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Improved Vision-Based Lane Tracker Performance Using Vehicle Localization

Sayanan Sivaraman and Mohan Manubhai Trivedi

Abstract— **In this paper, we present improved lane tracking using vehicle localization. Lane markers are detected using a bank of steerable filters, and lanes are tracked using Kalman filtering. On-road vehicle detection has been achieved using an active learning approach, and vehicles are tracked using a Condensation particle filter. While most state-of-the art lane tracking systems are not capable of performing in high-density traffic scenes, the proposed framework exploits robust vehicle tracking to allow for improved lane tracking in high density traffic. Experimental results demonstrate that lane tracking performance, robustness, and temporal response are significantly improved in the proposed framework, while also tracking vehicles, with minimal additional hardware requirements.**

Index Terms - **Lane Keeping, Vehicle Detection, Driver Assistance.**

I. Introduction

It is well established that computer vision will play an ever increasing role in the development of active safety systems for intelligent driver assistance [24]. Vision has been an active area of research in the intelligent vehicles community, for the detection of pedestrians [8], vehicles [21], [22], and lanes [2], [16]. Active safety systems based on vision based sensing of vehicles and lanes have the potential reduce the likelihood of accidents and save lives.

While robust lane marking detection and tracking for driver assistance has been well-studied in the field, it is known that many lane keeping systems fail in high density traffic scenarios [16], [14]. While there has been some recent research into fusing lane and vehicle detections using vision [12], it has been largely limited to improving the performance of vehicle detection by using lane detection to narrow the search area.

This study introduces lane tracking using vehicle localization, incorporating a robust active learning based vehicle detection system [21], [22] with lane tracking. The resulting system can perform in higher density traffic, and improves the performance, robustness, and spatio-temporal response of lane tracking systems. The approach we introduce uses only one camera, and requires no additional hardware for system implementation.

II. Related Research

We divide our literature review into two subsections. The first details related research in lane detection and tracking. The second details recent advances in vehicle detection and tracking.

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Sayanan Sivaraman and Mohan M. Trivedi are with the Laboratory for Intelligent and Safe Automobiles, University of California, San Diego, USA
ssivaram@ucsd.edu, mtrivedi@ucsd.edu

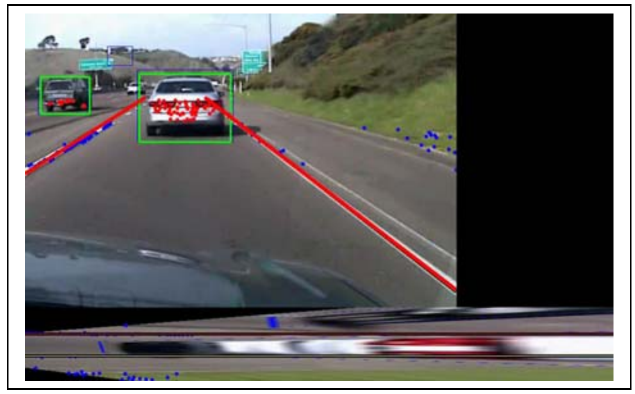

Fig. 1. Lane and Vehicle Tracking system performance. Green boxes indicate tracked vehicles, and red lines indicate tracked lane positions. Blue circles indicate markings used for lane localization. Red circles indicate lane markings that have been eliminated because of their overlap with tracked vehicles.

A. Lane Detection and Tracking

At its most basic level, lane keeping for driver assistance consists of locating lane marking, fitting the lane markings to a lane model, and tracking their locations temporally with respect to the ego vehicle. Various vision based methods have been used for identification of lane markings. Image descriptors that have been successfully used for lane marking localization include steerable filters [16], [17], [2], adaptive thresholds [18], edge detection, global thresholds, and top hat filters [26].

While certain lane marking descriptors may have advantages such as orientation invariance [16] or computational simplicity [26], it is important to choose lane marking extractors specific to the roads where a system is to be deployed. A thorough side by side comparison of lane feature extractors can be found in [26]. In [14], a novel lane marking detection scheme using SVM classifiers is employed. While computationally more expensive, such machine learning based lane marker detections promise greater robustness.

Road models used in lane detection and tracking systems generally try to approximate the clothoid structure which is often used in road construction [16]. This is often done via a parabolic or cubic fitting of the lane markings [18]. In [16], this is achieved via fitting an adaptive road template to the viewed data. In[14], RANSAC has been used to fit lane markings.

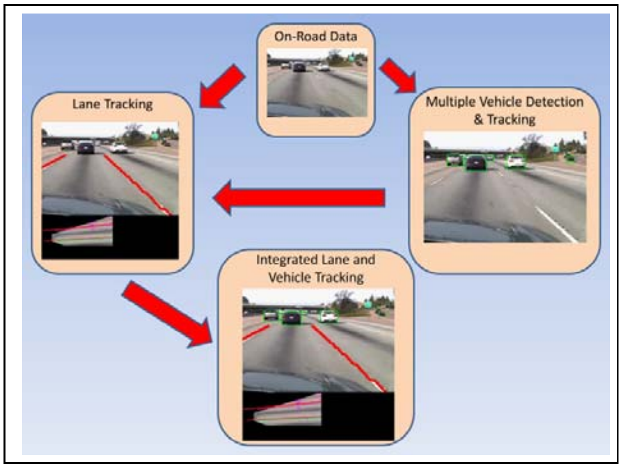

Fig. 2. Lane and Vehicle Tracking framework overview.

Fig. 3. Camera view of the highway.

Lane tracking has been implemented in [16], [17], [18], [2] using Kalman filters, which tend to work well for straight, structure roads. However, Kalman filtering for lane tracking can be problematic when roads curve or there are other discontinuities. Particle filtering [13] has gained popularity in lane tracking, as it can integrate multiple hypotheses for lane markings [5], [14]. In [15], a hybrid Kalman Particle filter has been implemented for lane tracking, which combines the stability of the Kalman filter with the ability to handle multiple cues of the particle filter.

B. Vehicle Detection

While the most popular vehicle detection systems found in consumer products are the radars used for adaptive cruise control, it is known that such these commercial grade sensors have limited angular range, only able to detect vehicles directly in front of the ego vehicle. Using vision for vehicle detection can recognize and track vehicles across multiple lanes [22].

Robust recognition of other vehicles on the road using vision is a challenging problem. Highways and roads are dynamic environments, with ever-changing backgrounds and illuminations. The ego vehicle and the other vehicles on the road are generally in motion, so the sizes and locations of vehicles in the image plane are diverse. There is high variability in the shape, size, color, and appearance of vehicles found in typical driving scenarios [23].

Vehicle detection and tracking has been widely explored in the literature in recent years [22]. In [23], a variety of features were used for vehicle detection, including rectangular features, Gabor, and HOG. The classification performance of SVM's and NN classifiers was also explored.

In [9], the effect of varying the resolution of training examples for vehicle classifiers was explored, using rectangular features and Adaboost classification [7]. Rectangular features and Adaboost were also used in [21], integrated in an active learning framework for improved on-road performance.

In [11], vehicle detection was performed with a combination of triangular and rectangular features. In [10], a similar combination of rectangular and triangular features was used for vehicle detection and tracking, using Adaboost classification. In [3], a statistical model based on vertical and horizontal edge features was integrated with particle filter vehicle tracking. Particle filter tracking was also used in [22]. In [12], lanes and vehicles were both tracked using particle filters, and it was shown that coupling the two has the potential to improve the performance of each system.

III. Lane Tracking with Vehicle Localization

In this study, we integrate lane tracking with vehicle detection. Initially, vehicles are detected using the same vehicle detection system detailed in [21]. Vehicle localization is easily included into this system, as in [22]. Locations where vehicles are located and tracked are marked, and lane markings are sought. Vehicle locations are excluded from the lane marking search area. Lanes are then tracked using a Kalman Filter [16]. The following subsections briefly detail the modules used in the presented system. Figure 2 shows an overview of the proposed system framework.

A. Lane Detection and Tracking

While simple edge-based lane marking detection is possible on well-marked, uniform roads, it is well known that simple edge detection generally fails in real-world driving scenarios [26]. Among the series different lane marking descriptors used in the literature, steerable filters have been shown to warrant their computational cost in certain driving scenarios.

In particular, in driving environments where lane markings are not uniform, steerable filters' ability to seek out both line and 'bot dot' lane markings is advantageous. In addition, on roads where the lane markings are old and worn out, or where the the color of the road and the color of the lane markings do not differ substantially, steerable filters have been shown to perform robustly over great distances [16], [2].

In this study, we use a filter bank consisting of three separable filters, which are based on the second derivatives of Gaussian filters. The filters are convolved with an inverse perspective mapping of the camera view through the vehicle's windshield, which roughly corresponds to a driver's view

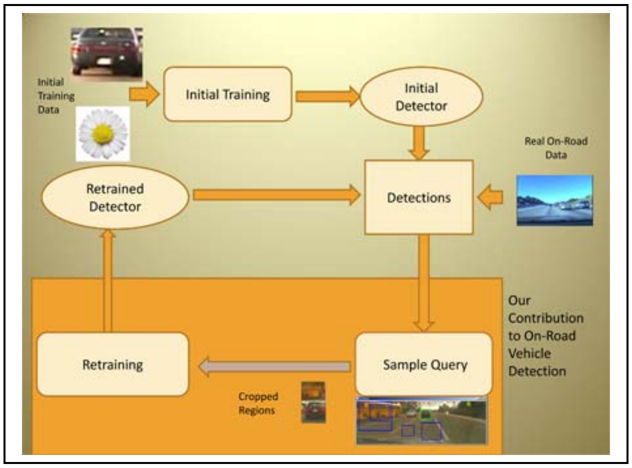

Fig. 4. Active Learning framework for on-road vehicle detection [22]

[16]. It can be shown that the response of any rotation of the second derivative of Gaussian filter by an angle θ can be computed using equation 1. G_{xx}, G_{yy}, and G_{xy} correspond to the second derivatives in the x, y, and x-y directions, respectively.

$$G2^{\theta} = G_{xx}cos^2\theta + G_{yy}sin^2\theta + 2G_{xy}cos\theta sin\theta \quad (1)$$

In order to solve for the maximum and minimum response angles θ_{min} and θ_{max}, we differentiate equation 1, and set equal to zero. This gives us equation 2, where A is given in equation 3.

$$G2^{\theta_{min/max}} = G_{yy} - \frac{2G_{xy}^2}{G_{xx} - G_{yy} \pm A} \quad (2)$$

$$A = \sqrt{G_{xx}^2 - 2G_{xx}G_{yy} + G_{yy}^2 + 4G_{xy}^2} \quad (3)$$

We track the positions of the right lane, left lane, lane width, and the ego vehicle's lane position using a Kalman Filter, as in [2].

B. Active Learning for Vehicle Detection

While prior studies in vehicle detection explored the effect on vehicle detection performance of feature sets [10], image resolution [9], and classifiers [23], it is shown in [21], [22] the significant contribution that active learning brings to on-road vehicle detection. Active learning refers to a paradigm in which during learning process, the most informative examples are chosen for training a discriminative classifier [4]. By basing the training of a vehicle detector on the examples that are most likely to result in misclassification, it is possible to train a more robust on-road vehicle detector with fewer training examples [22].

Active learning research studies are often concerned with reducing the *Region of Uncertainty* in the decision space [4]. Given a training set, feature set, and classifier, there are regions in the decision space that are not unambiguously defined. Active learning seeks to reduce this Region of Uncertainty to improve classifier performance [6], often by querying informative samples, known as *selective sampling* [4].

Defining a query function to select the most informative examples is a crucial part of the active learning paradigm [6]. While studies in pedestrian detection have taken a probabilistic approach to querying informative examples [6], such approaches can require extensive manual annotation if retraining with independent examples is desirable.

In this study, a semi-supervised query of independent training examples has been implemented, as in [1], [21], [22]. An initial classifier is trained, and then evaluated on independent on-road data. Misclassifications are marked by the user, and all detections and annotations are archived for retraining [22]. Figure 4 depicts the general active learning framework employed.

For on-road vehicle detection, we utilize an Ababoost [7] cascade classifier, using Haar-like features, as initially proposed in [27]. The set of Haar-like rectangular features is well suited to detecting vehicles, as they respond strongly to vertical and horizontal edges and bars, as well as symmetric structures [27], [9]. The Adaboost classifier uses the the Haar-like feature responses as weak learners, and makes a decision based on a weighted majority of the feature responses [7].

C. Vehicle Tracking Using Condensation Filter

We integrate a Condensation filter for vehicle tracking, which propagates the densities of vehicles from frame to frame, represented by a confidence weighted set of particles [13]. Then density of prediction of the state is based on prior measurements is $p(x_t|Z_{t-1})$, where x is the state and Z is the set of all observed measurements. Random samples are used to predict the state using a dynamic system model. Finally, a new measurement is taken and each of the multiple position hypotheses is weighted, yielding a representation of the observation density $p(z_t|x_t)$ [13].

Figure 5 shows vehicle detections and the collection of particles used for prediction. It is shown in [22] that integrating Condensation tracking with the active learning based

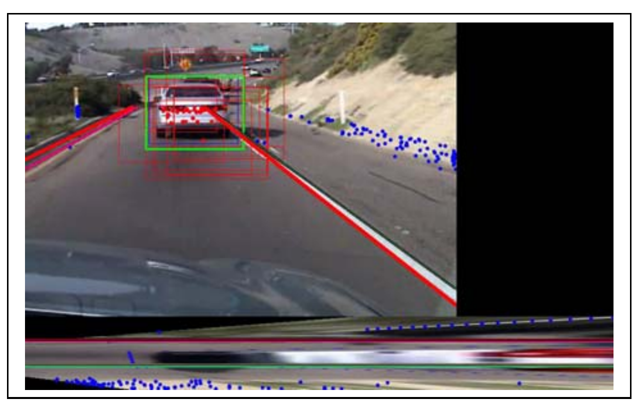

Fig. 5. Lane and Vehicle Tracking with candidate particles shown. Red boxes indicate a particle with medium confidence. Green boxes are the state predictions. Blue boxes are the vehicle detections. The bottom section shows a bird's eye view using the inverse perspective mapping.

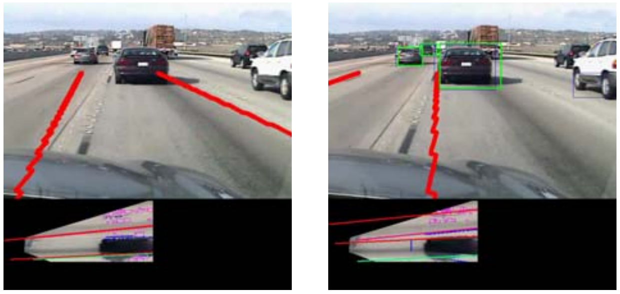

Fig. 6. a) Stand-Alone Lane Tracker Output, Frame 226. We note that although it is 0.133 seconds after the lane change, the lane tracker has not recognized the lane change yet, and indicates lane markers bisecting the vehicle in front. b) Lane and Vehicle Tracker has already changed lanes, as well as tracking the nearby vehicles.

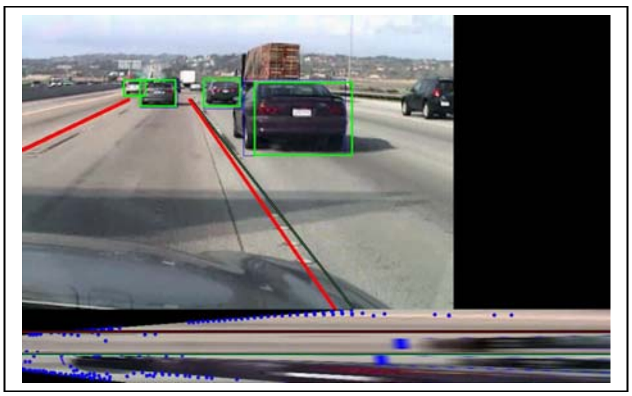

Fig. 7. Lane and Vehicle Tracking performance in dense traffic. The bottom section shows a bird's eye view using the perspective mapping.

detections yields a very robust on-road vehicle detection and tracking system. Final system performance in dense traffic is indicated in 7.

IV. Experimental Validation

For experimental validation, we choose two 500-frame long highway sequences, corresponding to roughly 17 seconds of footage each. The first sequence was captured on a highway with bot-dot lane markings. The segment corresponds to roughly half a kilometer of dense traffic, and there are many vehicles on the road. We evaluate this sequence with a system look-ahead distance of 30 meters. The second sequence was captured while merging onto the highway, following a single vehicle in front. We evaluate this sequence with a system look-ahead distance of 100 meters. We have used two different look-ahead distances to demonstrate the generality of this approach. Fully annotated ground-truth data for these data sequences will be made publicly available, pending approval, at http://cvrr.ucsd.edu/LISA/index.html.

For vehicle detection and tracking, we use two performance metrics. The first is the $Recall$, and the second is the $1 - Precision$, as used in [22]. Figure 8 plots the $Recall$ vs. $1 - Precision$ for the first data sequence. We note the improvement that temporal filtering makes in system performance.

For lane keeping, we take into consideration two performance metrics. The first is the mean absolute error between tracked lane measurements and ground truth. The second is the standard deviation of the error between tracked lane measurements and ground truth. These performance metrics have been used in [16], [17], [2].

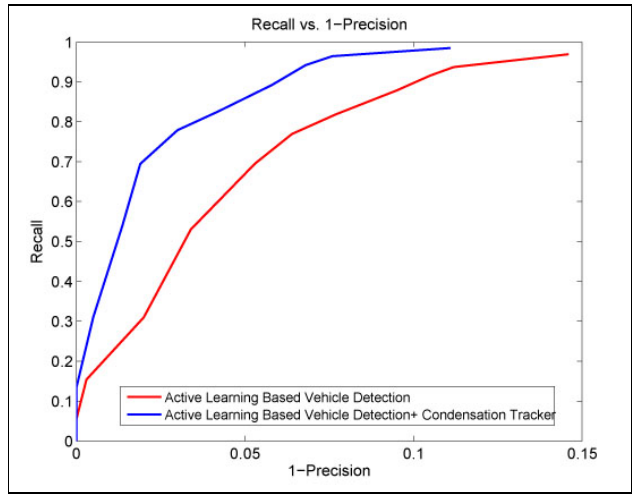

Fig. 8. Plot of $Recall$ vs. $1 - Precision$ for active learning based vehicle detection, Sequence 1, and active learning based vehicle detection+ condensation tracking. Note the improvement that tracking makes in system performance.

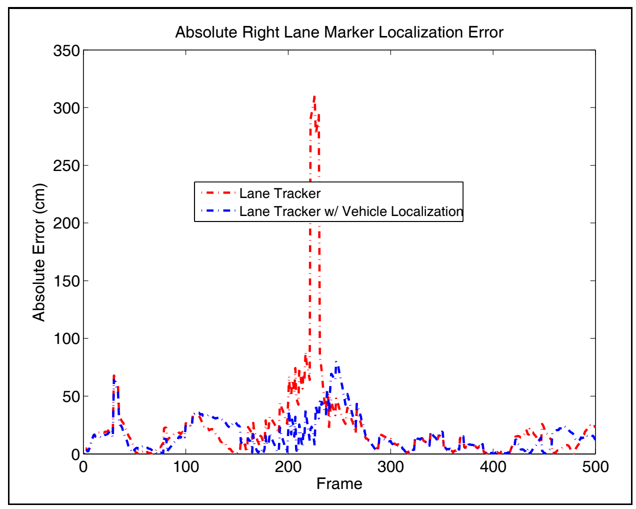

Fig. 9. Plot of absolute localization error vs. time, sequence 1. Note the spike in absolute error for the stand-alone lane tracker, as it does not detect the lane change until 9 frames after it has happened.

We compare the performance of the Lane and Vehicle tracking system with that of the lane tracking system alone. Table I shows lane keeping performance on the first dataset. Using robust vehicle detection and tracking improves the performance of lane tracking in dense traffic, as highlights of the vehicle are not erroneously interpreted by the lane tracking system as lane markers. We observe a decrease in absolute mean localization error and standard deviation of error for both right and left lane markers.

The first data sequence contains a lane change which occurs at frame 222 of 500. It has been reported in the

TABLE I

LANE TRACKING RESULTS, SEQUENCE 1

Lane Tracking System	**Mean Absolute Error, Left Lane Marker *(cm)***	**Mean Absolute Error, Right Lane Marker *(cm)***	**Standard Deviation of Error, Left Lane Marker *(cm)***	**Standard Deviation of Error, Right Lane Marker *(cm)***	**Lane Change Detection Delay (sec)**
Lane Tracking	31.6	22.4	2.1	2.6	0.30
Lane and Vehicle Tracking	29.13	**15.8**	1.7	**.97**	**0**

TABLE II

LANE TRACKING RESULTS, SEQUENCE 2

Lane Tracking System	**Mean Absolute Error, Left Lane Marker *(cm)***	**Mean Absolute Error, Right Lane Marker *(cm)***	**Standard Deviation of Error, Left Lane Marker *(cm)***	**Standard Deviation of Error, Right Lane Marker *(cm)***
Lane Tracking	65.4	45.2	3.91	2.45
Lane and Vehicle Tracking	**27.9**	**17.3**	1.8	**1.0**

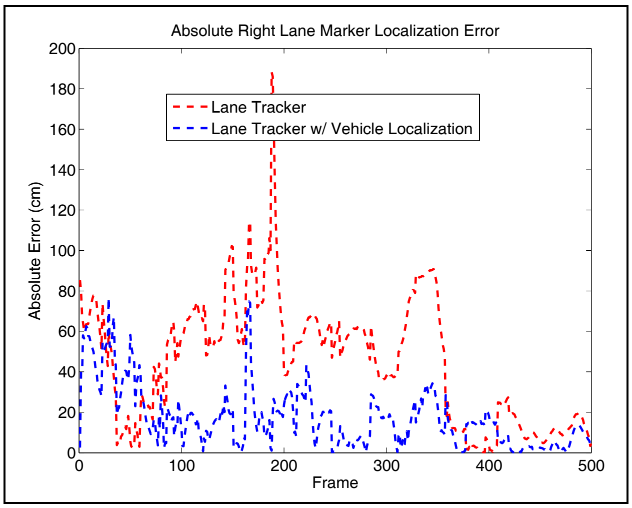

Fig. 10. Plot of absolute localization error vs. time, sequence 2. In this sequence, there are no lane changes, just lane following. Notice the error in lane tracking alone, caused by erroneous lane marker identification due to the vehicle ahead.

Fig. 11. a) Stand-Alone Lane Tracker Output, Frame 28. The blue circles indicate detected lane markings. We note that the lane tracker has picked up many erroneous lane markings due to the vehicle ahead, and as such, the tracked lanes are bisecting the vehicle. b) Lane and vehicle tracking. The lane markings that overlap with the tracked vehicle are ignored, indicated in red. The tracked lane markings are more accurate.

literature that many lane trackers fail in dense traffic [16] and have difficulty during lane changes [14]. By selecting such a segment, we aim to demonstrate the power of integrating vehicle tracking with lane tracking. Ground truth was annotated by hand. Figure 3 shows the camera view.

The lane change is identified by the system using the state vector from the Kalman filter. When the ego-vehicle's position within the lane exceeds the lane boundary, the system identifies a lane change. Interestingly, we also observe that while the lane tracker alone has a delay of 0.30 seconds in detecting the lane change, the lane and vehicle tracker has no delay in recognizing the lane change. Given that driving is a time-critical task, and drivers' have their own latency in responding to stimuli, the minimal delay is preferable in recognizing a lane change. Figure 9 plots the absolute error over time. We reiterate that the observed gain in performance has been performed with one camera, so there is no additional hardware required.

Figures 6(a) and 6(b) show the respective system outputs in frame 226, 0.133 seconds after the lane change has occurred. We note that while the Lane and Vehicle tracking system has already recognized the lane change, the lane tracker alone still believes that the ego vehicle is in the right lane. In addition, the stand-alone lane tracker's lane markings are bisecting the vehicle directly in front.

The second dataset does not contain any lane changes, and consists simply of following a vehicle on the highway. Figure 10 plots the absolute error over time, and Table II shows lane keeping performance on the second dataset.

We note that integrating vehicle tracking consistently results in better lane keeping performance. Figures 11(a) and 11(b) demonstrate the erroneous lane marking identifications that can result from other vehicles on the road. We note that there is a large difference in the localization of the left lane marking between the two systems. Green boxes indicate tracked vehicles, blue dots indicate identified lane markings, and red dots indicate lane markings that have been eliminated from the lane tracking because they coincide with vehicle locations. These erroneous markings can have a detrimental effect on lane tracking performance.

V. CONCLUDING REMARKS

In this research study, we have introduced Lane and Vehicle Tracking using a single camera. Lane tracking has been performed using a bank of steerable filters and Kalman filtering. Robust vehicle detection has been achieved using an active learning approach, further detailed in [22]. Vehicle tracking been implemented using Condensation tracker [13]. The full system requires minimal additional hardware and performs robustly in dense traffic situations, even during lane changes. In addition, it is shown in experimental validation that the lane tracking performance, robustness, localization, and temporal response are improved when including vehicle tracking. This study lays the foundation for further research in integrated vision systems for driver assistance. Further studies will include a more general approach to integrated lane and vehicle tracking, as well as dynamic trajectory learning, similar to that in [19].

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