Scale Invariant Feature Transformed Based Vehicle Detection: A Review

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Abstract—*Advanced driver assistance systems (ADAS) face many challenges in night-driving situations where due to poor illumination conditions the detection of other vehicles on the road becomes quite difficult. Traditional approaches attempt to use complex enhancement algorithms that consume a lot of computational power and are sensor dependent.*

This dissertation investigates the techniques for Scale-Invariant Feature Transform-based vehicle detection. A novel system that can heartily distinguish and track the development of vehicles in the video frames is proposed. The system consists of two noteworthy modules: a symmetry based item detector and a Kalman filter based vehicle tracker.

Keywords — *Vehicle Detection, Scale invariant feature transform (SIFT), keypont.*

I. Introduction

One of the main technologies for crash avoidance are driver assistance systems. The purpose of the driver assistance systems is to perceive the surrounding using different sensors, identify critical situations and provide the information to the driver. In extreme cases, the system may even take automatic evasive action to prevent a collision. Examples of driver assistance systems for crash avoidance are such as the forward collision warning, brake assistance and lane departure warning systems. These are part of the active safety systems since they take proactive steps to prevent an accident before it happens. On the other hand, passive safety systems such as seatbelt, airbags and crumple zones reduce the severity of injuries during a collision. The focus in automotive safety systems is now on the driver assistance systems for preventing the accident itself.

Different sensors can be used to collect the information about the road conditions for a driver assistance system. These can be ordered into two principle bunches: active and passive sensors. Active sensors such as radar transmit radio waves into the atmosphere. The signals are reflected by other objects and captured by a detector. The distance of the object can be calculated by measuring the time traveled by the signals. Other active sensors use the same concept but operate at different regions of the electromagnetic spectrum, for example LIDAR (Light Detection and Ranging) uses infrared signals and LADAR (Laser Detection and Ranging) uses laser waves. The main advantage of the active sensors is their capability to measure distance directly without requiring high computational resources. They are additionally more vigorous to environment variety such as illumination changes caused by shadow, fog, rain or different times of day. Optical sensors such as normal cameras are the most common passive sensors used in a vision-based driver assistance system. Such sensors have attracted a lot of attention 3 in the past decade because of the availability of low cost and high resolution cameras as well as the increasing processing speed of computers. Another key advantage of using an optical sensor is its ability to give a richer description about the vehicle‘s surroundings compared to the active sensor. Some applications such as lane detection and object identification have to rely on the captured visual images to extract the required information. The passive sensors are also free from interference problems commonly faced by the active sensors. However, detection based on the optical sensor is highly dependent on the quality of the captured images, which can be easily affected by the lighting and environment conditions. Therefore, vision based vehicle detection systems require more complicated image processing algorithms and higher computational resources to extract the required information from the captured images.

II. Literatur Servey

The most common approach of vision-based vehicle location comprises of the accompanying two stages: vehicle cueing and vehicle verification. The purpose of the cueing stage is to search through the whole image to find all possible vehicle candidates. Then the verification stage validates the identified candidates as either vehicle or non vehicle. Once a vehicle is verified, it be passed to a tracking function which monitor the movement of the vehicle in consecutive video frames. When moving from one stage to the following stage, the amount of information to be processed is reduced. This will allow more sophisticated and time consuming algorithms to be carried out on a smaller region of the image. Although it is possible to skip the cueing stage and just using a verifier to scan for vehicles in the whole image, this approach is not commonly used since it requires a high computational load. Most verification algorithms are computationally intensive and applying them on every region of the image will be very time consuming.

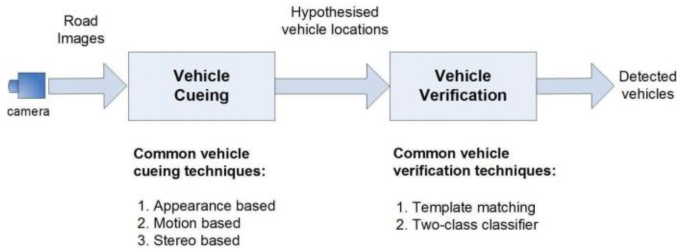


Figure 2.1: The two-stage approach for vision-based vehicle detection

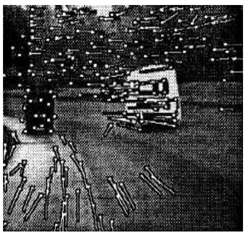
The following sections review some current techniques for vehicle cueing and verification. The review will focus on the mo based vehicle detection techniques. Some representative systems for each technique will also be described.

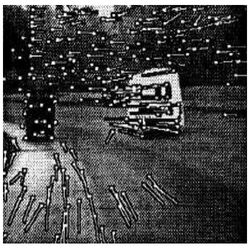
2.2 Monocular-based vehicle cueing techniques

The purpose of vehicle cueing is to identify the possible vehicle locations in the captured image and mark them as regions-of-interests (ROIs). For a system with radar and vision fusion, the determination of ROIs is done by analyzing the distance and the relative speed information collected by the radar. Different vision and radar fusion techniques were proposed in [7–9]. For systems with stereo cameras such as in [10–12], the disparity map or the inverse perspective mapping computed from the stereo images was used to find the possible vehicle locations. For a monocular-based system, the determination of the vehicle locations has to be done by analyzing the vehicle‘s motion or appearance. The motion based technique requires the analysis of several image frames to detect moving objects based on their optical flows. On the other hand, the appearance based vehicle detection technique analyses a single image to find visual cues to segment the vehicles. The following subsections explain these two techniques and review some of the representative literature.

2.2.1 Motion Based Vehicle Cueing

Motion based approach exploits the temporal information to detect vehicles. The optical flow fields from a moving vehicle can be calculated by matching pixels or feature points between two image frames. Dense optical flow such as the method suggested by Horn and Schunck [13] matches every pixel in the image based on their intensity. This technique requires huge computational effort and therefore is not so suitable for real-time application. On the other hand, sparse optical flow tracks a set of specific features from a vehicle such as corners [14] or color blobs [15]. After the optical flow fields are calculated, moving objects can be segmented from the image by clustering the fields based on their positions, magnitudes and angles. A motion based vehicle detection system called Scene Segmenter Establishing Tracking (ASSET-2) was proposed by Smith in [14]. The system uses features based (sparse) optical flow for motion estimation. First, the corner‘s features in the image was extracted using either the Smallest Univalue Segment Assimilating Nucleus (SUSAN) [16] or Harris [17] corner detectors. Then the features are tracked over several frames to create the optical flow fields. A flow segmenter‘ is used to cluster the fields based on their flow‘s variations. Finally the bounding box and centroid of the resulting clusters are calculated and used as the hypothesized vehicles. The system requires high computational load and therefore they used special hardware acceleration to attain real-time performance.





(a) (b)

Figure 2.2: ASSET-2 sparse optical flow based vehicle detection. (a) The flow vectors. (b)Result of clustering the flow vectors and their bounding boxes.(Figures taken from [14]).

A similar vehicle detection system proposed by Yanpeng et al. [18] uses the SUSAN features to estimate the sparse optical flow fields. They proposed a technique to improve the flows calculation using a 3-D Pulse Coupled Neural Network (PCNN) [19]. In their experiments, they showed that the accuracy of the motion based detection depends on the relative speed between the host and the preceding vehicles. Vehicles with small relative speed (< 10 km/h) achieved low detection rate (69.1%). For this reason, they also used appearance based technique (shadow underneath the vehicle and edges) in the detection. A techniq ue for grouping the clusters of optical flow into individual moving objects was proposed by Willersinn et al. [20] (Figure 2.3). First, the detected clusters are projected into a plane (P) which is parallel to the road surface. Starting at point W, which has been identified as an outer boundary point of a vehicle, a search area is set up based on the expected minimum and maximum vehicle's width. If the search is successful, a coordinate is calculated using the coordinates of all compatible flow clusters found in that area. This coordinate is used to estimate the width and the centre point of the vehicle.

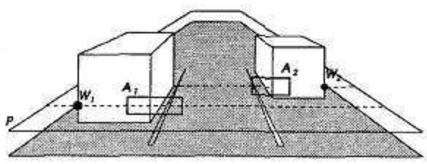


Figure 2.3: Search windows (A1 and A2) are set up on plane P to group the corresponding clusters for each vehicle.

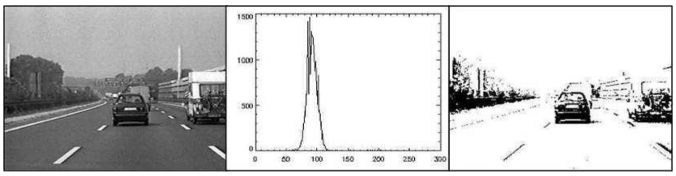
A motion based method is effective for detecting moving objects, however it is computationally intensive and requires analysis of several frames before an object can be detected. It is also sensitive to camera movement and may fail to detect objects with slow relative motion. This is a major disadvantage for driver assistance applications since the onboard camera may vibrate when the vehicle is moving and the relative motion between the test vehicle and a distant vehicle is usually small.

2.2.2 Appearance Based Vehicle Cueing

The appearance-based cueing technique detects vehicles based on some specific appearances of a vehicle's rear view. Examples of the appearances are the shadow underneath the vehicle [21, 22], vertical and horizontal edges [23], corners [24], symmetry [25], texture, colour and the vehicle's lights They are reviewed in the following subsections.

Shadow Underneath The Vehicle

The shadow underneath the vehicle which is usually darker than the surrounding road surface can provide a cue for vehicle location. In [21], Christos et al. evaluated the histogram of the paved road to find a threshold for segmenting the shaded areas on the road. The locations of shaded areas together with edge information are used to hypothesis the location of vehicles. Detection based on the shadow is simple and fast. However, it may fail when the colour of the road pavement is uneven or when the road surface is cluttered with shadows from nearby buildings, overhead bridges or trees. In the morning or evening, a long shadow is cast at one side of the vehicle. This will produce a hypothesized location which is not at the centre of a vehicle.



(a) (b) (c)

Figure 2.4: Vehicle cueing based on shadow. (a) An example road scene. (b) Histogramof road pavement. (c) Image is thresholded to extract the shadow and edges of the vehicle.(Figures taken from [21]).

Horizontal and Vertical Edges

Most vehicles' rear view show strong vertical and horizontal edges. These characteristics can be used to hypothesis the presence of a vehicle. A group of horizontal and vertical edges that form a rectangular shape with an aspect ratio between 0.4 and 1.6 are good candidates for potential vehicles. Different techniques of edge detection can be used. For example Canny, Sobel or morphological edge detections. Jin et al. used the shadow underneath the vehicle as an initial cue for a possible vehicle. Then they located the position of the vehicle based on the projection maps of its horizontal and vertical edges (Figure 2.5). Zehang et al. [38] proposed a multi-scale approach to detect a vehicle's edges using three different image resolutions. Betke [23] suggested a coarse to fine search technique to detect distant vehicles. The coarse search looks for groups of prominent edges in the image. When such groups are found, a finer search is performed in its surrounding region to locate rectangular shaped objects. One major difficulty for detecting vehicles based on the horizontal and vertical edges is due to the interference from outliers edges generated by the background objects such as buildings, lamp posts or road dividers. It is also difficult to select an optimum threshold for the edge detection in order to capture most of the vehicle's edges with minimum edges from the background..

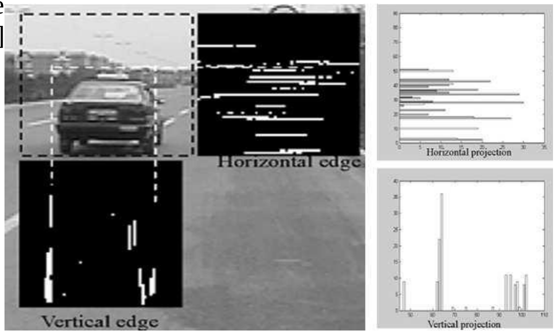
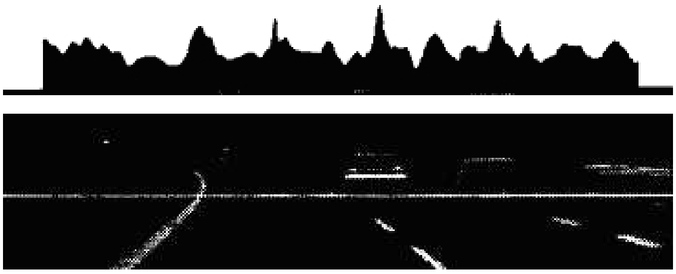


Figure 2.5: Vehicle cueing based on edge information.

Symmetry

Symmetry is one of the prominent visual characteristics of a vehicle. Most vehicles' rear or front views are symmetrical over a vertical centerline. Therefore, it is possible to hypothesis the locations of vehicles in the image by detecting the regions with high horizontal symmetry. Some of the literature that uses symmetry for vehicle detection are from Bensrhair et al., Bin et al., Wei et al., Zielke et al., Kuehnle et al. And Du et al. [26–28, 25, 29, 30]. In general, the proposed symmetry detection technique uses a symmetry operator to calculate the symmetry value of an image region. Different pixel characteristics can be used in the calculation. They include gray scale value, binary contour, horizontal edges, colour and feature points. Zielke et al. [25] proposed a method to detect the centre line of the leading vehicle based on the image intensity symmetry. The vehicle's bounding box is estimated by performing edge detection and finding pairs of edges that are mutually symmetric with respect to a detected symmetry axis. Kuehnle et al. proposed a system that uses three different symmetry criteria for locating vehicles: contour symmetry, gray level symmetry and horizontal line symmetry. The histograms generated from these criteria are used to find the vehicle's centre line. Symmetry is a useful cue for detecting vehicles. However it requires comparatively higher computational load. Some literature such as proposed to use this approach for vehicle verification where only a small region of the image needs to be processed by the symmetry operator.



(a)

(b)

Figure 2.6: An example of symmetry based vehicle detection: (a) An example road scene.(b) The plot of intensity based symmetry. (Figures taken from [25]).

Corners

The general shape of a vehicle is rectangular with four corners. This characteristic can be exploited to hypothesis the presence of a vehicle. In [24], Bertozzi et al. used four different image templates (Figure 2.7) to detect all the possible vehicle's corners in the image. A possible vehicle is detected if there are four matching corners with enough edge pixels at the positions corresponding to the vehicle's sides. In, the corner detection process is sped up by using a common double-circle mask to detect all types of corners (Figure 2.8). The detected corners are then clustered based on their types and locations. Finally, the features of the corners in each cluster are extracted and used as the input to an SVM classifier to determine whether it belongs to a vehicle.

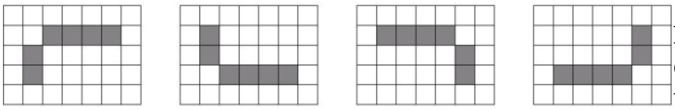
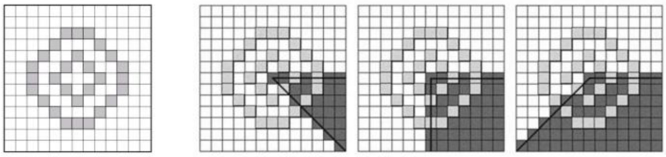


Figure 2.7: Four different masks are used to detect the four corners of a rectangle. (Figures taken from [24]).



(a) (b) (c) (d)

Figure 2.8: A double-circle mask for corner detection (a). In (b), (c) & (d), the mask is used to detect different shapes of corners.

Colour

Colour can be a useful cue for segmenting the vehicle from the background. Most vehicles have a homogenous colour different from the road surface and the background objects. This fact is exploited in [32] to segment the vehicles from the images. The authors proposed a color transform model to find the important vehicle colour' for locating possible vehicle candidates. The pair of red brake lights and yellow signaling lights can also be a cue for detecting the vehicles. In [41], Ming et al. used a colour segmentation technique for detecting the vehicle's tail lights. Vehicles are hypothesised from pairs of horizontal light blobs(Figure 2.9).

(a) (b)

Figure 2.9: Vehicle cueing based on colour: (a) Original image (b) Detected tail lights from colour segmentation.

However, colour based object detection is very sensitive to illumination change and the reflectance properties of the object. For an outdoor environment, these properties may change under different weather conditions or during different times of the day. This will increase the difficulty in vehicle detection based on colour.

Texture

The texture of a vehicle is different from its surrounding road surface or vegetation. By using statistical analysis on the image's texture, for example entropy or co-occurrence matrix, the locations of vehicles in the image can be segmented (Figure 2.10). However, this technique could generate a lot of false detections especially in an urban environment. This is because the texture for some of the manmade structures such as buildings, sign boards or overhead bridges may resemble a vehicle.

(a) (b) (c)

Figure 2.10: Vehicle segmentation based on local image entropy. (a) An exampleroad scene. (b) Image local entropy. (c) Segmentation result.

Tail Lights

During night time, the tail lights are the main cue for detecting vehicles when other features are vague. Yen et al. proposed a system for detecting vehicles at night time. Vehicles are located by detecting the bright objects that belong to the headlights or taillights of the vehicles.Bright objects are extracted using spatial clustering and segmentation. A heuristic rule-based technique is used to analyze the light pattern and the results are used to

(a) (b) (c)

Figure 2.11: Vehicle detection based on tail lights: (a) An example of night time road environment. (b) Bright objects extraction. (c) Result of spatial clustering of the bright components.

hypothesisthe location of vehicles. Combining Multiple Cues Some literature uses multiple cues to detect vehicle. For instance in [22], Bright objects are extracted using spatial clustering and segmentation. A heuristic rule-based technique is used to analyze the light pattern and the results are used to hypothesisthe location of vehicles. Combining Multiple Cues Some literature uses multiple cues to detect vehicle. For instance in [22], Leeuwen et al. employed a method that merges shadow, entropy and symmetry features for vehicle cueing. Their procedure starts with the identification of all image regions that potentially belong to the shadow underneath the vehicles. Then all the rows with low entropy in the detected region are removed and its horizontal intensity symmetry is checked to determine whether it belongs to a vehicle. Vehicle detection using multiple cues is more robust since one cue may compensate the weakness of the other. However, it requires higher computational resources for calculating the additional cue which might be redundant.

2.3 Vehicle Verification

The output of the cueing stage is a set of ROIs in the image that possibly contain vehicles. They will be validated in the verification stage where the false detections are removed. Usually the detected ROIs are cropped from the image, scaled to a uniform size and have their contrast normalized before the verification process. The verification techniques can be categorized into two groups: (1) correlation based approaches using template matching and (2) learning based approaches using an object classifier.

2.3.1 Template Matching

The correlation based method uses a predefined template and calculates the correlation between the ROI and the template. The resulting correlation value is used as a similarity measure for vehicle verification. Since there are many possible vehicle‘s modals with different appearances on the road, a loose‘ and general template that includes the common features of a vehicle is usually used. These features include the rear window and number plate, a rectangular box with specific aspect ratio and the shape pattern from two vertical edges and a bottom horizontal line. A vehicle could appear in different sizes depending on its distance from the camera. Therefore, the 16correlation test is usually performed at several scales in the ROI. The intensity of the image is also normalized before the correlation test in order to get a consistent result.The biggest drawback for the fixed template method is the difficulty in getting a proper vehicle template that can fit all variants of vehicles.

Therefore, instead of using a fixed generic template, some literature proposed using dynamic templates. In this approach, once a vehicle is detected using the generic template, the template for the subsequent detection is created on-line by cropping the image of the detected vehicle. The advantage of dynamic tracking is that it is able to accurately track different models of vehicles once the vehicle is correctly detected. However, if there is a false detection and a dynamic template is generated based on the wrong result, all subsequent tracking will also be wrong. Mingxiu et al. proposed a template update mechanism to address this problem. The reliability of template matching is measured based on the edges, area and aspect ratio of the target. The online update of the template is only done when this reliability measure is above a certain threshold. Hu et al. have also used a dynamic template method for vehicle verification. However, the quality of matching and the template update is monitored by estimating their vitality‘ values. The vitality‘ of a tracked vehicle increases when there is a sequence of successful template matching, while it decreases after a sequence of bad matches. When the vitality‘ value falls to zero, the vehicle is assumed to be no longer valid and it is removed from the tracking list.

2.3.2 Classifier-based Vehicle Verification

This approach uses a two-class image classifier to distinguish between vehicle and non-vehicle. The classifier learns the characteristics of the vehicle‘s appearance from the training images. The training is normally based on a supervised learning approach where a large set of labeled positive (vehicle) and negative (non-vehicle) images are used. The most common classification schemes for vehicle verification include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Mahalanob is distance and AdaBoost. To facilitate the classification, the training images are first preprocessed to extract some representative features. The selection of features is very important in order to achieve good classification results. A good set of features should be able to capture most of the variability of the vehicle‘s appearances. Different features for vehicle classification have been proposed in the literature; Thebmost common being Histogram of Oriented Gradient (HOG), Gabor, Principal Component Analysis (PCA) and Haar Wavelets. HOG feature captures the local histogram of an image‘s gradient orientations in a dense grid. It was first proposed by Dalal for human classification. Mao et al. used the HOG feature trained on a linear SVM classifier to detect preceding vehicles. They showed that the system is able to detect vehicles in different traffic scenarios but no quantitative result was given. Paul et al. proposed a system for classifying the orientation of a vehicle, where a set of orientation specific HOG features is created and trained on the SVM classifiers. Their test results show that the orientation specific classifiers can achieve 88% classification accuracy. Papageorgiou et al. used Haar wavelets transform to extract the vehicle‘s features and trained them using the SVM classifier. Three oriented wavelets responses: horizontal, vertical and diagonal are computed at different scales to allow a coarse to fine representation of the wavelets responses. They achieved a 90% detection rate when experimented on their vehicle data sets. However, a high number of false detections (10 per image) is also reported. Viola et al. used a similar set of Haar wavelet features but they employed the AdaBoost training algorithm and constructed a cascade of increasingly more complex classifiers. The speed up of the Haar feature extraction is achieved by using an integral image technique. They tested the system for face detection and reported a 76% to 94% detection rate. However, the system also has high false detection (average 1.3 per image). In, Lienhart et al. Addressed this problem by introducing a richer set of Haar-like features and reported an average reduction in false alarm by 10%. Chunpeng et al. applied the same framework as to detect cars and buses from video images. However, the results are not so encouraging since only 71% detection rate (at 3% false detection) is achieved. Gabor features capture the local lines and edges information at different orientations and scales. They have been commonly used for texture analysis of images . Zehang et al. tested the Gabor features trained on the SVM classifier for vehicle detection. The evaluation results show that the classifier can achieve 94.5% detection rate at 1.5% false detection. They also show that the classifier outperforms a PCA feature based ANN classifier. Another paper by the same authors investigated a technique to select the Gabor parameters (orientation and scale) based on the Genetic Algorithm. They found that the most important orientations of a filter are consistent with the orientation of the vehicle edges, which are at 0◦ , 45◦ , 90◦ and 135◦ . The best scales are also tuned to encode the implicit information present in vehicle images. Hong et al. used boosted Gabor features and an SVM classifier for vehicle detection. Their technique selects the Gabor filter‘s parameters (orientation and scale) through learning from examples. Using this technique, they reported a 96% detection rate. In, Yan et al. combined Gabor and Lagendre moment features for vehicle detection. They evaluated the performance of the features on the SVM classifiers and reported a detection rate of 99% at 1.9% false detection. Principal Components Analysis (PCA) can be used to reduce the dimension of the image data by projecting the data into a new sub-space (eigenspace) and extract only the representative features. Truong et al. used the PCA to build a feature vector for vehicle , naming it Eigenspace of vehicle'. An SVM classifier is used for the classification. The authors reported a 95% detection rate using their test data. Alonso et al. used the Mahalanobis distance classifier to verify vehicles. Three different measures are used in the classification: a symmetry measure, a shadow model likelihood measure and a rectangular likelihood measure. These measures are concatenated to form the feature vector. The Mahalanobis distance between a candidate's feature vector and the vehicle's class centroid is used to decide whether it belongs to a vehicle. Handmann et al. proposed a texture based vehicle classification technique. This technique calculates texture features using the Co occurrence Matrix and uses a Multilayer Perceptron (MLP) Artificial Neural Network (ANN) as the classification scheme. A candidate image is classified as either car, truck or background. However, no quantitative result was given. In, Milos used a similar technique as HOG for feature extraction. But instead of calculating the histogram of gradient, the histogram of the redness measure for the tail lights is calculated. The AdaBoost learning algorithm is used to construct a cascade of weak classifiers. The author used the system to recognize the rear w of Honda Accord cars and reported a 98.7% detection rate at 0.4 false detection. Vehicle verification based on a classifier has become more popular in recent years. This is because they are generally more accurate compared to the template matching techniques. Although there are many different types of features and classification schemes proposed in the literature, it is very hard to make a fair comparison from their published results since they have been tested using different data sets and performance measures. There is also a lack of representative data sets and common benchmark to access the performance of different vehicle classification systems.

III. CONCLUSIONS

A SIFT-based vehicle detection method has been presented that finds symmetric constellations of features in images and allows efficient computation of symmetries in the image plane. Its performance has been demonstrated on a diverse range of real images. The method simultaneously considers symmetries over all locations, scales and orientations, and was shown to reliably detect bilaterally symmetric figures in complex backgrounds, and handle multiple occurrences of symmetry in a single image. The method relies on the robust matching of feature points generated by modern feature techniques such as SIFT. However, it is not restricted to any one such technique; rather, it provides a means to compute symmetry from features, with the requirements that these features facilitate orientation invariant matching and have an associated orientation measure. Once a vehicle is verified, the movement of the vehicle in the subsequent video frames will be monitored by a tracking function. The tracking function exploits the temporal coherence of the consecutive video frames to narrow down the areas for re-detecting a vehicle. This will improve the re-detection rate as well as reduce the processing time. In this research, a Kalman filter and a reliability point system are integrated into the tracking function to improve the efficiency of the tracking. The key findings from this part of the study are: (1) A Kalman filter can efficiently predict the movement of a vehicle by only tracking its position in the image plane. The irregularities and errors in the detection can also be smoothed by the Kalman filter; and (2) The proposed reliability point system can provide a simple and fast solution to handle the problem of momentarily missed or wrong detection. The experimental results have shown that the proposed tracking function can successfully track the preceding and the overtaking vehicles in consecutive video frames. Integration of different components to form a robust vehicle detection system finally, a complete system is formed by the integration of the above two components. The system provides a novel solution to the SIFT-based vehicle detection. Experimental results have shown that the system can effectively detect multiple vehicles on the highway and complex urban roads under varying weather conditions.

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