Promotionsthema

2013-06-11

Sebastian Türmer

Vehicle detection in aerial imagery from dense urban areas

Detecting vehicles in order to count them and to get their position is a topic of particular importance as it can provide valuable information for real time traffic management as well as for traffic planners. This information can be used to secure mass events or to provide support to rescue crews in the case of disasters. Very popular ways to gather traffic data are for instance induction loops or stationary video cameras. However, this infrastructure can be damaged in the event of disasters – a time when traffic information becomes even more important.

Generally, a wide area can be better examined at the same time by remote sensing methods. Satellites are not frequently available but aircrafts can be at a certain location within a short time. In order to provide the car detection ability, the development of a robust car detection method for aerial images is intended. Operational approaches use standard object detection approaches where detectors based on high-level features are trained with machine learning algorithms. The drawbacks of these methods are the manual interaction during the training step and the missing robustness when the properties of the data changes due to another sensor. Additionally, a top-performing detector needs carefully selected training data and iterative back porting of false positives. This back porting needs to be critically observed because a drifting of the detector has to be avoided. This means if the detector is trained using certain false negative samples, it could omit some important positive detections as consequence. Another problematic issue is the inaccuracy of road databases especially in urban areas. These databases are usually used to extract roads or areas where cars are expected. However, roads can hardly be accurately recorded in areas with high buildings and urban canyons due to a lack of satellites from Global Navigation Satellite Systems. Sometimes even road databases are not available due to frequently moving construction sites. Then methods have to be developed to tackle false positive detections resulting from elements of façades or dormers which have a similar rectangular shape as cars. Considering the mentioned problems when cars have to be extracted from aerial images, leads to the following proposed technique.

Firstly, an important point is to avoid a strong dependence on the accuracy of road databases for the whole detection process. Therefore, road databases are used but only to coarsely select trafficable areas. Coarsely extracted road segments are helpful because the subsequent detection process is speeded up. More accurate trafficable areas are extracted by assuming that in densely populated cities trafficable areas are often ground areas. These ground areas are automatically extracted from two consecutive images. A disparity map is calculated using the semi-global matching algorithm. Subsequently, a threshold is automatically determined to separate ground from non-ground regions.

Secondly, an object-based strategy is carried out. The previously obtained regions are smoothed to rectify the appearance of color from diverse objects which are inherently affected due to different illumination. The smoothing is a crucial step where contours of objects have to be preserved but the final color gradient of the objects should be more homogenous. Afterwards, a color region growing algorithm is applied which results in several candidate regions. These candidates are further examined by geometric filters related to its shape and form. The region growing and filtering procedure removes homogenous areas as well as certain objects (e.g. road markings) which often cause confusion for gradient based detectors.

The remaining candidate regions are then examined by a detector based on gradients (HoG features) trained by a machine learning algorithm (AdaBoost). However, it is important to note that the detector is only very inattentively trained. That means just a few training samples are used and a few iteration steps of the learning algorithm are carried out. The goal is to minimize the manual effort and to generalize the

car extraction strategy as good as possible. Finally, a strategy is presented which combines object-based and high-level feature-based techniques.
Further experiments aim to get information about the possible incorporation of moving vehicles into the previously presented approach. Moving vehicles are generally easier to detect and a co-registration of consecutive images followed by simple difference images can give very convincing results.
Finally, as last experimental investigation the impact of color is examined. Most previously done research focusses on gray value images only or passes color features to the learning algorithm without a transparent in-depth evaluation.

Generally, due to the use of disparity maps it is expected to enhance the car detection quality in densely populated inner city areas. Objects on the top of buildings should now be accurately excluded from the detection process.
The object-based processing step should be able to detect car candidates in different datasets (different sensor and slightly different resolution) without adjustment of the parameter settings. Besides homogeneous areas, also objects posing difficulties to the gradient based detector should be excluded (e.g. road markings or bicycle paths). Finally, the presented overall strategy should be able to accurately detect cars from complex aerial scenes of inner city areas. The presented strategy is tested with images of 12 cm resolution from the 3K+ camera system and with images of 20 cm resolution from the UltraCam Eagle camera system.