sum_i \mu_A(v_i, D_i, d_i)} \tag{1}$$

with its standard deviation σ_v

$$\sigma_v = \frac{\sqrt{\sum_i (\bar{v} - v_i)^2 \cdot \mu_A^2(v_i, D_i, d_i)}}{\sum_i \mu_A(v_i, D_i, d_i)} \tag{2}$$

Applying a minimum threshold on the summed up weights of a section, we meet the circumstance that there are only false alarms in a free flow section. If the sum of the weights of a section is below the threshold, all detections of this section are removed. Finally, objects with a velocity $\nu_i < \bar{\nu} - 2 \cdot \sigma_\nu$ are regarded as outliers and eliminated. A refined and unweighted average velocity is determined from the remaining detections. The resulting distribution is unbiased under the assumption that all false alarms have been eliminated.

4 Results and Analysis

4.1 *Results of Vehicle Tracking with Normalized Cross Correlation*

Vehicle tracking was tested on data obtained at a flight height of 1000 m (15 cm GSD) and at a flight height of 2000 m (30 cm GSD). Fig. 6 shows a typical result on tracking vehicles from the first image of an image sequence to the next image. On images with a resolution of 15 cm GSD, vehicle tracking on motorways performs pretty well with a correctness of better than 90% and a completeness of almost 90% on each image pair. On images obtained

Fig. 6: Car tracking by normalized cross correlation of a group of cars detected in the first image of a sequence (left) to the second image (right).

Fig. 7: Resulting velocities of vehicles measured by car tracking.

from higher flight levels (30 cm GSD) tracking still works fine with a completeness of 90% while having a correctness of 75%. We attribute the good tracking performance on low flight heights to the fact that with a resolution of 15 cm GSD vehicle details like sunroof, windscreen and backlight, and body type go into the correlation which simplifies finding the correct match. However, these details are not anymore seen at higher flight levels. In Fig. 7 the resulting velocities of the tracked cars are shown.

4.2 *Results of Vehicle Tracking Using Velocity and Trajectory Evaluation*

The tracking with image triplets has been tested on an image sequence consisting of four images with a GSD of 30 cm. In this example, the detection has been carried out manually with considering a reasonable detection characteristic and quality. Overall, 50 objects have been selected containing of 33 vehicles and 17 false alarms (see Fig. 8). Therefore, a detection completeness of 100% and a correctness of 66% is given.

The results of the tracking are depicted in Fig. 9. Only one object has been tracked incorrectly, however, the tracking failed for seven objects including three vehicles. This results in a tracking completeness of 86% and a correctness of 98%. Tests on other data delivered similar tracking quality measures. Note that we do not distinguish between false alarms and correct detections but only consider the mere outcome of the tracking procedure.

Using the analysis of velocities, eleven false alarms could be eliminated (cf. Fig. 10) while two false alarms could not be found. In addition, no vehicle has been falsely removed from the tracking results. This leads to a final complete-

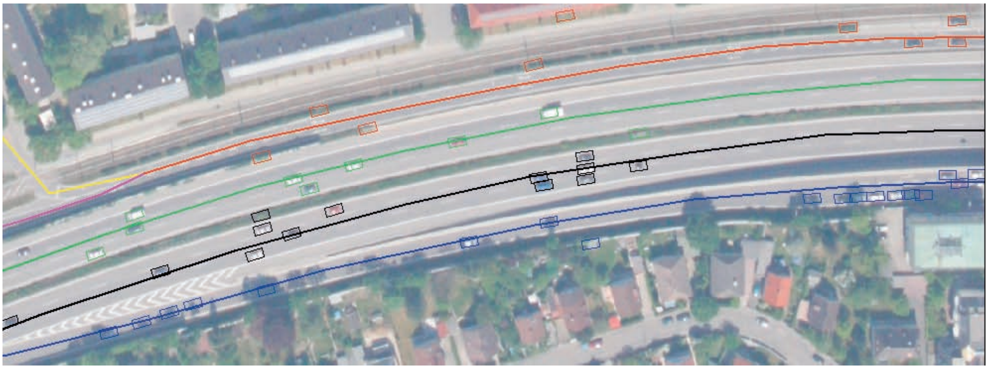


Fig. 8: Detected vehicles with color coded assignments to road polygons of the database.

Fig. 9: Results of tracking using image triplets with trajectories of tracked objects. Red crosses indicate detections where the tracking failed.

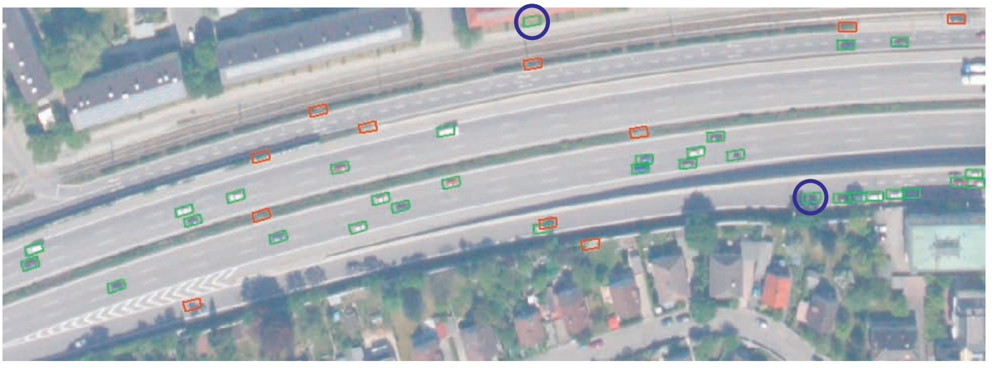


Fig. 10: Refined track results. Green: Detected and tracked vehicles. Red: Eliminated false alarms after velocity evaluation. Blue circle: False alarm which has not been eliminated.

ness of 90% and a correctness of 93%. Since we started with 100% detection completeness, it is obvious that the initial detection quality will directly influence the final completeness. However, a poor initial detection correctness can be improved significantly.

One of the remaining false alarms has been tracked incorrectly and, thus, has been assigned with a wrong velocity. The other one was located in the vicinity of a cue of standing vehicles and was assumed to belong to this group of cars. Consequently, these false alarms do not influence the traffic data in a critical manner since they do not significantly increase the traffic density or falsify the average velocity.

5 Conclusions

In this paper, two approaches for the detection and monitoring of moving traffic using airborne image sequences are presented. The shown results and quality measures demonstrate the contribution of the proposed approaches, in particular the introduction of traffic model knowledge enhances the correctness of the tracking results. Both tracking systems run currently independent from each other, but an integration of both approaches in terms of a consecutive system is a possible future enhancement. In particular, the second system, the advanced vehicle tracking exploiting model knowledge of velocity and trajectory evaluation, can be regarded as a subsequent step to the tracking algorithm presented at first.

An interesting point of further investigations could be the utilization of the traffic model in an enhanced way. Up to now, the extracted and tracked vehicles are used to enrich the traffic models and traffic simulations. Here, the focus is on reliable and robust results to guarantee for stable numeric models concerning the traffic monitoring. A further step could be an iteration in terms of introducing the updated traffic model again in the extraction and tracking process. For example, the enriched traffic model could allow for input information enabling less strong extraction parameters for the detection and tracking of the vehicles. Obviously, the enhanced tracking results will improve the traffic model once again.

References

Börner, A., Ernst, I., Ruhé, M., Sujew, S. & Hetscher, M., 2004: Airborne Camera Experiments for Traffic Monitoring. – International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences **35** (B1): 243–248.

Busch, F., Glas, F. & Bermann, E., 2004: Dispositionssysteme als FCD-Quellen für eine verbesserte Verkehrslagerekonstruktion in Städten – ein Überblick – Straßenverkehrstechnik **09/04**.

Butenuth, M., 2007: Segmentation of Imagery Using Network Snakes. – Photogrammetrie – Fernerkundung – Geoinformation **1/07:** 7–16.

BUTENUTH, M., 2008: Topology-Preserving Network Snakes. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **37** (B3a): 229–234.

CEDRAS, C. & SHAH, M., 1995: Motion-based Recognition: A Survey. – Image and Vision Computing **13** (2): 129–155.

ERNST, I., SUJEW, S., THIESSENHUSEN, K.-U., HETSCHER, M., RASSMANN, S. & RUHÉ, M., 2003: LUMOS – Airborne Traffic Monitoring System. – Proceedings IEEE International Conference on Intelligent Transportation Systems, on CD.

HINZ, S., 2004: Detection of Vehicles and Vehicle Queues in High Resolution Aerial Images. – Photogrammetrie – Fernerkundung – Geoinformation **3/04:** 201–213.

HINZ, S., BAMLER, R. & STILLA, U., 2006: Theme issue "Airborne and Spaceborne Traffic Monitoring". – ISPRS Journal of Photogrammetry and Remote Sensing **61** (3/4).

KURZ, F., MÜLLER, R., STEPHANI, M., REINARTZ, P. & SCHROEDER, M., 2007: Calibration of a Wide-angle Digital Camera System for Near Real-time Scenarios. – Proceedings High Resolution Earth Imaging for Geospatial Information, on CD.

LEITLOFF, J., HINZ, S. & STILLA, U., 2009: Automatic Vehicle Extraction from High Resolution Satellite Images of City Areas. – IEEE Transactions on Geoscience and Remote Sensing (in press).

LENHART, D. & HINZ, S., 2006: Automatic Vehicle Tracking in Low Frame Rate Aerial Image Sequences. – International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences **36** (3): 203–208.

LENHART, D., HINZ, S., LEITLOFF, J. & STILLA, U., 2008: Automatic Traffic Monitoring based on Aerial Image Sequences. – Pattern Recognition and Image Analysis **18** (3): 400–405.

LEWIS, J.P., 1995: Fast Normalized Cross Correlation. – Vision Interface, Canadian Image Processing and Pattern Recognition: 120–123.

REINARTZ, P., LACHAISE, M., SCHMEER, E., KRAUSS, T. & RUNGE, H., 2006: Traffic Monitoring with Serial Images from Airborne Cameras. – ISPRS Journal of Photogrammetry and Remote Sensing **61** (3–4): 149–158.

ROSENBAUM, D., KURZ, F., THOMAS, U., SURI, S. & REINARTZ, P., 2009: Towards Automatic Near Real-time Traffic Monitoring with an Airborne Wide Angle Camera System. – European Transport Research Review **1** (1): 11–21.

SCHAEFER, R.-P., THIESSENHUSEN, K.-U. & WAGNER, P., 2002: A Traffic Information System by means of Real-time Floating-car Data. – Proceedings of ITS World Congress, on CD.

STEGER, C., 2001: Similarity Measures for Occlusion, Clutter, and Illumination Invariant Object Recognition. – Pattern Recognition, Springer Verlag, Berlin, Germany: 148–154.

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** (3): 973–979.

TOTH, C.K. & GREJNER-BRZEZINSKA, D., 2004: Traffic Management with State-of-the-art Airborne Imaging Sensors. – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **35** (2): 848–853.

TOTH, C.K. & GREJNER-BRZEZINSKA, D., 2006: Extracting Dynamic Spatial Data from Airborne Imaging Sensors to Support Traffic Flow Estimation. – ISPRS Journal of Photogrammetry and Remote Sensing **61** (3–4): 137–148.

ULRICH, M., 2003: Hierarchical Real-Time Recognition of Compound Objects in Images. – Dissertation, German Geodetic Commission (DGK) **C 568**.

YAO, W., HINZ, S. & STILLA, U., 2008a: Automatic Analysis of Traffic Scenario from Airborne Thermal Infrared Video. – International Archives of Photogrammetry, Remote Sensing and Spatial Geoinformation Sciences **37** (B3a): 223–229.

YAO, W., HINZ, S. & STILLA, U., 2008b: Automatic Vehicle Extraction from Airborne LiDAR Data of Urban Areas Using Morphological Reconstruction. – 5th IAPR Workshop on Pattern Recognition in Remote Sensing, Florida, USA.

ZADEH, L., 1965: Fuzzy Sets. – Information and Control **8** (3): 338–353.

Addresses of the Authors:

Dr.-Ing. MATTHIAS BUTENUTH, Dipl.-Ing. DOMINIK LENHART, Technische Universität München, Lehrstuhl für Methodik der Fernerkundung, D-80333 München, Tel.: +49-(0)89-28922671, Fax: +49-(0)89-2809573, e-mail: matthias.butenuth@bv.tum.de, dominik.lenhart@bv.tum.de.

Dr.-Ing. PETER REINARTZ, Dr. rer. nat. DOMNIK ROSENBAUM, Deutsches Zentrum für Luft- und Raumfahrt, Institut für Methodik der Fernerkundung, D-82234 Wessling, Tel.: +49-(0)8153-282757, Fax: +49-(0)8153-281444, e-mail: peter.reinartz@dlr.de, dominik.rosenbaum@dlr.de.

Prof. Dr.-Ing. STEFAN HINZ, Universität Karlsruhe, Institut für Photogrammetrie und Fernerkundung, D-76128 Karlsruhe, Tel.: +49-(0)721-6082314, Fax: +49-(0)721-6088450, e-mail: stefan.hinz@ipf.uni-karlsruhe.de.

Manuskript eingereicht: Mai 2009
Angenommen: Juli 2009