VECTOR: Trajectory Analysis for Advanced Highway Monitoring

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Abstract

In a world that is increasingly reliant on automobiles, efficient management of the transportation network is a key functionality of intelligent transportation systems (ITS). A wide range of these ITS applications rely on the extraction of current data as well as historical information in order to perform appropriately. This work presents a novel computer vision based approach for traffic management. The VECTOR system processes live video traffic streams to track individual vehicles, classify vehicle type, and accumulate essential highway management measurements. This system provides a front end collection tool that can be used for a wide variety of other transportation tasks including congestion analysis, speed compliance and flow analysis, as well as trajectory pattern analysis. The system provides real-time situational awareness to highway monitoring and presents a trajectory analysis framework that can be extended into vehicle based monitoring.

1 Introduction

The last 100 years has brought great advancements and developments in personal transportation transforming the horse drawn world into one dominated by automobiles. The emergence of the automobile has opened up the world, providing almost unlimited access and mobility. In the United States alone, a staggering 240 million vehicles travel over 12 million miles annually on a network consisting of 4 million miles of road whose maintenance costs $40 million [1]. Such a large infrastructure has immediate social, economic, energy, and environmental impact. Motor vehicle taxes generate $30 billion annually. Americans use 175 billion gallons of fuel for highway travel releasing a number of emissions into the air. Between 1995 and 2001 there was 10% increase in average commute time. People were traveling the same distance but witnessed a speed drop and increased delay while stuck in congested traffic [2]. Perhaps most alarming were the 2.5 million injury accidents and 41 thousand motor vehicle related fatalaties in 2008 [3]. These numbers represent just a small portion of worldwide dependence on automobiles and emerging countries such as India and China will dramatically effect the future of transportation.

In order to manage such a vast transportation network, it is essential to invest in intelligent transportation systems (ITS) technologies. ITS solutions provide the means to extract and manage information necessary for continued advancement. Without their use it would be impossible to continually monitor our roadways, as no human could process such large amounts of data. The key requirements for successful ITS systems are the ability to extract and process data in real-time, provide robustness to a wide range of operating conditions, and technologies that can adapt to changes in the environment which is essential for long term deployment.

In this work we present a novel video camera based highway monitoring tool, the visual VEhicle Classifier and Traffic flOw analyzeR (VECTOR) [4]. VECTOR processes live video streams to accurately track each individual vehicle, classify vehicle type, and collects essential highway traffic measurements. Using these measurements, highway flow is analyzed to characterize link efficiency as well as to build behavior models for speed compliance. The vehicle trajectories are collected and used to automatically build a model of the typical scene behaviors. This model allows a succinct description of live activity, the detection of abnormalities, and prediction of future behavior. The trajectory analysis framework developed for infrastructure based monitoring is extended for moving platforms. Using cameras and other in vehicle sensors, the local micro traffic behavior can be analyzed from cars on the road.

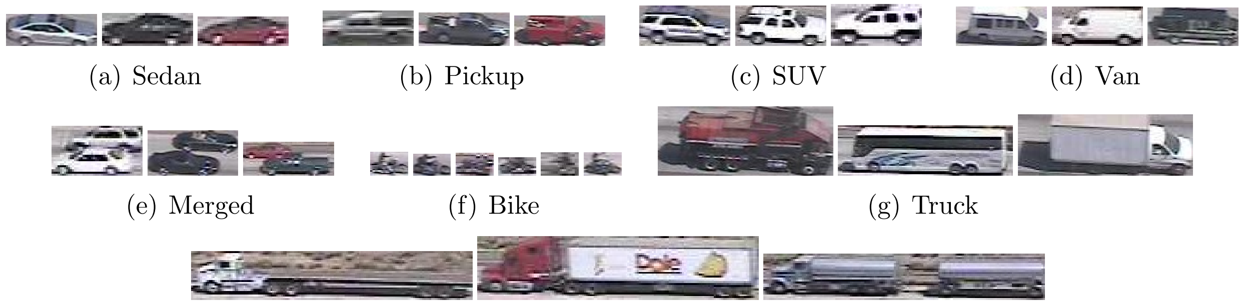


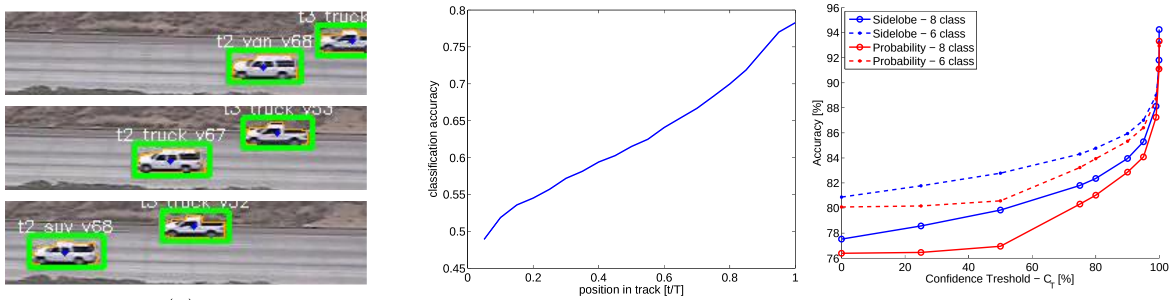
Figure 1: Sample images from each vehicle class.

2 VECTOR Measurements

The VECTOR module was designed for real-time highway traffic analysis. In addition to loop detector type measurements essential for highway management, VECTOR determines the types of vehicles on the road over time. Accumulated traffic statistics are used to build a traffic model useful for online traffic flow analysis, such as detection of dangerous behavior.

2.1 Target Tracking

Vehicles are detected using an adaptive background subtraction scheme which allows the background to be updated in real-time. The background, corresponding to the highway without cars, is modeled and is modified to reflect the current scene configuration. This adaption is important because the system must be able to work through a wide range of environmental conditions such as changing illumination. The background subtraction step highlights vehicles in the image which are then tracked for the time spent in the camera field of view. The motion of each vehicle is modeled with a Kalman filter which enables vehicle matching across video frames. The trajectories obtained through visual tracking are important to many further analyses as they provide compact records of motion and characterize behavior of each vehicle on the road.



(a) (b) (c)

Figure 2: (a) Vehicle correctly classified as SUV after initially estimated as VAN and TRUCK. (b) Classification accuracy is improved by leveraging evidence accumulated by tracking. (c) Accuracy can be improved by focusing on highly confident examples (those with large amounts of evidence).

2.2 Vehicle Classification

In addition to recording trajectories, a key functionality of the VECTOR system is the identification of vehicle type. Using the 2001 National Household Travel Survey conducted by the U.S. Department of Transportation [2], the 8 different classes of vehicles shown in Fig. 1 are considered {Sedan, Pickup, SUV, Van, Semi, Truck, Bike, Merged}. Knowledge of vehicle type is essential for a wide range of highway management functions such as estimating emissions [5] or infrastructure load assessment [6]. This detailed real-time fleet composition is currently a missing component is most emission studies.

While tracking a vehicle, a number of measurements are taken to describe its shape and appearance which provide a unique identifier. This measurement vector is compared with entries in a database and the best fit is determined to be the specific vehicle type. The classification occurs for each vehicle at every frame it is visible by the camera. Because a camera is an area sensor, it provides a number of different views of the same vehicle. This information redundancy is exploited to improve the final vehicle classification. Rather than relying on a single vehicle signature, the signatures acquired during tracking are used together to refine the classification result and overcome noisy measurements. Figs. 2(a) and

2(b) shows how the vehicle type classification improves as more information is used during tracking. A vehicle can be initially misclassified but as more evidence is accumulated the correct type is indicated. Decisions made based on just the first image of a vehicle can be quite poor but by the end of a track the type is known with high confidence. Full details of the track based classification scheme can be found in [7, 8].

2.3 Traffic Statistics

Accurate highway planning and management relies on a number of performance measures and use real-time as well as historical data. Currently, this information obtained through the use of inductive loop sensors which provide two basic measurements, flow and occupancy. Flow is the number of vehicles and occupancy is the amount of time a loop is active in a given time interval. While effective and ubiquitous, they require digging up of the road making them prohibitive to maintain. In CA, among the 26000 loop sensors, approximately 25% do not supply usable data. Video cameras provide an alternative solution for traffic statistic accumulation that can be unobtrusively mounted along the roadside.

The VECTOR system delivers flow ($\frac{\#vehicles}{time}$), density ($\frac{\#vehicles}{distance}$), and speed (MPH) estimates in 30 second intervals, averaged over a 5 minute window. The speed is measured for each and every vehicle, which is difficult to do with loop detectors. The quality of VECTOR's parameter extraction is presented in Fig. 3. Figs. 3(a) and 3(b) show system performance compared with manually counted vehicles and Figs. 3(c) and 3(d) provide longer time scale comparison with loop detector data using the freeway performance measurement system (PeMS) maintained by UC Berkeley [9] with both displaying high agreement. This shows that camera based sensors can integrate into the current loop based highway system seamlessly.

Since VECTOR does vehicle type classification, it is possible to extract more rich traffic

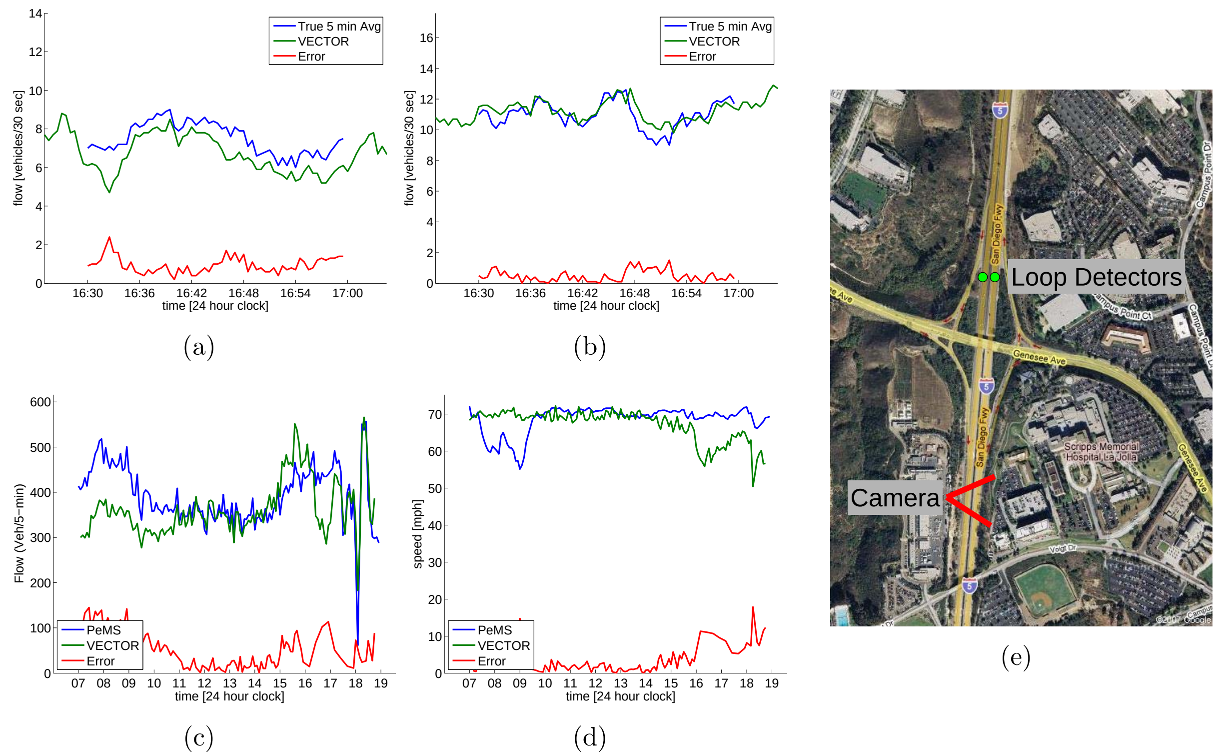
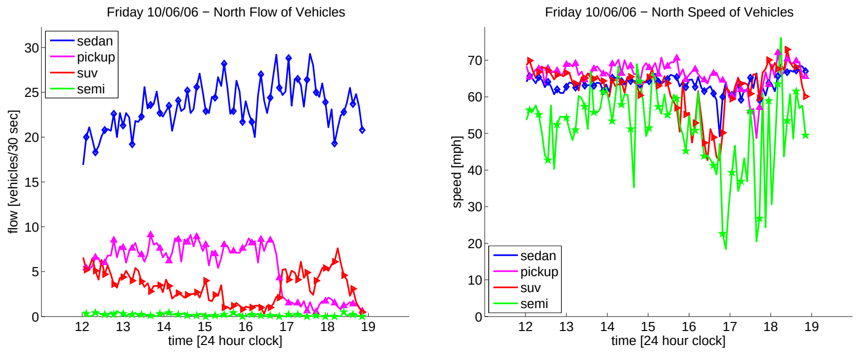


Figure 3: Comparison of VECTOR traffic parameter extraction with true flow in (a) lane 1 and (b) lane 4. PeMS provides a system for longer time scale evaluation of (c) flow and (d) speed. Comparison between PeMS data and the VECTOR module shows strong agreement. (e) Camera and PeMS loop detector sensor configuration on opposite sides of the Genesee Ave. ramp.

measurements. The flow and speed are compiled for each type of vehicle and show in Fig. 4. These parameters are essential for understanding the differing effects of commercial or private vehicles on highway control and for the study of environmental impact from emissions.

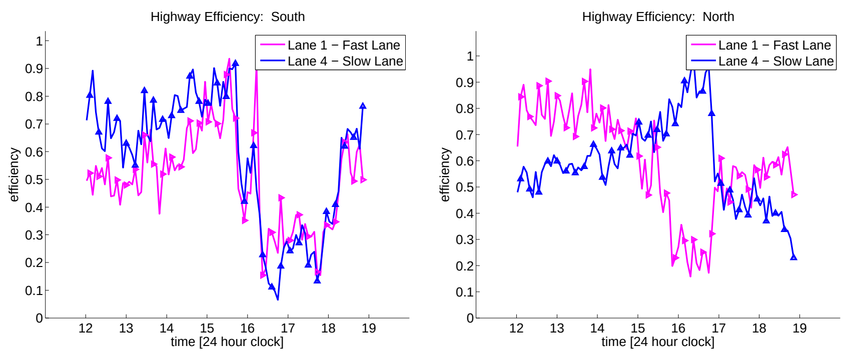
3 Traffic Flow Analysis

Using the measurements calculated by the VECTOR system it is possible to design specific traffic flow analysis modules. These modules could be designed for traffic management personnel or another end user. Examples analysis blocks are for calculating the link usage efficiency or to measure speed compliance.



(a) (b)

Figure 4: Traffic statistics (a) flow and (b) speed separated by vehicle type.

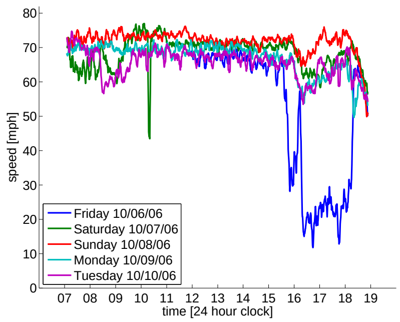


(a) (b)

Figure 5: Highway lane efficiency. (a) Southbound efficiency is low during the evening commute because of congestion. (b) Northbound efficiency drop in fast lane not because of congestion but because of under utilization.

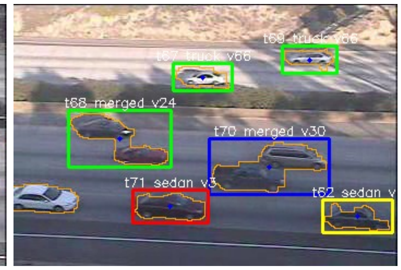
3.1 Highway Efficiency

Chen *et al.* used flow and speed to show congestion is not caused by demand exceeding capacity but because of inefficient operation of highways during periods of peak demand [10]. Fig. 5 shows lane efficiency of the north and south bound directions of the highway. Congestion is clearly evident during the evening commute, where the efficiency drops significantly (Fig. 5(a)). It is interesting to note that while the efficiency of the south bound direction drops because of congestion the north bound highway does not suffer from congestion but rather under utilization (low flow).



(a)

(b)



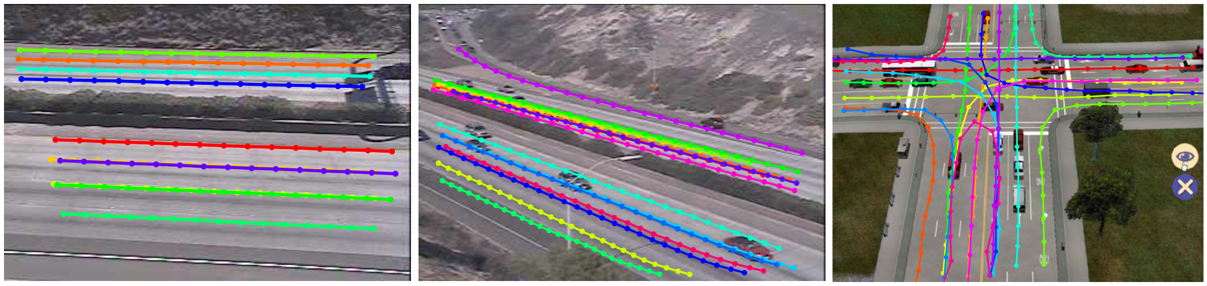
(c)

Figure 6: Speed profiling based on daily models {speeding, normal, slow, stopped} = {blue, green, yellow, red}. (a) Speed characteristics for different days of the week. (b) Normal free flowing traffic. (c) Commuter congestion causes differing characteristics in either highway direction. The normal speed at this hour southbound is significantly slower than northbound.

3.2 Speed Compliance

The efficiency module above indicates spatial and temporal traffic variations. These daily variations can be tracked and modeled using historical measurements. Fig. 6(a) shows the speed fluctuations over the course of a week. There is a significant slowdown during the Friday evening commute not seen on other days.

VECTOR uses these daily speed models to indicate the motion state of vehicle during online tracking by the color a bounding box {speeding, normal, slow, stopped} = {blue, green, yellow, red}. Sample output frames are shown in Fig. 6. Notice the northbound lanes in Fig. 6(c) are moving freely at high speed while the southbound lanes have much slower normal speeds because of congestion (30 mph is considered speeding). This speed compliance tool can be used as a basic dangerous situation indicator. Vehicles driving well over the normal limit might lead to accidents (fast cars in congestion). Researchers in Japan have even used speed information to detect incidents, such as stalled vehicles, from congestion [11].



(a) (b) (c)

Figure 7: Typical trajectory patterns. (a) Profile view of highway traffic on I5 with the lanes clearly demarcated. (b) 3/4 view of I5 obtained by adjusting the PTZ camera parameters. (c) Example of typical intersection patterns corresponding to the acceptable intersection maneuvers.

4 Trajectory Pattern Analysis

When monitoring traffic, a good indication of behavior is motion. Previously we mentioned how the VECTOR system used estimated speed to determine if a vehicle was traveling normally. Motion also indicates when a lane change occurs or if someone is breaking to avoid a collision. Motion is captured by trajectories which indicate the spatio-temporal characteristics of objects and encode behavior. Careful study of these trajectories allows activity inferencing [12].

4.1 Learning Typical Patterns

A key observation for trajectory analysis is that typical actions are repetitive while the unusual do not occur often. This indicates that through sufficient observation one is likely to observe and can learn all the prototypical behaviors for a given scene. In order to learn typical patterns, a training database of trajectories is accumulated. The training database is then condensed into a small set of typical behaviors through clustering. Each cluster corresponds to similar actions. Unfortunately, the number of typical behaviors for a scene is not usually known a priori and must be estimated. We first cluster trajectories into a large

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

Figure 8: Abnormal tracks not adhering to prototypical paths

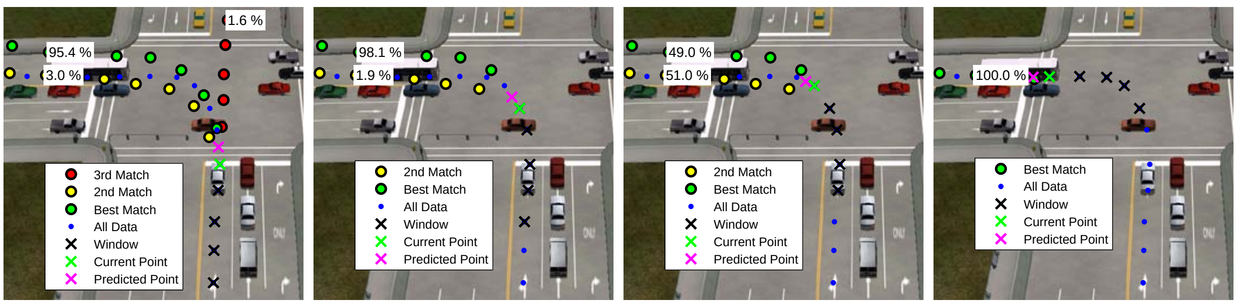
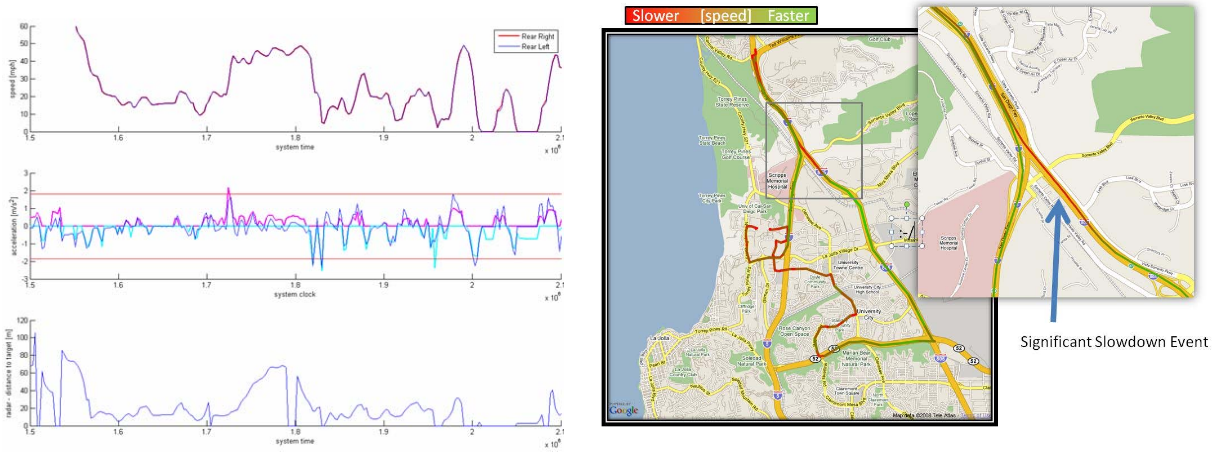


Figure 9: Left turn prediction behaves as expected. As more data points are collected the prediction better matches the true lane.

number of small groups which we suspect to be greater than the true number of activities. The small clusters are then agglomeratively merged into larger more typical clusters. In Fig. 7, the typical patterns are shown for a number of different transportation scenes. The prototype patterns correspond to the lanes of the highway or to the allowable maneuvers at an intersection.

4.2 Behavior Analysis

A vocabulary to describe behavior is established by learning the typical scene patterns. During live video analysis, object activity can reference this learned set. For every frame a vehicle is observed, its current behavior is determined by its best match in the reference set. Similar to the VECTOR classification scheme, as more trajectory data is accumulated it is possible to improve the activity estimate. While interesting, it might be more important to detect not the typical behaviors but the abnormal. Anomalous trajectories arise when



(a) (b)

Figure 10: (a) Vehicle sensor measurements from CAN. (b) GPS based mapping provides competely network coverage.

something out of the ordinary occurs. These abnormalities are detected when none of the reference set adequately explain the observed motion. A collection of abnormal trajectories are presented in Fig. 8. These are of utmost importance because they can indicate unsafe behavior or perhaps a distressed vehicle.

Another useful analysis capable with trajectory analysis is intent prediction. Instead of determining what is occurring now it is possible to guess what will happen in the future. This type of prediction is much more powerful than simple one step prediction associated with Kalman or particle filters because the prediction looks further into the future and is conditioned by actual observed behaviors. Fig. 9 shows the evolution of a left turn. The probability of a behavior is shown in the white box over the associated pattern. Early into the left turn maneuver it is unclear which lane the vehicle will turn into but as more information is obtained the estimate improves. This type of anlaysis is of great importance for intersection safety [13, 14]. Using predicted paths, the probability and time to collision can be assessed. One can envision a future where an intelligent intersection can warn approaching vehicles of danger.

Figure 11: LISAQ collects video from 8 different cameras which capture the interior and surround of the vehicle.

5 In-Vehicle Trajectory Analysis

Another key tool for ITS highway monitoring are the vehicles on the road themselves. Everyday cars travel freely along the country's road networks providing greater coverage than any loop or camera sensor could hope to achieve. The situations and interactions encountered by every driver on a daily basis can be leveraged to provide a more complete view of traffic. Auto companies are equipping vehicles with advanced sensors which can provide a wealth of information about both the current vehicle state as well as local driving conditions. By utilizing these sophisticated sensing devices, new insights can be gleaned and more effective control and safety strategies can be implemented.

The Laboratory for Intelligent and Safe Automobiles (LISA) at UCSD provides a unique

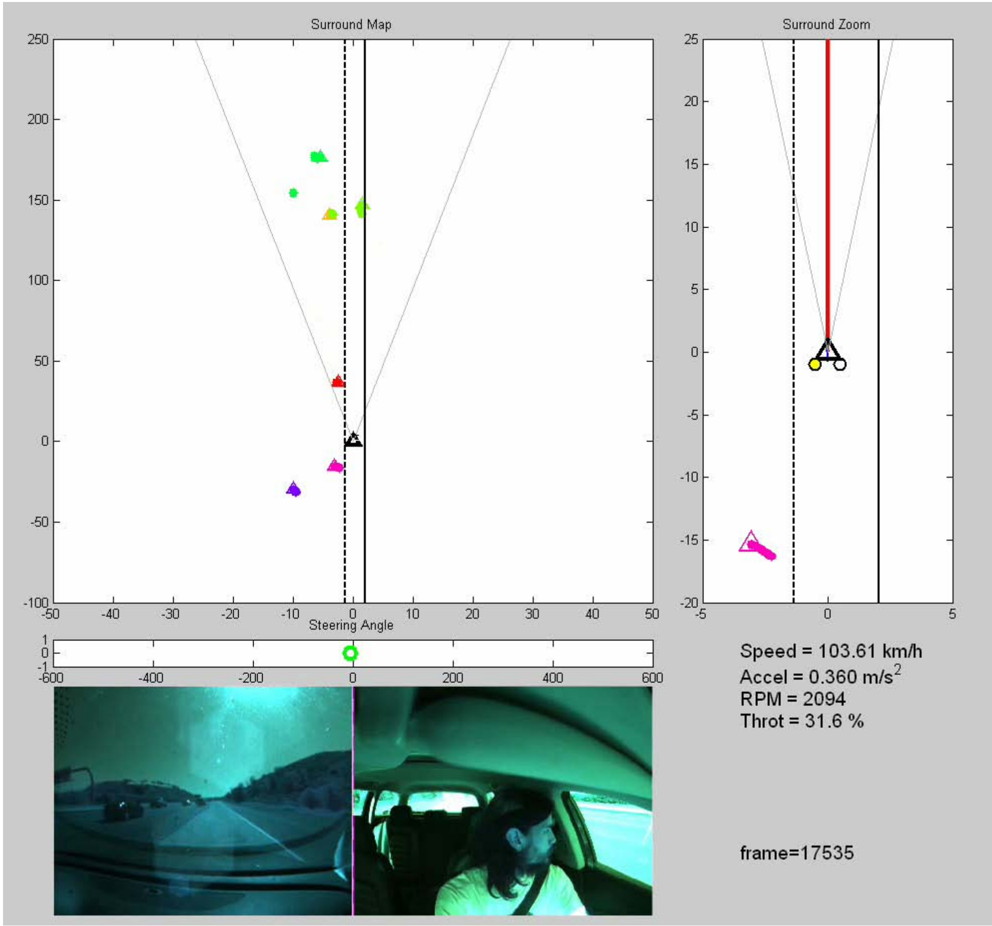


Figure 12: The LISA testbeds allow the collection of CAN measurements from the vehicle sensors as well as video to monitor both the surround and interior to provide a holistic driving view. The surround views show each obstacle vehicle in color. One second of trajectory history is shown by the colored dots in the surround zoom view.

testbed to explore approaches to making more safe and "intelligent" vehicles. Each is a mobile computing platform that is able to collect and analyze, in real-time, measurements from the on-board vehicle sensors via CAN (Fig. 10(a)), GPS (Fig. 10(b)), and a host of sensors, *e.g.* video cameras (Fig. 11) and radar, designed to capture the interior and exterior of the car.

Fig. 12 provides a visualization of data collected from LISA. Two cameras provide a view of the driver and out the front windshield. To the right a selection of CAN measurements are displayed which indicate the current state of the vehicle. The two upper panes show the vehicle surround and denotes other vehicles in color. Each obstacle is tracked (see the pink trajectory in the surround zoom pane) and the resulting trajectory is used to assess the driving situation. Similar to the infrastructure mounted cameras, the trajectories from this moving platform give an indication of behavior. Prototypical driving behaviors can be learned to explain longitudinal and lateral motion which includes acts such as acceleration, braking, lane change, and turns. The future behavior of the surround obstacles as well as the ego-vehicle, since its motion provides another track, can be predicted with the prototype motion models. This prediction allows assessment of the safety of the traffic configuration. Further, the criticality of ego-maneuvers can be evaluated and a driver can be warned when a desired move would result in unsafe outcome.

6 Future Directions

ITS technologies ample opportunities for exciting new research. Continual improvement of systems to ensure real-time, robust, and adaptive solutions is necessary. This incorporates more general computer vision issues such as robust tracking through harsh elements, shadows, and heavy occlusion. Safety can be further improved by defining safety performance measures to asses the the effectiveness of the driver assistance systems that are now being developed [15]. Infrastructure based safety systems will need to convey information to road drivers and in a way that is informative but not distracting necessitating work in communications and human factors. But the future of ITS does not rely solely on computer vision. True ITS systems will require elegant fusion of a wide variety of data sources (integration of VECTOR, loop sensors, and vehicle based sensors). The future of ITS will be shaped by urban and highway planners, scientist, and policy makers all working together to improve travel.

7 Concluding Remarks

This work presented the visual VEhicle Classifier and Traffic flOw analyzeR (VECTOR) system. An ITS technology aimed a highway monitoring, VECTOR tracked vehicles, classified vehicle type, and accumulated traffic statistics. Using this information, the system was able to assess high efficiency, determine speed compliance, and understand and predict behavior. This system demonstrated the power of computer vision technologies for ITS which can be reconfigured for a wide variety of analyses. The infrastructure based solution was extended for monitoring within a advanced sensor equipped vehicle. The future of ITS depends on the integration of these types of systems as the front end data collection tools for higher level understanding of transportation issues.

Acknowledgments

This work has been supported by wide range of agencies and industry partners, NSF, Caltrans, DOD, TSWG, UC Discovery Grants - DIMI, Volkswagon-Audi, Nissan, and Daimler Chrysler. We would like to thank all our sponsors as well as our collaborators and CVRR colleagues for continued assistance.

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