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A Review of Recent Developments in Vision-Based Vehicle Detection

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***Abstract*—This document provides a review of the past decade's literature in on-road vision-based vehicle detection. Over the past decade, vision-based surround perception has matured significantly from its infancy. We detail advances in vehicle detection, discussing representative works from the monocular and stereo-vision domains. We provide discussion on the state-of-the-art, and provide perspective on future research directions in the field.**

***Index Terms* - Active Safety, Driver Assistance, Real-time Vision, Machine Learning.**

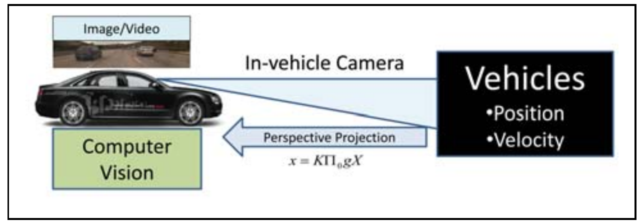

Fig. 1. Vision for on-road vehicle detection uses cameras, which sense the ambient light. Points in the camera's field of view are mapped to pixels via perspective projection. Computer vision techniques, further detailed in this paper, recognize and localize vehicles from images and video.

I. Introduction

TEns of thousands of drivers and passengers die on the roads each year, with most fatal crashes involving more than one vehicle [1]. The research and development of advanced sensing, environmental perception, and intelligent driver assistance systems presents an opportunity to help save lives and reduce the number of on-road injuries. In recent years, there has been significant research effort dedicated to the development of intelligent driver assistance systems and autonomous vehicles, intended to enhance safety by monitoring the on-road environment.

In particular, the on-road vehicle detection has been a topic of great interest [2]. A variety of sensing modalities have become available for on-road vehicle detection, including radar, lidar, and computer vision. Imaging technology has progressed immensely in recent years. Cameras are cheaper, smaller, and of higher quality than ever before. Concurrently, computing power has increased dramatically. Further, in recent years, we have seen the emergence of computing platforms geared towards parallelization, such as multi-core processing, and graphical processing units [GPU]. Such hardware advances allow computer vision approaches for vehicle detection to pursue real-time implementation.

Vision-based vehicle detection uses one or more cameras as the primary sensor suite. Cameras measure the ambient light in the scene. In its simplest form, a digital imaging system consists of a lens, and an imaging array, typically CCD or CMOS. Within the field of view of a vehicle-mounted camera, a point in the 3D world is mapped to a pixel in a digital image [3]. Going from pixels to vehicles is not straight-forward. A visual object detection system requires camera-based sensing to measure the scene's light, as well as computational machinery to to extract information from raw image data [3]. Figure 1 depicts vehicle detection using vision.

With advances in camera sensing and computational technologies, advances in vehicle detection using monocular vision, stereo-vision, and sensor fusion with vision have been an extremely active research area in the intelligent vehicles community. On-road vehicle tracking has also been extensively studied. It is now commonplace for research studies to report the ability to reliably detect and track on-road vehicles in real-time, over extended periods [4], [5], [6]. Table I highlights representative works in vision-based vehicle detection.

In this paper, we provide a review of vision-based vehicle detection. We concentrate our efforts on works published since 2005, referring the reader to [2] for earlier works. We then review vision-based vehicle detection, commenting on monocular vision and stereo-vision. We provide our insights and perspectives on future research directions in vision-based vehicle detection.

II. Monocular Vehicle Detection

We divide vehicle detection approaches into two broad categories: appearance-based, and motion-based methods. Appearance-based methods recognize vehicles directly from images, that is to say that they go directly from pixels to vehicles. Motion-based approaches, by contrast, require a sequence of images in order to recognize vehicles. As monocular images lack direct depth measurements, appearance-based methods are more common in the monocular vehicle detection literature.

A. Appearance: Features

Early works in monocular vehicle detection used symmetry and edge features to detect vehicles in images [26], [27], [28], [29]. In recent years, there has been a transition from simpler image features like edges and symmetry, to general and robust features sets for vehicle detection. These feature sets, now common in the computer vision literature, allow for direct classification and detection of objects in images. HOG and Haar-like features are extremely-well represented in the vehicle detection literature, as they are in the object detection literature [30], [31].

Histogram of oriented gradient [HOG] features [30] have been used in a number of studies [32], [33]. In [34], the

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TABLE I
REPRESENTATIVE WORKS VISION-BASED VEHICLE DETECTION

Monocular Vision			
Research Study	**Motion/ Appearance**	**Description**	**Comments**
Sun et al., 2006 [7]	Appearance	HOG and Gabor features, SVM and neural network classification	Feature and classifier evaluation. Evaluation on static images.
Zhu et al., 2006 [8]	Motion	Dynamic background modeling of overtake area	Validation on real-world video, with ego-motion compensation.
Wang and Lien, 2008 [9]	Appearance	Statistical modeling of local features	Detection of sedans in statics image. Evaluation is performed on static images.
Diaz-Alonso et al., 2008 [10]	Motion	Optical flow for blind spot detection	Detection results were validated with lidar for ground truth, and TTC validation.
Chang and Cho, 2010 [11]	Appearance	Haar-like features, boosted classification, online learning	Online learning allows for adaptation to new environments.
Sivaraman and Trivedi, 2010 [12]	Appearance	Haar-like features, Adaboost classification, active learning	Active learning shown to improve detection and false alarm rates, evaluated on highway video.
Yuan et al., 2011 [13]	Appearance	HOG features, SVM classification. Orientation determined using multiplicative kernel learning	Vehicles are oriented using matched detectors. The same framework was shown to work for hand gestures and head rotation.
Jazayeri et al., 2011 [14]	Motion	Optical flow, hidden Markov model classification	Modeling the position and motion of preceding vehicles in the image plane.
Niknejad et al., 2012 [15]	Appearance	HOG features, deformable parts-based model	Adaptive threshold for detection in urban environments.
Lin et al. 2012 [16]	Appearance	SURF and edge features, probabilistic classification, blind spot detection	Front and side car models were evaluated to accommodate different views of blind-spot vehicles.

Stereo Vision			
Research Study	**Motion/ Appearance**	**Description**	**Comments**
Chang et al. 2005 [17]	Appearance	Size, width, height, image intensity features, Bayesian classification	A combination of object geometry, template-matching, image features, and depth map features were used for vehicle detection from single stereo pair. Evaluation in parking lot.
Cabani et al. 2005 [18]	Appearance	Color, 3D vertical edges	Sparse stereo matching using L*a*b* color image pairs, and vertical edges, in order to detect vehicles and obstacles.
Franke et al., 2005 [19]	Motion	Optical flow	Optical flow interest points are tracked in the image plane, and their corresponding 3D positions and velocities are tracked using Kalman filtering.
Badino et al., 2007 [20]	Motion	Occupancy grid, free space computation	6D vision points are tracked. Stochastic occupancy grids are solved using dynamic programming, and free space is computed.
Barrois et al., 2009	Appearance	Clustering of 3D points, vehicle orientation estimation	Clustering of points in 3D using polar iterative closest point algorithm. Points are fit to a cuboid model, and pose is inferred.
Barth and Franke, 2009 [21]	Motion	Optical flow, clustering 6D points	6D vision points are tracked over time, with objects formed by clustering using the Mahalanobis distance.
Broggi et al., 2010 [22]	Appearance	V-disparity, clustering in the disparity space	Detection in the disparity space image.
Danescu et al., 2011 [23]	Motion	Optical flow, particle-based occupancy grid	Occupancy grid cells are represented by particles that serve a dual purpose. In a conventional particle filtering framework, each cell as a position and velocity. Particles also carry a probability of the cell's occupancy.
Erbs et al., 2011 [24]	Motion	Tracking stixels, fitting probabilistic cuboid model	Stixels, vertical intermediate representations of 3D points, are tracked using Kalman filtering. Stixels with similar motion are fit to a cuboid model for vehicle detection and tracking.
Perrollaz et al., 2012 [25]	Motion	Optical flow, spatio-temporally smoothed occupancy grid	The occupancy grid is also smoothed in the time and spatial domains to account for noise and outliers.

symmetry of the HOG features extracted in a given image patch, along with the HOG features themselves, was used for vehicle detection. HOG features are descriptive image features, allowing for for determination of vehicle pose [35]. The main drawback of HOG features, is that they are quite slow to compute. Recent work has tackled the speed bottleneck by implementing HOG feature extraction on a graphical processing unit [GPU] [36].

Haar-like features have also been used for vehicle detection in a number of studies [7] [37][38] [39] [33] [12] [40]. Haar-like features are popular for two main reasons. First, Haar-like features are well-suited to the detection of horizontal, vertical, and symmetric structures. Second, by using the integral image [31], feature extraction is very fast, allowing for real-time performance on a standard CPU.

While studies that use either HOG or Haar-like features comprise a large portion of recent vehicle detection works, other general image features have been used. SIFT features [41] were used in [42] to detect the rear faces of vehicles, including during partial occlusions. In [16], a combination of speeded-up robust features [43] and edges is used to detect vehicles in the blind spot. In [44] Gabor and Haar features were used for vehicle detection. Gabor features were used in [7], in concert with HOG features. Dimensionality reduction of the feature space, using a combination of PCA and ICA was used in [9] for detecting parked sedans in static images.

B. Appearance: Classification

Classification methods for appearance-based vehicle detection have followed the general trends in the computer vision and machine learning literature. In [7], [45], artificial neural networks were used to classify extracted features for vehicle detection.

Support vector machines [46] have been widely used for vehicle detection, often using HOG features [29], [7], [33], [32]. The HOG-SVM formulation was extended to detect and calculate vehicle orientation using multiplicative kernels in [13].

Adaboost [47] has also been widely used for classification, largely owing to its integration in cascade classification in [31]. The combination of Haar-like feature extraction and Adaboost classification has been used to detect rear faces of vehicles in [38] [48] [49]. The combination of Haar features and Adaboost classification was used to detect parts of vehicles in [50]. In [51], Waldboost was used to train the vehicle detector.

Generative classifiers have been less common in the vehicle detection literature. It often makes sense to model the classification boundary between vehicles and non-vehicles, rather than the distributions of each class. In [16] a probabilistically-weighted vote was used for detecting vehicles in the blind spot. In [14], motion-based features were tracked over time, and classified using hidden Markov models. In [9], Gaussian mixture modeling was used to detect vehicles in static images. In [42], hidden random field classification was used to detect the rear faces of vehicles.

Recently, there has been interest in detecting vehicles as a combination of parts. The motivation consists of two main goals: encoding the spatial configuration of vehicles for improved localization, and using the parts to eliminate false alarms. In [16], a combination of SURF and edge features are used to detect vehicles, with vehicle parts identified by keypoint detection. In [42], vehicles are detected as a combination of parts, using SIFT features and hidden Conditional Random Field classification. In [52], spatially-constrained detectors for vehicle parts were trained; the detectors required manual initialization of a reference point. The deformable parts-based model [53], [54], using HOG features and the Latent-SVM, has been used for on-road vehicle detection in [55], [15]. In [50], the front and rear parts of vehicles were detected independently, and matched using structural constraints, encoded by an SVM.

C. Motion-Based Approaches

Motion-based monocular vehicle detection has been less common that appearance-based methods. In [56], [57], adaptive background modeling was used, with vehicles detected based on motion that differentiated them from the background.

Optical flow [58], a fundamental machine vision tool, has been used for monocular vehicle detection [59]. In [60], a combination of optical flow and symmetry tracking was used for vehicle detection. In [14], interest points that persisted over long periods of time were detected as vehicles traveling parallel to the ego vehicle. Ego-motion estimation using optical flow, and integrated detection of vehicles was implemented in [61], [62], [63]. In [10], optical flow was used to detect overtaking vehicles in the blind spot.

III. Stereo-vision for Vehicle Detection

Motion-based approaches are more common than appearance-based approaches to vehicle detection using stereo-vision. Multi-view geometry allows for direct measurement of 3D information, which provides for understanding of scene, motion characteristics, and physical measurements. The ability to track points in 3D, and distinguish moving from static objects, affects the direction of many stereo-vision studies. While monocular vehicle detection often relies on appearance features and machine learning, stereo vehicle detection often relies on motion features, tracking, and filtering.

A. Appearance-Based Approaches

Exclusive reliance on appearance cues for vehicle detection is not as common in stereo-vision as monocular vision. While motion-based approaches are more common, even studies that rely on motion for vehicle detection often often utilize some appearance-based stereo-vision techniques for initial scene segmentation, including free space understanding [20], and ground surface modeling [64]. In [17], features such as size, width, height, and image intensity were combined in a Bayesian model to detect vehicles using a stereo rig. In [65], a histogram of depths, computed from stereo matching, was used to segment out potential vehicles.

Various studies have utilized clustering in the depth map for object detection, often using euclidean distance to cluster point clouds into objects [66], [67]. Clustering was also used for object detection in [68]. In [69], clustering was implemented using a modified version of iterative closest point, using polar coordinates to segment objects. The implementation was able to detect vehicles, and infer the vehicle's pose with respect to the ego vehicle. Clustering was used in tandem with image-based mean shift algorithm for vehicle detection in [70].

B. Motion-Based Approaches

The use of motion features heavily in stereo-based vehicle detection. The foundation for a large portion of stereo-vision analysis of the on-road scene starts with optical flow [58]. In many studies, interest points are tracked in the monocular image plan of one of the stereo rig's cameras, and then localized in 3D using the disparity and depth maps [71]. Optical flow is also used as a fundamental component of stereo-vision analysis of the on-road scene in [72] [73] [74] [65] [75] [76] [77] [23] [71] [70].

In [71], the concept of 6D-vision, the tracking of interest points in 3D using Kalman filtering, along with ego-motion compensation, is used to identify moving and static objects in the scene. In [24], tracked 3D points, using 6D vision, are grouped into an intermediate representation consisting of vertical columns of constant disparity, termed stixels. Stixels are initially formed by computing the free space in the scene, and using the fact that structures of near-constant disparity stand upon the ground plane. The use of the stixel representation considerably reduces the computation expense over tracking all the 6D vision points individually. The tracked stixels are classified as vehicles using probabilistic reasoning and fitting to a cuboid geometric model.

Occupancy grids are widely used in the stereo-vision literature for scene segmentation and understanding. In [68][78], scene tracking and recursive Bayesian filtering is used to populate the occupancy grid each frame, while objects are detected via clustering. In [23], the occupancy grid is populated using motion cues, with particles representing the cells, their probabilities the occupancy, and their velocities estimated for object segmentation and detection.

IV. Discussion and Future Directions

While vehicle detection has been an active research area for quite some time, open challenges still remain. Monocular and stereo-vision vehicle detection each have their established paradigms. Monocular vehicle detection largely relies on a feature extraction-classification paradigm, based on machine learning. Stereo-vision's typical paradigm consists of ego-motion compensation, tracking feature points in 3D, distinguishing static from moving points, and associating moving points into moving objects [23]. There is ample space for more integrated approaches, that borrow key elements from each paradigm.

Monocular vehicle detection largely relies on a feature extraction-classification paradigm, based on machine learning. This approach works very well when the vehicle is fully-visible. In particular, robustly detecting partially-occluded vehicles using monocular vision remains an open challenge. Early work in this area is ongoing, based on detecting vehicles as a combination of independent parts [50], but detecting partially-occluded vehicles remains a challenging research area. Using parts to detect vehicles has been implemented in [15], but the recognition still has difficulty with occlusions. Future works will need to include motion cues into monocular vehicle detection, to identify vehicles as they appear, while seamlessly integrating them into machine learning frameworks. Further, it is challenging to develop a single detector that works equally well in all the varied conditions encountered on the road. Scene-specific classifiers, categorizing the on-road scene as urban vs. highway, cloudy vs. sunny could augment the performance of vehicle detectors, utilizing image classification as a preprocessing step [79].

Object detection using stereo-vision has also made great progress over the past decade. Stereo-vision methods typically recognize vehicles in a bottom-up manner. This is to say that the typical paradigm consists of ego-motion compensation, tracking feature points in 3D, distinguishing static from moving points, and associating moving points into moving objects [23]. Finally, moving objects are labeled as vehicles by fitting a cuboid model [77], or clustering [69]. While these methods have made great progress, complex scenes still present difficulty [24]. Integration of machine learning methodology could increase the robustness of existent stereo-vision approaches, and has the potential to simplify the vehicle detection task. Research along these lines has been performed by using machine learning based detection on the monocular plane, integrating stereo-vision for validation and tracking [80], [5], [65]. Future work could involve a more principled machine learning approach, learning on motion cues, image cues, and disparity or depth cues.

As the cost of active sensors, such as radar and lidar, continue to reduce, integration of these sensing modalities with vision will continue to increase in prevalence. Automotive radar and lidar systems are fairly mature in their ability to detect objects and obstacles, but their ability to distinguish vehicles from other objects is limited. As lane tracking cameras become standard options on serial production vehicles, the opportunity to integrate vision with active sensing technology will present itself, with vision providing an intuitive level of semantic abstraction. Future works will need a principled, object-level fusion of vision and radar/lidar for vehicle detection [81]. Such an information fusion could reduce estimation covariance and enhance robustness, although the asynchronous nature of the multiple modalities will need to be handled [82].

V. ACKNOWLEDGMENTS

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