surfaces, and reflected beams caused by nearby moving vehicle lights. Similarly, Fig. 3 shows the foreground object images extracted by background-subtraction based methods. Therefore, performing vehicle detection and recognition for nighttime traffic surveillance requires an effective approach for correctly and rapidly locating and extracting the salient features of vehicle lights under poorly illuminated conditions. this would enable the efficient extraction and segmentation of the object regions of moving vehicles.

Figure 4: Results of performing the bright-object segmentation process on the traffic-scene images in Fig. 1. (a) Lighting objects extracted from Fig.1(a).(b) Lighting objects extracted from Fig. 1(b).

Therefore, this section presents a fast bright-object segmentation process based on automatic multilevel histogram thresholding. The proposed method extracts the bright-object pixels of moving vehicles from image sequences of nighttime traffic scenes. The first step in the bright-object extraction process is to extract bright objects from the road image to facilitate subsequent rule-based classification and tracking processes. To reduce the computational complexity of extracting bright objects, we first extracted the grayscale image, i.e., the *Y* -channel, of the grabbed image by performing an RGB-to-*Y* transformation.

To extract bright objects from a given transformed gray-intensity image, the pixels of bright objects must be separated from other object pixels of different illuminations. For this purpose, we have presented a fast effective multilevel thresholding technique. In this paper, this effective multilevel thresholding technique is applied to automatically determine the appropriate levels of segmentation for extracting bright-object regions from traffic-scene image sequences. More detailed descriptions of this multilevel thresholding technique can be found in. By applying this multilevel thresholding technique, the lighting object regions of moving vehicles can be efficiently and adaptively segmented under various environmental illumination conditions in different nighttime traffic scenes as in Fig. 1(a) and (b). As a result, lighting objects can be appropriately extracted from other objects contained in nighttime traffic scenes. Accordingly, as Fig. 4(a) and (b) shows, performing this lighting object segmentation process successfully separates the lighting objects of interest in Fig. 1 into thresholded object planes under different environmental illumination conditions in nighttime traffic scenes.

Our approach comprises the following steps:

- *Calibration:* the calibration is done offline tocompute the camera parameters. This is useful to know the world (meter) positions and distances of features. Camera calibration is not detailed in the paper. Appropriate methods can be found in the literature.
- *Pre-processing:* this step detects the illuminationcondition (day or night-time) based on the histogram of the image and time of the day. It can also (optionally) stabilize the camera to remove the shakes for better estimation of vehicles' position; and can set the Regions Of Interests (ROI) where to look for features.
- *Image features extraction:* extracts the imagefeatures needed to detect vehicle features. The image features can be extracted in parallel to save computational time.
- *Candidates of vehicle feature:* fuses image featuresto detect potential (candidate) vehicle features such as windshields or headlights. The independent features can be processed in parallel. Each vehicle feature has a confidence value.
- *Vehicles:* fuses vehicle features to detect potential vehicles. Each vehicle has a confidence value which is computed from the confidences of the vehicle's features and then updated over time. The vehicle confidence can decrease or increase based on the tracking results. The candidate vehicles are feed backed to the *pre-processing* layer to dynamically update the stabilization method and the ROIs.
- Thecandidate vehicles are also feed backed to the *vehiclefeature* layer for the matching process between theprevious features and current ones.
- *Tracking:* the tracker tracks the vehicle features of each vehicle (headlights, windshields) on road plane. This allows using traffic-domain rules to improve the performance.

3. Overview

The system we propose consists of sixstages:

1. *Segmentation*: In this stage, the vehicles areseparated from the background in the scene.
2. *Region Tracking*: The result of the segmentationstep is a collection of connected regions. This stage tracks regions over a sequence of images using a spatial matching method.
3. *Recovery of Vehicle Parameters*: To enableaccurate classification of the vehicles, the vehicle parameters such as length, width, and height need to be recovered from the 2D projections of the vehicles. This stage uses information about the camera's location and makes use of the fact that in a traffic scene, all motion is along the ground plane.
4. *Vehicle Identification*: Our system assumes that avehicle may be made up of multiple regions. This stage groups the tracked regions from the previous stage into vehicles.
5. *Vehicle Tracking*: Due to occlusions, noise, etc. there isn't necessarily a one-to-one correspondence between regions and vehicles, i.e. a vehicle may consist of multiple regions and a single region might correspond to multiple vehicles. To enable tracking of vehicles despite these difficulties, our system does tracking at two levels – region level and the vehicle level.
6. *Vehicle Classification*: After vehicles have been detected and tracked, they are classified.

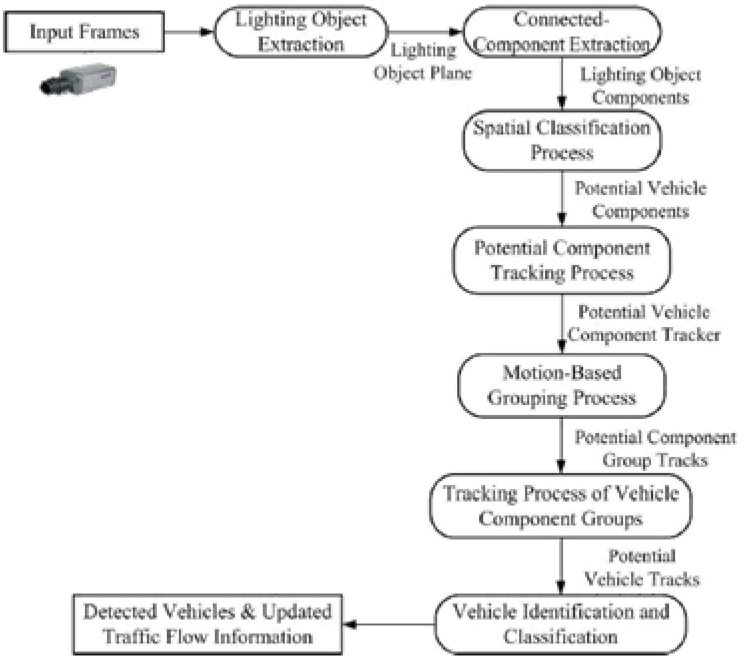

Figure 5: Block diagram of the proposed nighttime traffic surveillance system

This approach can detect vehicles without motion information, allowing static or slowly moving vehicles to be efficiently detected from image sequences. Most of the aforementioned methods rely on some hypothetical vehicle appearance cues, which are only valid and efficient in daytime with sufficient ambient illuminations. However, at night, and under darkly illuminated conditions in general, headlights and taillights are the only salient features of moving vehicles. In addition, there are many other sources of illumination that coexist with vehicle lights in nighttime traffic scenes, including street lamps, traffic lights, and ground-level road reflector plates. These non vehicle sources of illumination make it very difficult to obtain cues for detecting vehicles in nighttime traffic scenes. To detect salient objects in nighttime traffic surveillance, Beymer*et al.* presented a feature-based technique that extracts and tracks the corner features of moving vehicles instead of their entire regions. Their approach works in both daytime and nighttime traffic environments and is more robust to partial or complete occlusions. However, this technique suffers from high computational costs, as it must simultaneously process numerous features of moving vehicles and is unable to classify the types of vehicles detected. However, contrast and interframe change information are sensitive to the lighting effects of moving vehicle headlights, resulting in erroneous vehicle detection. Recently, vehicle lights have been used as salient features for nighttime vehicle detection applications for traffic monitoring systems and driver assistance systems. For traffic surveillance applications, these methods use morphological operations to extract candidate headlight objects and then performs shape analysis, template matching, or pattern classification to find the paired headlights of moving vehicles.

4. Vehicle Detection

Prior to vehicle detection, image buffers along road axes obtained from road database are cut out of the georeferenced images. This reduces the search space for vehicles in the images. Then all roads are straightened along road axes, so that vehicles traveling along each road in the image are aligned in the same direction. This reduces calculation time, since the classifiers of vehicle detection do not have to be rotated. In this work the vehicle detection is performed in three stages.

The parameters of the algorithm have been tuned for the used image resolution of 20 cm by 5-fold cross validation. These parameters mostly reflect geometrical properties of the vehicle clusters. Thus 80% the non-vehicle areas can be rejected from further processing. Nearly all remaining wrong hypotheses are classified in the last processing stage. Therefore, a number of statistical values are calculated from geometric and radiometric properties of the remaining clusters in the confidence image and in all channels of the RGB image. Due to the partially high correlation between those channels the total number of more 100 statistical features is reduced by principal component analysis (PCA) transformation to the first 40 components which contain 99% of the descriptive information. This reduced feature set is used to train a Support Vector Machine (SVM). The slack variables and kernel type of the SVM are also optimized for the specific resolution by cross validation leading to an average False-Positive-Rate of approximately 12 %. As it will be shown 4 section, this accuracy is reflected in the correctness of the numerical evaluation. Figure 3 shows the results of the interest point operator (marked by circles) and the final vehicle detection (marked by crosses).

5. Vehicle Tracking

Vehicle tracking between two consecutive images of the burst is done by template matching based on normalized cross correlation. At each position of a detected vehicle in the first image of the image sequence a template image is created. Then, in the second image of the sequence a search space for this vehicle is generated. Its size and position depends on the position of the vehicle in the first image, driving direction obtained from NAVTEQ road database, and the expected maximum speed for the road plus a certain tolerance. Within that search space, the template is correlated and the maximum correlation score is stored in connection with the template position within the maximum appeared. This normally represents the found match of each vehicle in generally. The correlation is done in RGB-color space. Fig 4 shows a typical result of the tracking algorithm obtained on the motorway A96 near Munich. Left image was taken 0.5 s before right image. The dashed lines show corresponding matching pairs from normalized cross correlation. Since all images are stored with their recording time, vehicle speed can directly be calculated from both the Figure 4: Tracking of a group of cars on motorway A96 near Munich. Corresponding matches are marked by dashed lines. Mind, that the motorbike was not tracked, because it was not detected (the classifier of detection was not trained to two-wheeled vehicles).

Position of the vehicle detected in the first image and the position of the corresponding match in the second image. Then, vehicle tracking is applied to the following image pair of the sequence. Several measures to chase mismatches are imlemented mainly based on plausibility of velocity and driving direction, constance of velocity and driving direction within a burst, and plausibility of individual speed and direction with respect to local average values. Several potential mismatches as well as matches based on false positive vehicle detection can be eliminated that way. After traffic data extraction the results are immediately copied to PC 5 (Fig. below) and directly sent to the ground via S-band downlink. There, data can be used in a traffic internet portal for road level of service visualization and for traffic simulation.

6. Vehicle Detection at Night

The scene appearance at night is very different from daytime; the only salient visual features are headlights and their beams, street-lamps, and horizontal signals such as zebra crossings (see Fig. below). After masking the lane area, the scene becomes even simpler, since out-oflane “distractors”, such as street-lamps, are removed.

Our main goal is to identify vehicles in terms of *pairs of headlights*; this is a simplifying assumption, since vehicles with single headlight, such as motorbikes, can be present. Nevertheless, we neglect them, since they do not have significant impact on typical traffic flow parameters like throughput, congestion probability, and queue length.Fig.above shows the inspected area (below the horizontal white line), where headlights’ pairs can bereliably detected; objects spanning the separation line are also removed.

Since the image histogram is strongly bimodal, binarization can be easily achieved with non-linear operators such as thresholds or quadratic operators (Fig. above).After these steps, we discriminate between headlights’ pairs and other objects, such as their beams, and horizontal signals. While all still objects could be separated by motion analysis, this is not true for beams. Thus, we decided to perform headlight detection via morphological analysis, by taking into account aspects like shape, size and minimal distance between vehicles;Final verification is based on correlation between headlights belonging to a same pair; correlation is performed by matching luminance values along the normal to the main traffic direction. Data was captured with different cameras in an effort to assess how sensor independent the system was. However due to the different way in which different sensors interpret colour it was found that the colour filter parameters of the red threshold had to be slightly adjusted for optimal operation between different sensors. Future work could involve introducing a calibration technique so camera sensors could be changed, and the system less sensor dependant. A test plan was created with a view to capturing test data in simple situations. The plan involved video sequences with various permutations of the following options.

- Street lit environment / no lighting
- Tail lights / brake lights
- Indicator lights flashing intermittently
- Different distances
- Approaching target vehicle / target vehicle departing

In an intelligent transportation system, traffic data may come from different sensors such as loop detectors, ultrasonic sensors, or cameras. The use of video cameras (many of which are already installed to survey road networks), coupled with computer vision techniques, offers an attractive alternative to other sensors. Video-based camera systems are more sophisticated and powerful because the information content associated with image sequences allows precise vehicle tracking and classification. In contrast, spot sensors have limited capabilities and are often both costly and disruptive to install. Successful video-based systems for urban traffic monitoring must be adaptive to different weather and illumination conditions. The main difficulties come from cast shadows, vehicle headlights, and noise. Under sunlight, for example, cast shadows always accompany the moving vehicles. Thereby, it may be easily regarded as a part of the vehicle and result in incorrect segmentation. At night, vehicle headlights and bad illumination (which may cause strong noise) can also cause many difficulties for the detection task.

Therefore, moving vehicle detection under such situations is always an important but challenging work. There are many published works concerning moving object detection, including vehicle detection and human detection. Among them, there is some literature addressing casting shadow elimination. A model of a cast shadow was established on the assumption of knowing the occurrence time, the location of the light source, the scene’s geometry, and the shape of the moving object.

In this paper, we will propose an algorithm for moving vehicle detection. Different from previous works, this algorithm learns from the known examples and does not rely on the prior model of vehicles, lighting, shadows, or headlights. First, the background of the scene is estimated adaptively. Then, the image is divided into many small non-overlapped blocks. By subtracting the current image from the background, the blocks with an intensity change can be found as the candidates for vehicle parts.

Object detection and tracking at night is very important for night surveillance, which is key part of 24 h visual surveillance. In this paper, we proposed object detection and tracking algorithm for night surveillance based on inter-frame differences. Object detection is based on local contrast changes and detection results are improved by tracking the detected objects from one frame to the next. Experiments demonstrate that our algorithm has the ability to detect and track objects robustly at night under conditions in which more conventional algorithms fail. There are several parameters and thresholds in the new algorithm.

Some parameters are adjusted adaptively, for example, the threshold to determine significant inter-frame differences and the threshold on the differences between contrast scores. Other parameters such as the size of rectangular region for contrast measure, the threshold on contrast measure, and the threshold on the distance measure between two rectangles are chosen by hand. In the future, we will use a multi-scale algorithm, similar to those used in face detection, to decide the size of the rectangular region for contrast measure. The threshold on contrast measure will be decided by a learning algorithm. These methods for computing thresholds automatically will improve our system greatly. Video-based camera systems are more sophisticated and powerful because the information content associated with image sequences allows precisevehicle tracking and classification.

In contrast, spot sensors have limited capabilities and are often both costly and disruptive to install. Successful video-based systems for urban traffic monitoring must be adaptive to different weather and illumination conditions. The main difficulties come from cast shadows, vehicle headlights, and noise. Under sunlight, for example, cast shadows always accompany the moving vehicles.

7. Conclusion and Future Scope

This paper has proposed effective nighttime vehicle detection and tracking system for identifying and classifying moving vehicles for traffic surveillance. The proposed approach uses an efficient and fast bright-object segmentation process based on automatic multilevel histogram thresholding to extract bright objects from nighttime traffic image sequences. This technique is robust and adaptable when dealing with varying lighting conditions at night. Actual vehicles and their types can then be efficiently detected and classified from these tracked potential vehicles to obtain traffic flow information from traffic monitoring images. Experimental results and comparison with existing methods have shown that the proposed system is effective and offers advantages for vehicle detection and classification for traffic surveillance in various nighttime environments. For further studies, the vehicle type classification function can be further improved and extended by integrating some sophisticated machine learning techniques such as support vector machine classifiers on multiple features, including vehicle lights and vehicle bodies, to further enhance the classification capability on more detailed vehicle types, such as sedans, buses, trucks, lorries, and light and heavy motorbikes.

References

[1] Yen -Lin Chen, Member, IEEE, Bing-Fei Wu, Senior Member, IEEE, Hao-Yu Huang, and Chung-Jui Fan, “A Real-Time Vision System for Nighttime Vehicle Detection and Traffic Surveillance”IEEE transaction on industrial electronics, VOL. 58, NO. 5, MAY 2011.

[2] V. Kastrinaki, M. Zervakis, and K. Kalaitzakis, “A survey of video processing techniques for traffic applications,” *Image Vis. Comput.*, vol. 21, no. 4, pp. 359–381, Apr. 2003.

[3] W.-L. Hsu, H.-Y., M. Liao, B.-S.Jeng, and K.-C. Fan, “Real-time traffic parameter extraction using entropy,” *Proc. Inst. Elect. Eng.—Vis. Image SignalProcess.*, vol. 151, no. 3, pp. 194–202, Jun. 2004.

[4] M.-C. Huang and S.-H.Yen, “A real-time and color-based computer vision for traffic monitoring system,” in *Proc. IEEE Int. Conf. Multimed. Expo*, May 2004, pp. 2119–2122.

[5] C. Stauffer and W. E. L. Grimson, “Adaptive background mixture models for real-time tracking,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recog.*, Jun. 1999, pp. 246–252.

[6] J. Kong, Y. Zheng, Y. Lu, and B. Zhang, “A novel background extraction and updating algorithm for vehicle detection and tracking,” in *Proc. IEEE Int.Conf. Fuzz. Syst. Knowl. Discovery*, 2007, pp. 464–468.

[7] S. Gupte, O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos, “Detection and classification of vehicles,” *IEEE Trans. Intell. Transp. Syst.*, vol. 3, no. 1, pp. 37–47, Mar. 2002.

[8] B.-F. Wu, S.-P.Lin, and Y.-H. Chen, “A real-time multiple-vehicle detection and tracking system with prior occlusion detection and resolution,” in *Proc.IEEE Int. Symp. Signal Process. Inf. Technol.*, Dec. pp. 311–316.