

Towards Cooperative, Predictive Driver Assistance

Sayanan Sivaraman and Mohan M. Trivedi

Abstract—In this work, we describe research directed towards cooperative, predictive driver assistance. We describe predictive driver assistance systems, which aim to make longer-term predictions about the on-road environment, supporting positive HMI with the driver. Given the rapid development of advanced sensing, computational, and algorithmic technologies, intelligent vehicles are now approaching an era in which the vehicle can maintain a full panoramic awareness. Thus, the instrumented vehicle will be available to help the driver navigate the on-road environment, when the driver requests it. As predictive driver assistance systems are developed, it will be shown that cooperative integration, across vehicles, will improve the performance and overall on-road safety. We divide the scope of cooperation systems into four main areas: in-vehicle systems cooperation, vehicle-driver cooperation, cooperation across vehicles (V2V), and finally cooperation with vehicles and infrastructure (V2I). Each level of cooperation will quantitatively improve on-road safety performance, and allow for increased sophistication and prediction.

Index Terms - Driver Assistance, Cooperative Systems.

I. INTRODUCTION

According to NHTSA, in 2009, automotive collisions in urban environments accounted for 43% of fatal crashes in the United States. Tens of thousands of peoples are killed on the roads each year, and most fatal crashes feature more than one vehicle [1]. As research in sensing and environmental perception progresses, there is great potential to save lives by developing advanced driver assistance systems. Over the past decade, there has been significant research effort dedicated to the development of intelligent driver assistance systems, intended to enhance safety by monitoring the driver and the on-road environment [2], [3]. In particular, surround analysis and understanding using vehicle-based sensing will be crucial to enhancing the safety of drivers, vehicle occupants, and other road users.

Until recently, decision-making for active safety in driver assistance has fit a binary decision paradigm. Systems based on fundamental on-road perception make simple decisions. In the case of lane estimation [4], lane departure warning (LDW) systems indicate when the vehicle is deviating or departing from the ego-lane. When a driver is being assisted, the feedback is delivered as *negative* HMI, communicating that the maneuver is *not* feasible.

Sensing technologies, computation, and algorithms are rapidly developing [5]. Coming generations of intelligent vehicles will have a sophisticated understanding of the on-road environment, featuring robust predictive capabilities. In this work, we explore the next generation of predictive driver assistance, which facilitates *positive* HMI. The systems discussed in this paper are intended to understand when a maneuver is feasible, and advise the driver *when* and *how* to execute the lane change or merge. Figure 1 illustrates the full

spectrum of maneuver-based decision systems in intelligent vehicles. At one end, we have fully manual driving. At the other, we have fully autonomous driving [6]. Successful integration of predictive driver assistance is a multi-faceted research task, brings together researchers from engineering, psychology, and human factors. Inherent in the successful integration will be navigating the various levels of cooperation required for safe, predictive, and successful driver assistance.

In this work, we examine cooperative, predictive driver assistance, focusing on cooperation and four different levels. First, we focus on in-vehicle systems cooperation, integrating multiple sensors and systems for enhanced performance. Then, we look at vehicle-driver cooperative driving, in which the driver relinquishes full control to the vehicle, and vice versa. We then look at cooperative safety across vehicles, with communication between vehicles using ad-hoc V2V wireless networks. Finally, we look at cooperation between vehicles and infrastructure nodes using V2I networks, for enhanced ramp metering and other improvements. Figure 2 outlines the proposed approach.

The remainder of this paper is structured as follows. The following section describes cooperative active safety within the vehicle, including multiple systems, predictive driver assistance, and driver-vehicle cooperation. Section 3 describes cooperation between vehicles (V2V), and with infrastructure (V2I). Section 4 presents quantitative results. Section 5 offers concluding remarks.

II. IN-VEHICLE COOPERATIVE, PREDICTIVE DRIVER ASSISTANCE

The first step in cooperative, predictive driver assistance involves integration across multiple systems on the same vehicle. While individual perception modules have often been developed with one objective in mind, we show in this section that integrating multiple systems can achieve two main objectives:

- Enhanced performance of each respective system
- Higher-level understanding, interpretation, and prediction on the road.

We examine each of these objectives, exemplified by recent works in the field.

A. Integrated Lane and Vehicle Tracking

Recent work in the intelligent vehicles literature has examined synergistic integration of lane and vehicle tracking for driver assistance. Integration results in a final system that improves on the performance of both lane tracking and vehicle tracking modules. Further, integration provides information of higher contextual relevance that neither the lane tracker nor vehicle tracker can provide by itself [7].

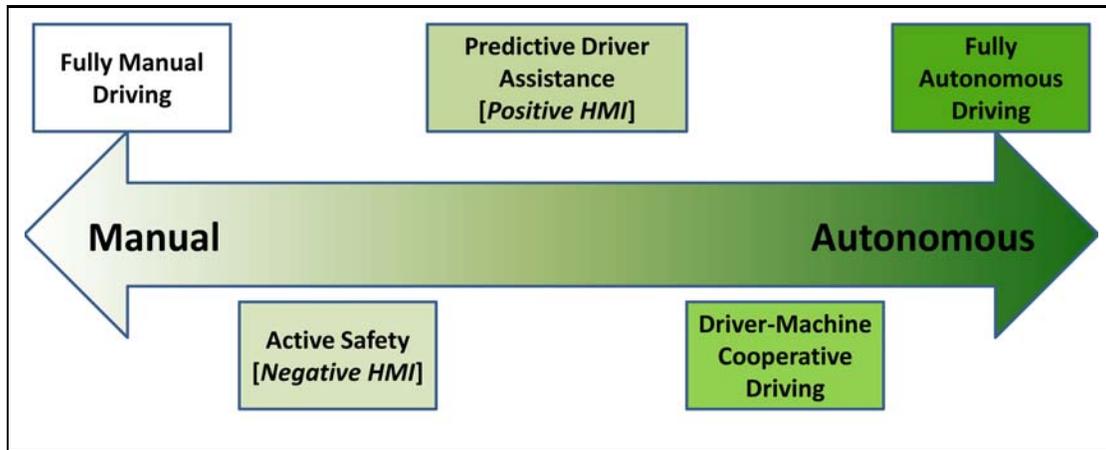


Fig. 1. The full spectrum of maneuver-based decision systems in intelligent vehicles, with implications for driving. At one end, there is fully manual driving. Active safety systems, such as lane departure warning (LDW) and side warning assist (SWA) are already becoming more commercially-available. Predictive driver assistance remains an open area of research. Cooperative driving will integrate predictive systems, and seamlessly allow hand-offs of control between driver and autonomous driving. At the far end of the spectrum is fully autonomous driving, with no input from the driver.

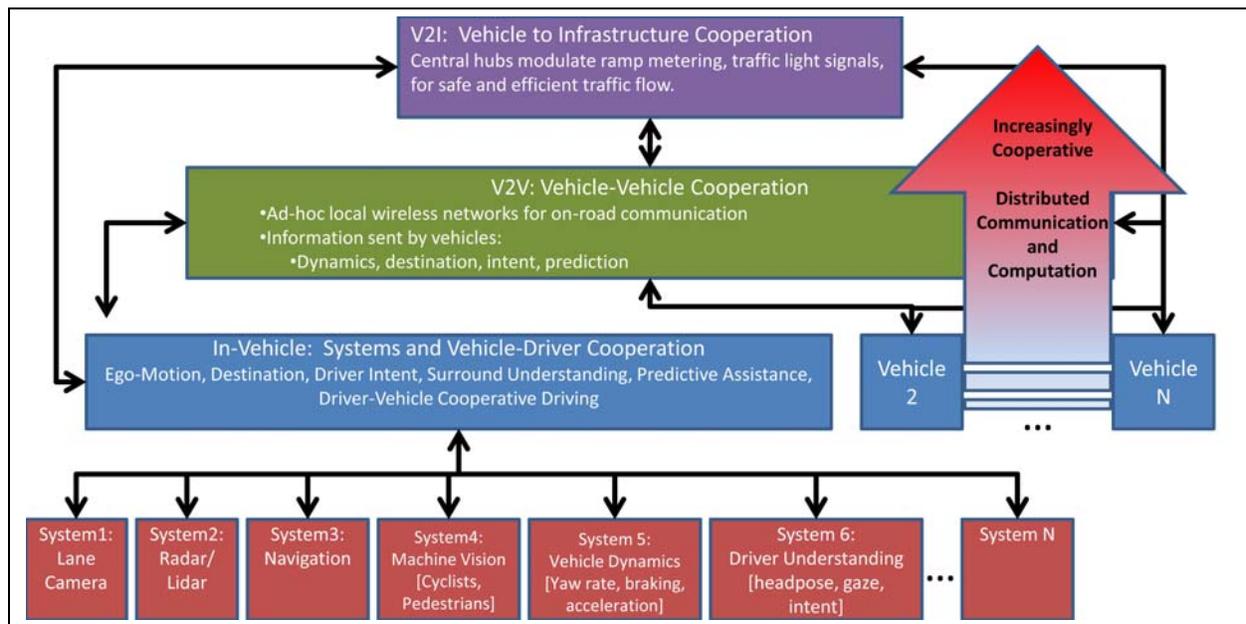


Fig. 2. Cooperative, Predictive Driver Assistance. At the lowest level of cooperation, vehicles integrate stand-alone active safety systems, resulting in improved quantitative performance, and enhanced predictive driver assistance. Vehicles and drivers also cooperate. Vehicles communicate with each other (V2V) using ad-hoc networks. Infrastructure nodes adaptively meter on-ramps and traffic signals using V2I communication.

Integration of lane and vehicle tracking achieves improved tracking performance of each module via system integration. The integration of the two systems can be framed in terms of a feedback loop in a partially-observed system, where lane and vehicle estimates are information states [8]. Lane observations augment estimation of the vehicles, while vehicle observations augment lane estimation. Figure 3(a) plots the localization estimates of the lane tracker, the integrated lane and vehicle tracking system, and ground truth on the same axis. We see a clear difference between the two systems. It is here that we observe the large change in lane localization

error due to changes in traffic density. Correspondingly, we see performance improvements in the vehicle tracker due to integration in figure 3(b). Cooperation between multiple systems is shown to quantitatively improve system performance in the vehicle [7].

B. Multi-System Cooperative Predictive Driver Assistance

Cooperative integration allows for higher-order functionality and predictive driver assistance. Cooperative systems integration allows for *new* functionalities to assist the driver. Integrating data from multiple sensors, we formulate a com-

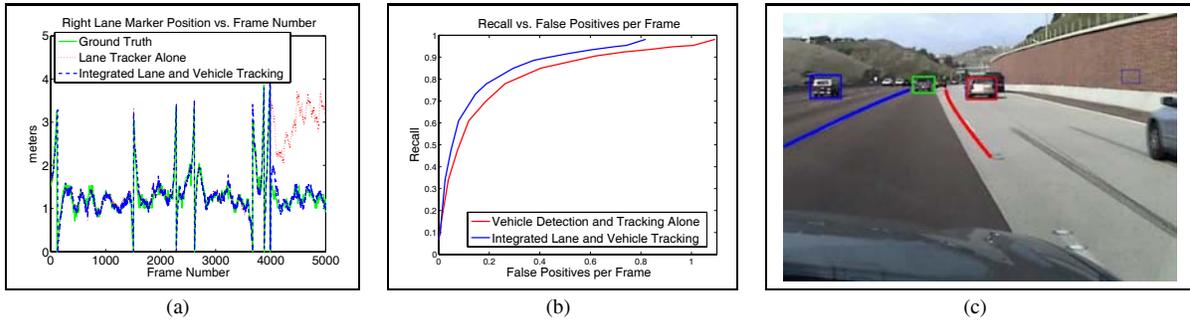


Fig. 3. 3(a) Estimated position of the right lane marker vs. frame number, showing improved performance using integration. At frame 4000, the vehicle performs a lane change, which the stand-alone lane tracker misses, while the integrated lane and vehicle tracking maintains tracking [7]. 3(b) Recall vs. False Positives per Frame, comparing vehicle detection and tracking alone [7]. Integrated lane and vehicle tracking has better performance in terms of false positives per frame. 3(c) Typical performance of integrated lane and vehicle tracking on highway [7].

compact representation for the on-road environment, the Dynamic Probabilistic Drivability Map, used for high-level interpreted data [9]. The DPDM readily integrates data from on-road tracking modules, in order to compute the drivability of the ego-vehicle's surround in accordance with physical and legal constraints.

The instrumented vehicle is shown in figure 5(a), and includes radar, lidar, and vision, enabling on-road vehicle tracking as depicted in figure 5(b). Beyond geometry, drivability cells carry a probability of drivability, based on sensor observations. Lane information comes from the lane estimation module, which tracks the lanes using the on-board forward-looking camera. Vehicles and obstacles are detected and tracked using a sensor fusion system based on lidar and radar sensors.

We define the space of sensor observations Y into tracked vehicles and objects V , and lane marker information L . At time k , we compute the probability of drivability for a given cell $P(D_k|Y_k)$, given the observations, using equation 1. We compute $P(D_k|Y_k)$ separately given V and given L , and take the minimum probability of drivability. We propagate probabilities to the next time instant using Π , the state transition matrix, where W_{k+1} is a martingale increment process. We use the DPDM, plotted in figure 5(c) [9], to solve for the minimum-cost solution to merging into the adjacent lane, recommending *when* and *how* to merge.

$$\begin{aligned}
 P(D_k|V_k) &= \frac{P(V_k|D_k)P(D_k)}{P(V_k)} \\
 P(D_k|L_k) &= \frac{P(L_k|D_k)P(D_k)}{P(L_k)} \\
 P(D_k|Y_k) &= P(D_k|V_k, L_k) = \min\{P(D_k|V_k), P(D_k|L_k)\} \\
 P(D_{k+1}|D_k) &= \Pi, D_{k+1} = \Pi D_k + W_{k+1}
 \end{aligned} \tag{1}$$

C. Vehicle-Driver Cooperative Driving

While autonomous driving has been an active and highly-publicized area of research, many challenges remain before

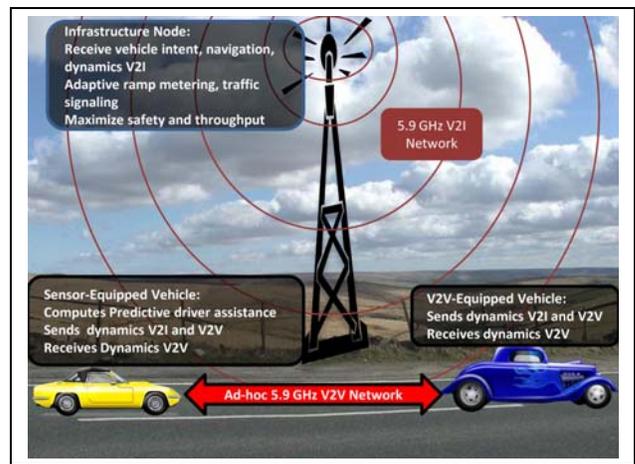


Fig. 4. Multi-level framework for cooperative active safety between vehicles (V2V), and between vehicles and infrastructure (V2I). V2V communication uses ad-hoc 5.9GHz networks. V2I uses standard IEEE 802.11p wireless protocol, with infrastructure nodes functioning as communication hubs.

full-scale deployment of autonomous vehicle is practical [10]. Robots can drive in controlled environments, even with other robotic vehicles on the road, but navigating typical traffic situations is still quite difficult. Currently, fully-autonomous research vehicles are expensive, and not yet practical for consumers.

There will be a gradual transition from today's fully-manual vehicles to vehicles that can perceive and understand driving [6], as well as the driver. To this end, the vehicle and the driver will participate in cooperative driving, seamlessly handing off control of the vehicle. Researchers are already studying driver-vehicle interactivity and vehicles' understanding of the attentional state of the driver [11]. It is shown [12] that autonomous braking can enhance the life-saving capabilities in forward collision situations.

III. PREDICTIVE DRIVER ASSISTANCE: V2V AND V2I INTEGRATION

Communication networks between vehicles (V2V), and between vehicles and infrastructure (V2I) are rapidly devel-

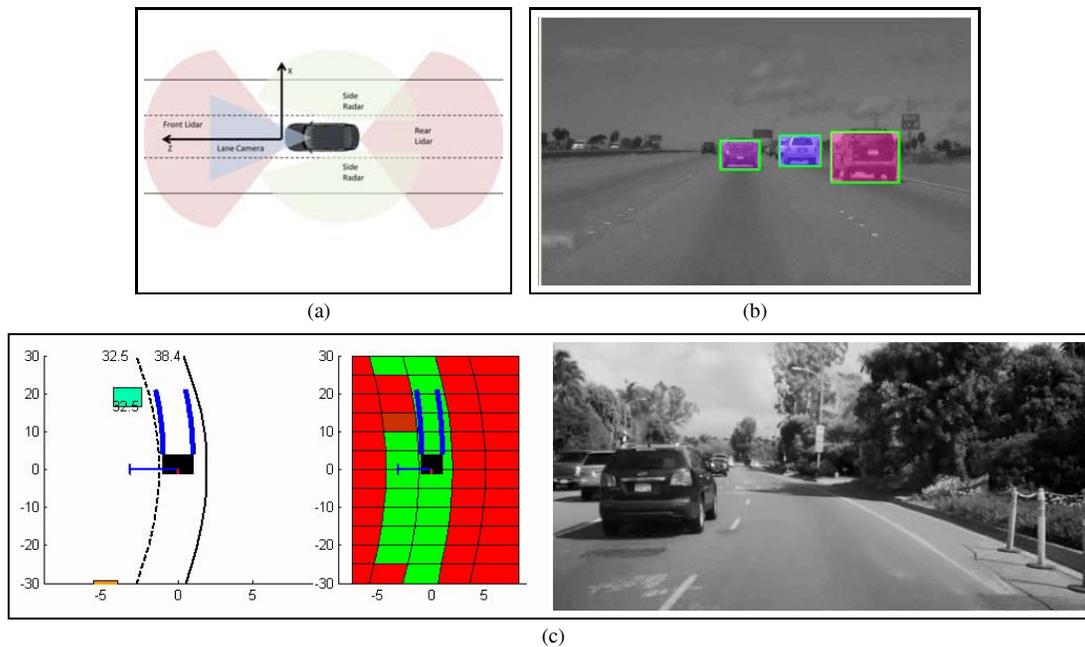


Fig. 5. 5(a) Advanced multi-sensor suite for advanced environmental perception will include vision, lidar, and radar, and feature near-360 degree field-of-view [9]. 5(b) On-road vehicle tracking [3], combining multiple sensing modalities. 5(c) Map of drivability, based on sensor fusion and probabilistic modeling [9]

oping [13], and will play an important role in cooperative active safety. The IEEE 802.11p standard, operating at 5.9GHz has been shown effective in research applications, such as robotic platooning [14]. Government-sponsored research in the areas of V2I [15] and V2V [16] has been gathering momentum. The DOT-sponsored Intellidrive project [17] has proposed several levels of communication protocols. However, industry-wide and governmental communication standardization will take time. Market penetration of new devices will also take time, with NHTSA estimating just 27% market penetration after 10 years [18]. Partial penetration of predictive driver assistance technologies, along with cooperative active safety at various levels, will still have a quantitative impact on safety.

We envision a multi-tiered market penetration of predictive driver assistance. At the high end, vehicles will be extensively instrumented for sensing [Figure 5(a)], computation, and communication. At the lower end of the market, new vehicles will be equipped with wireless communication for V2V and V2I. Figure 4 illustrates this scenario.

A. Vehicle-Vehicle Cooperative Predictive Driver Assistance

V2V communication will act as a proxy for sensor-equipped vehicles. The vehicles will transmit their locations and dynamics to the nearest vehicles, with each vehicle equipped with a routing switch for ad-hoc networking. While latency and missed packets are a drawback of V2V networks, the cost is favorable to advanced sensing technology [19]. Due to the extremely favorable cost, V2V communication will penetrate the market far sooner than advanced sensing such as lidar [6]. Transmitted dynamics will serve as a

substitute for vehicle detection and tracking, with active safety systems taking collision-avoidance action as necessary. V2V coordination has been shown effective for platooning, and has the potential to enhance throughput on busy roads [14], demonstrating the potential to alleviate rush hour traffic with autonomous driving.

B. Vehicle-Infrastructure Cooperative Predictive Driver Assistance

V2I communication will utilize a similar communication protocol as V2V, but infrastructure nodes will act as local hubs for local wireless networks. Vehicles equipped for communication will hop to the nearest available network, sending their dynamics and location. Using data sent by vehicles, infrastructure hubs can perform adapting metering for on-ramps and traffic signals. The adaptive metering will enhance safety, as well as maximizing throughput on busy roads. Performance using V2I will far exceed adaptive metering using inductive loop sensors, which are expensive and cover extremely limited range. Adaptive on-ramp metering has already been shown effective and safe in recent research studies, both in simulation and in real-world deployment [20], [21]. Nation-wide standards will need to be adopted for greatest impact, and the effectiveness will be more dependent on market penetration than V2V and in-vehicle cooperative active safety systems.

IV. COOPERATIVE PREDICTIVE DRIVER ASSISTANCE: EVALUATIONS AND IMPROVEMENTS

In order to measure the expected payoff for cooperative integrated safety, we perform simulations to illustrate the

relevant contributions. We quantify the contribution of cooperative safety by conducting Markov Chain Monte Carlo (MCMC) simulations based upon a typical merging scenario, with the initial positions and speeds of the oncoming and merging vehicles are randomly generated. We test four scenarios for a merging vehicle, into oncoming highway traffic. For each scenario, we run 100,000 simulations.

- Stock vehicles, with no predictive driver assistance
- Merging vehicle equipped with predictive merge driver assistance [9]
- Merging vehicle equipped with predictive merge driver assistance [9], communication with target vehicle using V2V
- Stock vehicles, with adaptive ramp-metering using infrastructure node, communication using V2I

We model the driver's reaction time according to [22], assuming the driver's reaction time is dependent on his anticipation of the merge event, which takes one of three cases: fully anticipated (0.7 sec.), unexpected (1.2 sec), or surprised (1.5 sec.). We assume each alertness level equally probable, with standard deviation of 0.1 seconds. Initial position and relative velocities of oncoming vehicles are randomly generated.

We model the V2V and V2I channels identically. Assumed operation consists of 100 meter line-of-sight, with no packet loss, at a 10-Hz message frequency, in line with real-world tests conducted using the protocol for autonomous cooperative driving [14]. Over the communication channels, we assume that a vehicle instrumented with advanced sensing sends its position, velocity, and necessary acceleration for safe merging to the nearest oncoming vehicle. Vehicles that are not instrumented with advanced sensing simply receive messages, and provide suggested accelerations to their drivers. The V2I for adaptive ramp metering aims to provide the merging vehicle a 1.5 timegap in which to merge.

We quantify the performance of the assistance frameworks using the minimum required acceleration necessary for safe merging, using dynamical equations [23]. As shown in figure 6, as the relative velocity between vehicles in the merge lane increases, so does the necessary acceleration for maintaining a safe distance. If at any point during a given merge, the necessary acceleration exceeds $7 \frac{m}{s^2}$, we categorize the event as a near-collision.

The red plot shows the necessary acceleration in the baseline case, in the absence of advanced sensing and wireless communications. The blue plot in figure 6 shows the necessary acceleration, assuming that the merging vehicle is equipped with advanced sensing, and merge assistance [9]. We see a reduction in the necessary safe acceleration, as the vehicle is aware of oncoming traffic due to sensor-based tracking. The vehicle's awareness of traffic conditions, and acceleration recommendations to the driver, reduce the driver's effective reaction time, allowing for safer merging.

The black plot in figure 6 represents the necessary acceleration for merging, assuming adaptive ramp metering based on V2I. In this situation, oncoming vehicles send their unique

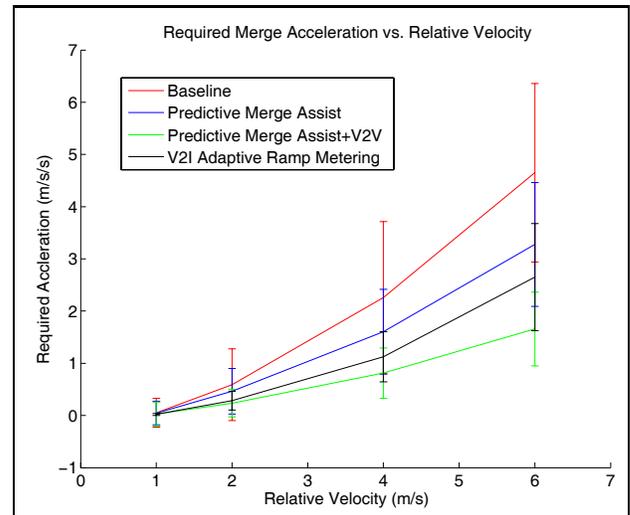


Fig. 6. Required acceleration to merge vs. relative velocity of oncoming vehicles. We see that predictive driver assistance improves the required acceleration over baseline. Predictive merge assistance combined with V2V communication gives the best results.

ID, position, and velocity, and the adaptive ramp attempts to facilitate safe merging by modulating the merging vehicle's entry into traffic, effectively increasing the timegap during merging. We see in the 6 that the adaptive ramp metering lowers the necessary acceleration for merging.

The green plot in figure 6 shows the necessary acceleration for merging, assuming that the merging vehicle is equipped with merge assistance [9], and both the oncoming and merging vehicle have V2V communications capabilities. In this case, the non-instrumented vehicle receives messages from the merging vehicle, detailing necessary accelerations. The communication channel conveys that the oncoming vehicle may have to reduce its speed, while the merging vehicle increases speed. The communication channel effectively reduces the effects of driver reaction time.

As shown in figure 6 and table I, predictive merge assistance offers great advantages and enhanced safety over the baseline case. Incorporating V2V communications improves the safety even moreso, supporting the claim that partial market penetration of predictive driver assistance systems will still have a great impact. V2I-based adaptive ramp metering also shows strong improvements. The best performance comes from partial market penetration of predictive driver assistance, combined with V2V communication. This result is encouraging, given that markets will adapt to new technology faster than governments will install new infrastructure.

Research challenges still remain in implementing these results for everyday driving. Currently, the sensing and computation used for research-grade intelligent vehicles [6], [9] is quite expensive, and beyond the reach of the typical consumer. As embedded sensors and computation become cheaper, these technologies will begin to make their way into production-mode vehicles. Implementation of the communi-

TABLE I
PERCENTAGE OF NEAR-COLLISIONS DURING MERGES

Driver Assistance	Baseline	Merge Assist	Merge Assist+V2V	V2I Adaptive Ramp Metering
Percentage	7.1%	0.81%	0.14%	0.27%

ation networks for V2V and V2I systems will also present challenges, such as achieving robustness and flexibility for the ad-hoc networks, and convincing auto manufacturers and governments to agree on a consistent standard.

V. CONCLUDING REMARKS

In this work, we have described future trends in active safety, built upon predictive driver assistance and cooperation between systems, vehicles, and infrastructure. Predictive driver assistance systems, equipped with high-fidelity sensing, will aim to make longer-term predictions supporting positive HMI with the driver. Beyond simply detecting and reacting to dangerous scenarios, intelligent vehicles will maintain a full awareness, standing ready and available to help the driver navigate the on-road environment. As predictive driver assistance systems are developed, it will be shown that integrating systems in a cooperative manner will improve the performance and overall on-road safety.

We have examined cooperation systems in four main areas: in-vehicle systems cooperation, vehicle-driver cooperation, cooperation across vehicles, and finally cooperation with vehicles and infrastructure. In-vehicle systems cooperation will quantitatively improve active safety performance, by leveraging multiple systems running in the same car. Vehicle-driver cooperative driving will integrate predictive driver assistance systems and autonomous driving, aiming for seamless transfers of control between the driver and the vehicle. Finally, cooperative active safety across vehicles, using V2V and V2I communication channels will quantitatively improve the performance of active safety systems.

ACKNOWLEDGMENTS

The authors would like to acknowledge support from the UC Discovery Program, as well as industry sponsors.

REFERENCES

- [1] US Department of Transportation - National Highway Traffic Safety Administration, "Traffic safety facts," 2011. [Online]. Available: <http://www-nrd.nhtsa.dot.gov>
- [2] M. M. Trivedi and S. Y. Cheng, "Holistic sensing and active displays for intelligent driver support systems," *IEEE Computer*, 2007.
- [3] S. Sivaraman and M. Trivedi, "Combining monocular and stereo-vision for real-time vehicle ranging and tracking on multilane highways," in *Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on*, Oct. 2011, pp. 1249–1254.
- [4] J. McCall and M. Trivedi, "Video-based lane estimation and tracking for driver assistance: survey, system, and evaluation," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 7, no. 1, pp. 20–37, march 2006.
- [5] S. Sivaraman and M. Trivedi, "Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis," *Intelligent Transportation Systems, IEEE Transactions on*, 2013.
- [6] A. Geiger, P. Lenz, and R. Urtasun, "Are we ready for autonomous driving?" in *Computer Vision and Pattern Recognition*, Providence, USA, June 2012.
- [7] S. Sivaraman and M. Trivedi, "Integrated lane and vehicle detection, localization, and tracking: A synergistic approach," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 14, no. 2, pp. 906–917, 2013.
- [8] R. J. Elliot, L. Aggoun, and J. B. Moore, *Hidden Markov Models: Estimation and Control*. Springer, 1995.
- [9] S. Sivaraman and M. Trivedi, "Merge recommendations for driver assistance: A cross-modal, cost-sensitive approach," in *Intelligent Vehicles Symposium (IV), 2013 IEEE Conference on*, June 2013.
- [10] J. Levinson, J. Askeland, J. Becker, J. Dolson, D. Held, S. Kammel, J. Kolter, D. Langer, O. Pink, V. Pratt, M. Sokolsky, G. Stanek, D. Stavens, A. Teichman, M. Werling, and S. Thrun, "Towards fully autonomous driving: Systems and algorithms," in *Intelligent Vehicles Symposium (IV), 2011 IEEE*, June 2011, pp. 163–168.
- [11] A. Doshi and M. Trivedi, "Attention estimation by simultaneous observation of viewer and view," in *Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on*, June, pp. 21–27.
- [12] K. Kusano and H. Gabler, "Safety benefits of forward collision warning, brake assist, and autonomous braking systems in rear-end collisions," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 13, no. 4, pp. 1546–1555, Dec. 2012.
- [13] J.-M. Chung, M. Kim, Y.-S. Park, M. Choi, S. Lee, and H. S. Oh, "Time coordinated v2i communications and handover for wave networks," *Selected Areas in Communications, IEEE Journal on*, vol. 29, no. 3, pp. 545–558, March 2011.
- [14] R. Kianfar, B. Augusto, A. Ebadighajari, U. Hakeem, J. Nilsson, A. Raza, R. Tabar, N. Irukulapati, C. Englund, P. Falcone, S. Papanastasiou, L. Svensson, and H. Wymeersch, "Design and experimental validation of a cooperative driving system in the grand cooperative driving challenge," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 13, no. 3, pp. 994–1007, Sept. 2012.
- [15] US Department of Transportation, "Cooperative intersection collision avoidance systems." [Online]. Available: <http://www.its.dot.gov/cicas/>
- [16] European Commission, "Safespot integrated project." [Online]. Available: <http://www.safespot-eu.org/>
- [17] US Department of Transportation, "Intellidrive." [Online]. Available: www.intellidrive.org
- [18] National Highway Traffic Safety Administration, "Vehicle safety communications project task 3 final report: Identify intelligent vehicle safety applications enabled by DSRC," March 2005. [Online]. Available: <http://www-nrd.nhtsa.dot.gov>
- [19] K. Lidstrom, K. Sjoberg, U. Holmberg, J. Andersson, F. Bergh, M. Bjade, and S. Mak, "A modular cacc system integration and design," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 13, no. 3, pp. 1050–1061, Sept. 2012.
- [20] V. Milanés, J. Godoy, J. Villagra, and J. Perez, "Automated on-ramp merging system for congested traffic situations," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 12, no. 2, pp. 500–508, June 2010.
- [21] D. Marinescu, J. Curn, M. Bourroche, and V. Cahill, "On-ramp traffic merging using cooperative intelligent vehicles: A slot-based approach," in *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, Sept. 2012, pp. 900–906.
- [22] M. Green, "How long does it take to stop?" methodological analysis of driver perception-brake times," *Transportation Human Factors*, 2000.
- [23] R. Schubert, K. Schulze, and G. Wanielik, "Situation assessment for automatic lane-change maneuvers," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 11, no. 3, pp. 607–616, sept. 2010.