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# Real-Time Video Based Highway Traffic Measurement and Performance Monitoring

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*Abstract*— **This paper presents a real-time highway monitoring system for tracking and classification of vehicles with the computation of traffic flow parameters from live video streams. The proposed system robustly detects and tracks vehicles during daylight hours and accurately classifies them into 8 different types by leveraging tracking information. The system is able to process video continuously over long time periods, accumulating large volumes of tracking data to build daily highway models consisting of the traffic flow parameters, density, flow, and speed. These daily models are used to categorize the speed profile of live traffic.**

## I. Introduction

Highway traffic management requires up-to-date data delivered in real-time along with historical data of traffic conditions to design effective control strategies. In California, inductive loop sensors deliver lane counts and occupancy every 30 seconds from locations all over the state. Berkeley's Freeway Performance Measurement Project (PeMS) [1] collects and analyzes data from over 26,000 individual lane detectors from 7 of the 12 California Department of Transportation (Caltrans) districts, investigating assorted performance measures. While this large infrastructure is already in place, it is not ideal. Only 60% of CA loop detectors supply usable data. Since the loop detectors must be installed in the road, adding and maintaining them is expensive and intrusive. The failure rate coupled with the cost of maintenance make alternative data collection methods desirable.

Cameras offer an attractive substitute to loop detectors since they can easily be deployed unobtrusively on the side of a highway and can also be used for other monitoring applications. Video provides a means for visual verification of results and is an active research field with the promise of added higher level analyses. Besides providing traffic measurements equivalent to loop detectors, using video to track vehicles in a scene reveals added information difficult to obtain using loop detectors such as accurate origin-destination maps and travel time, vehicle type classification [2], and irregular path and incident detection. Using video sensors allows collection of both loop detector type traffic measurements as well as precise track based analysis not possible with loop detectors.

In this paper a novel system, the visual VEhicle Classifier and Traffic flOw analyzeR (VECTOR), for highway monitoring is introduced. The system works continuously in real-time for robust vehicle tracking, traffic flow analysis, and event detection. In this work, vehicles are tracked and classified into 8 different classes and traffic statistics are accumulated to build a highway model used for live speed profiling.

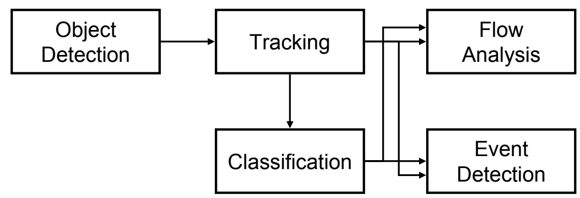



Fig. 1. VECTOR system flow diagram showing the main processing models: Object Detection, Tracking, Classification, Flow Analysis, and Event Detection.

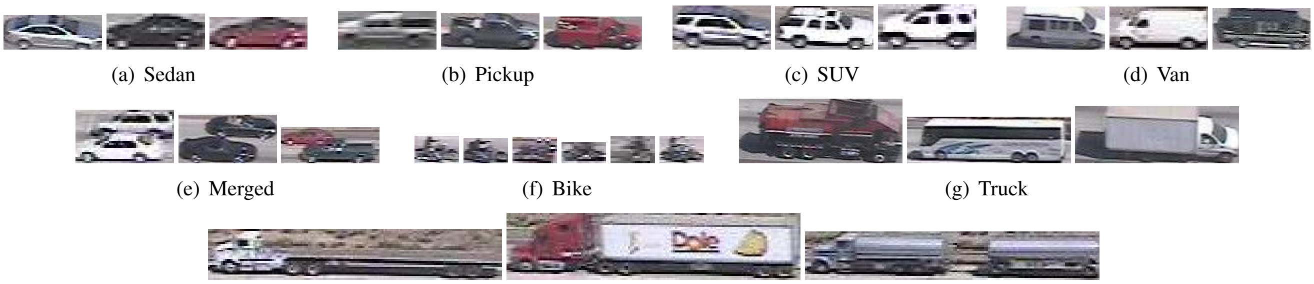
## II. System Overview

The VECTOR flow diagram is shown in Fig. 1 and a typical output frame is in Fig. 9(a). The front-end of the system consists of object detection by adaptive background subtraction, Kalman filter based tracking, and vehicle classification with tracking refinement [3]. The front-end results are further processed by the Flow Analysis module to generate a highway traffic model which is used for vehicle speed profiling by the Event Detection module.

## III. Classification

The VECTOR system classifies vehicles into the 8 different types, {Sedan, Pickup, SUV, Van, Semi, Truck, Bike, Merged}, seen in Fig. 2. These were selected because they were the most often occurring vehicle types from the 2001 National Household Travel Survey (NHTS) conducted by the U.S. Department of Transportation (DOT) [4]. The block diagram depicting the VECTOR classification scheme is in Fig. 3. After object detection, blob features are extracted, such as area, bounding ellipse, image moments, etc., and transformed using Linear Discriminant Analysis (LDA). The reduced feature set is given a frame classification using an weighted K Nearest Neighbor (wkNN) database and incorporated into a single track classification.

The Nearest Neighbor training set, $D = \bigcup_{c=1}^{C} D_c$, is constructed by collecting hand labeled examples for each



(a) Sedan (b) Pickup (c) SUV (d) Van

(e) Merged (f) Bike (g) Truck

(h) Semi

Fig. 2. Sample images from each vehicle class.

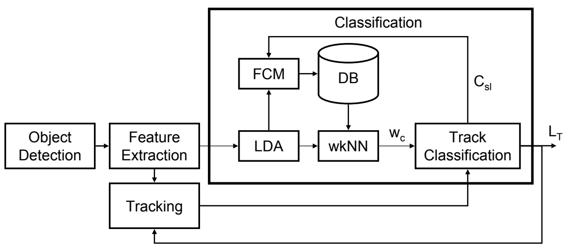



Fig. 3. Block diagram for the proposed classification scheme.

of the $C = 8$ vehicles types. Each potential vehicle, $x_{test}$, is given a soft class membership, $w_c$, at every frame by wkNN comparison,

$$w_c = \sum_{\substack{i=1 \\ x_i \in D_c}}^{K} \frac{1}{\| x_i - x_{test} \|}. \quad (1)$$

Through tracking, an appearance record of each vehicle is accumulated giving us $T$ object examples over the life of a track. Given these $T$ samples, a track label is generated by maximum likelihood estimation.

$$\begin{aligned} L_T &= \operatorname*{argmax}_c \sum_{t=1}^{T} ln\, p(x_t|c) \\ &= \operatorname*{argmax}_c \sum_{t=1}^{T} ln \frac{w_c^t}{\sum_c w_c^t}. \end{aligned} \quad (2)$$

The likelihood $p(x_t|c)$ of class c is approximated by normalizing the per frame class weight, (1), for each sample $t$ in a track to be a valid probability. The track class, $L_T$, is refined each frame the track is updated and more information is incorporated. The track label takes into account all the evidence gathered while tracking to make a decision on class type rather than just a single frame measurement that could potentially be corrupted by noise.

The confidence in classification label $L_T$ can be measured by the sidelobe ratio

$$C_{sl} = \frac{p_1 - p_2}{p_1}, \quad (3)$$

where $p_1$ and $p_2$ are the first and second highest track likelihoods. The sidelobe ratio gives a measure of how much stronger class $L_T$ is than the closest competing class. Highly confident tracks can be used to reinforce the training database, while low confidence samples are rejected.

The Classification Module outputs a class label (2) and confidence (3) for every vehicle and both are updated in an online fashion to leverage the added data compiled through tracking.

## IV. Flow Analysis

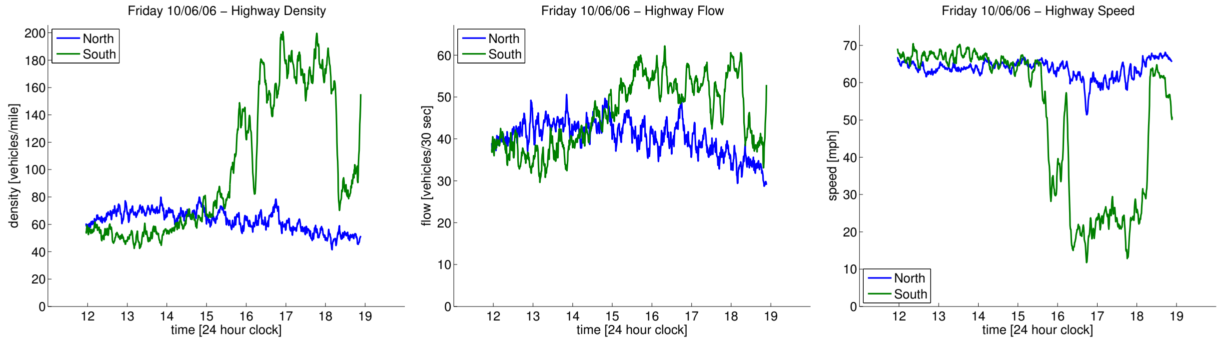
Using the system tracking + classification front-end, data is collected and a highway model is constructed indicative of normal traffic patterns. The highway model is a time series of fundamental highway usage parameters analogous to those obtained from loop detectors. This system delivers flow ($\frac{\#vehicles}{time}$), density ($\frac{\#vehicles}{distance}$), and speed (mph) estimates in 30 second intervals and averaged over a 5 minute window. The flow statistic is generated by counting the number of passing vehicles in a 30 second update interval. Density is the average number of vehicles in the camera view normalized by the roadway length. The speed is the average velocity estimate of all tracked vehicles converted from pixels/frame to mph by manual roadway calibration. Fig. 4 gives examples of the accumulated statistics in the north and south bound directions of US Interstate 5.

As done with loop detectors, each tracked vehicle is placed into a lane allowing separate observation of individual lane congestion behavior. Fig. 5 shows the south bound lane statistics. Congestion begins during the evening commute, 16:00-19:00, when density (Fig. 5(a)) in the slow lane reaches a critical maxima causing a significant drop in flow (Fig. 5(b)). The flow of the fast lane does not experience the same drop, but the congestion spills over from the slow lane causing a similar reduction in speed (Fig. 5(c)). This phenomenon demonstrates how a single lane effects the entire highway link performance.

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 [5]. Using the accumulated usage statistics, the highway efficiency, at a given time $t$, can be estimated, taking into account changes in flow, by

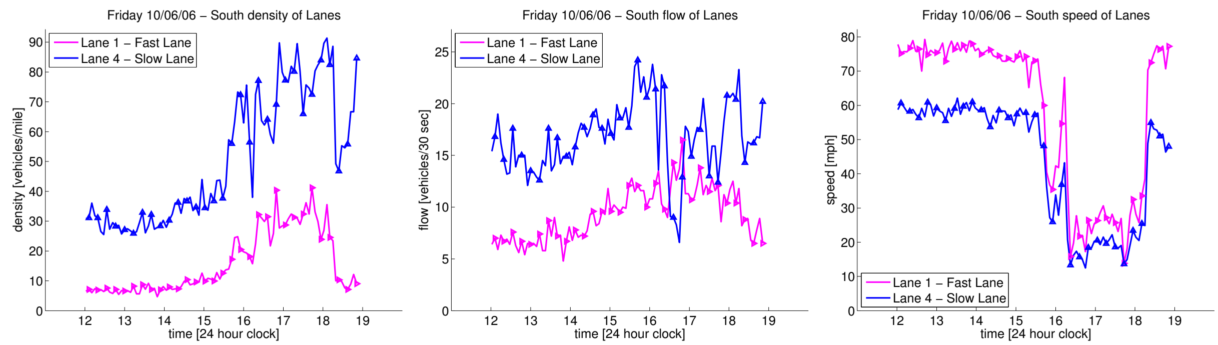
$$\hat{\eta} = \frac{flow(t) \times speed(t)}{flow_{max} \times speed_{max}}. \quad (4)$$

Fig. 6 shows lane efficiency of the north and south bound directions of the highway. Congestion is clearly evident



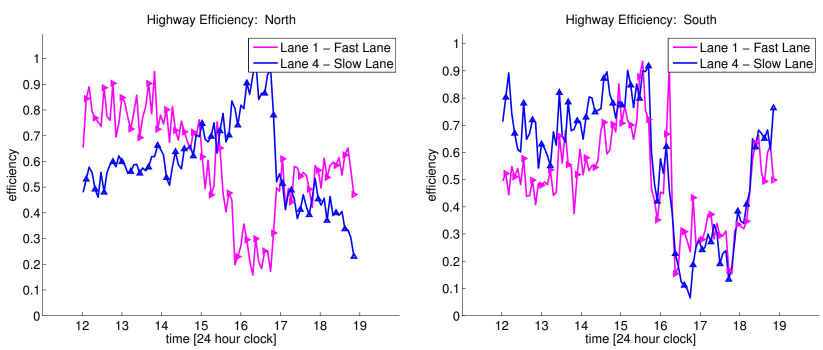

(a) Density (b) Flow (c) Speed

Fig. 4. Density, flow, and speed for north and south bound directions of Interstate 5.




(a) Lane Density (b) Lane Flow (c) Lane Speed

Fig. 5. Individual lane density, flow, and speed for south bound direction of Interstate 5.



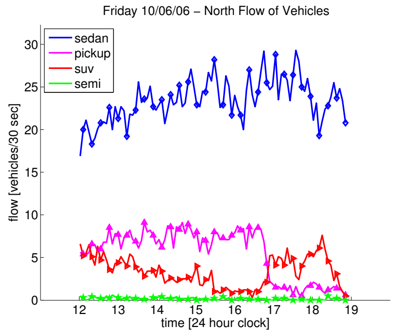

(a) Highway efficiency in north bound lanes. (b) Highway efficiency in south bound lanes.

Fig. 6. Highway lane efficiency.

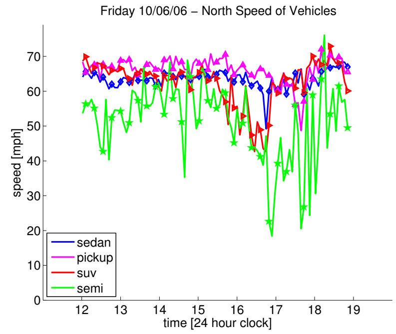
during the evening commute, where the efficiency drops significantly (Fig. 6(b)). It is interesting to note that while the efficiency of the south bound direction drops because of congestion the north bound highway does not suffer from congestion. The reduced efficiency in the fast lane is actually due to under utilization; the northbound flow is much lower than the average.

Besides reproducing loop detectors data for each lane, video provides a means for extracting more rich contextual information. Traffic parameters are compiled for each type of vehicle based on the vehicle classifier. Fig. 7(a) and 7(b) plot the flow and speed of each vehicle type on a weekday. This data is useful for understanding the differing effects of commercial or private vehicles on highway control and the study of environmental impact from emissions [6]. In Fig. 7(a) there are clearly many more sedans on the road than any other class of vehicles but during the evening commute the number of Pickups and SUVs on the road appear to switch; during the day there are more pickups and during rush hour there are more SUVs. In 7(b) it is noted that most of the vehicles travel at approximately the same speed (the speed of traffic) but the larger Semi trucks tend to travel slower than passenger vehicles, matching our intuition.

The large amounts of data collected by this system allows usage analysis not just over the course of a single day, but many days. To build a useful highway model, it is important to incorporate the differences in traffic behavior as a function of time. Fig. 8 demonstrates the differences in




(a) Highway flow for each vehicle class.




(b) Highway speed for each vehicle class.

Fig. 7. Traffic statistics separated by vehicle type.

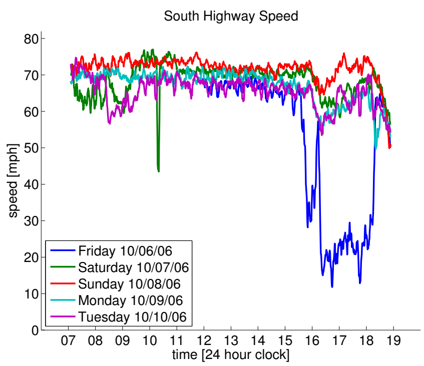



Fig. 8. Highway speed profile comparing weekend and weekday.

the speed profile for work and non-work days. The Friday congestion slow down between 16:00-19:00 is significantly greater than the other weekdays. While the Monday and Tuesday commute is noticeable, it is a more subtle speed disturbance. This demonstrates the need to model each day individually. Seven models are generated by averaging across specific days rather than all the days in a week.

The traffic parameter data is generated by the Flow Analysis module in real-time and stored in a database to build a highway model. This supply of historical information is required by California Partners for Advanced Transit and Highways (PATH) researchers for managing traffic congestion [7], is necessary for traffic prediction [8], and provides other application benefits by viewing data over time rather than just current conditions [9].

## V. Event Detection

The Event Detection module detects user events, which are predefined based on a priori scene knowledge, in an online manner. Example events of interest can be detection of a speeding vehicle or breach of a virtual fence [10] (place where vehicle is not allowed).

### A. Speed Profile

By using a database of historical speed measurements, a model of daily highway speed patterns can be constructed to incorporate the traffic speed fluctuations over the course of a week (Fig. 8).

The VECTOR system indicates the motion state of each vehicle during online tracking by the color of its bounding box; {speeding, normal, slow, stopped} = {blue, green, yellow, red}. In Fig. 9(b) a sedan is shown slowing down on the shoulder of the highway before coming to a complete stop in Fig. 9(c). The motion state is defined as

$$S_V(v) = \begin{cases} Stopped, & 0 \leq v < 0.15V_{avg}^t \\ Slow, & 0.15V_{avg}^t \leq v < 0.6V_{avg}^t \\ Normal, & 0.6V_{avg}^t \leq v < 1.1V_{avg}^t \\ Speeding, & 1.1V_{avg}^t \leq v \end{cases}, \quad (5)$$

where $V_{avg}^t$ is the average speed at time $t$ and $v$ is the estimated vehicle speed. The speed model currently considers normal speed as the daily average. Fig. 10(a) demonstrates the speed profiling at 18:30:00 during a Friday evening commute. The north and south bound directions have differing profiles ($V_{avg}$(South) $\approx$ 25MPH $\neq V_{avg}$(North) $\approx$ 70MPH) because there is southbound congestion but none going northbound.

## VI. Experimental Results

The following experiments test the accuracy of vehicle Classification and Flow Analysis modules. As a continuous and real-time system, VECTOR must perform during a variety of challenging situations seen in Fig. 10. The Classification module is tested by computing the classifier accuracy over the course of a single day. The Flow Analysis module is compared to hand counted flow and with inductive loop detector data from PeMS.

### A. Confidence Weighted Vehicle Classification

The wkNN database used for classification was constructed from 10 minutes of hand labeled training video. 60% of the detected vehicles in the training video was used to populate the training database. The accuracy of the Classifier module was assessed with a 24 hour test. A 5 minute clip was saved every hour over a 24 hour period and each vehicle was hand labeled into one of the 8 vehicle types. The classification results only consist of clips during the daylight hours between 06:00-20:00 because the Object Detection module failed during the lower light conditions (Fig. 10(c)). Fig. 11 presents the classification results using different confidence


(a) Typical output frame.

(b) Car slowing (yellow box) before stopping on the shoulder.

(c) Car coming to rest (red box) on the shoulder of the highway.

Fig. 9. VECTOR output with colored bounding boxes for motion state characterization.


(a) Friday high volume commute shows merged vehicles. The north and south bound directions have differing speed profiles because of the congestion.

(b) Water spray behind vehicles corrupting detection during a rainy day.

(c) Blurred vision and headlight detection during the evening.

Fig. 10. Difficult conditions encountered during daily VECTOR use.

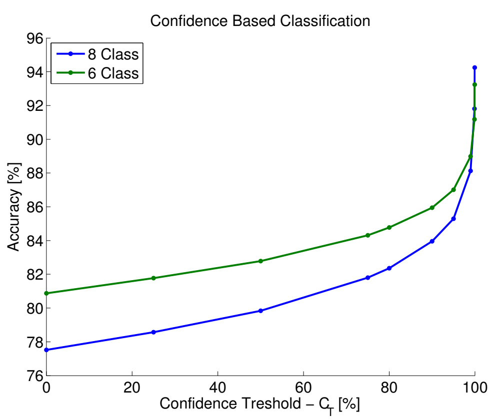


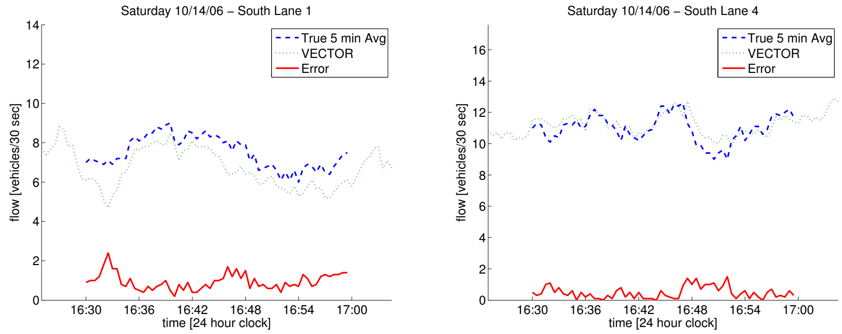

Fig. 11. Classification accuracy using different number of classes. The 6 class test combines SUV+VAN and Semi+Truck. Only vehicles with $C_{sl} > C_T$ are considered when determining the classification accuracy.

thresholds. Only the vehicles with confidence greater than the threshold, $C_{sl} > C_T$, are considered when determining the classification accuracy.The classification improves from 77.5% to 94% as confidence goes between 0% and 99.99% and the number of tracks used decrease from 6,500 to 1,336. In addition to the full 8 class problem, a smaller 6 class merged problem (SUV+Van and Semi+Truck) was evaluated. At low confidence there is a large 4% difference between the curves but at higher confidence the gap decreases. This demonstrates there is a tradeoff between classification accuracy, the number of vehicle types, and the confidence. This experiment shows that the VECTOR classification system provides good performance over the wide range of conditions encountered during a day.

### B. Traffic Flow Comparison

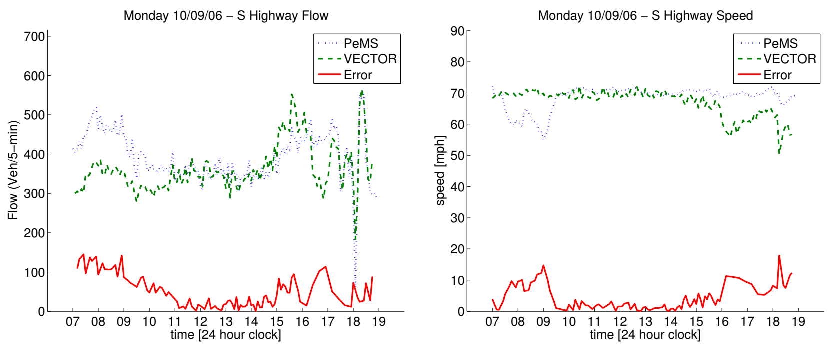
The accuracy of the Flow Analysis module was tested by comparing the estimated flow both with hand counted vehicle flow and separately with PeMS loop detector data. The true vehicle counts every 30 seconds from 30 minutes of video is averaged in 5 minute windows to make a direct comparison with the Flow Analysis output. Fig. 12 plots the 5 minute hand count average as a blue line, a green line represents the Flow Analysis output, and a red line as the error. With appropriate tuning of detection parameters, the ground truth flow error is usually less than 2 vehicles in every 30 second window demonstrating the estimate accuracy. The total error during the 30 minute test was 56.9 vehicles in lane 1 and 28.5 in lane 4.

The extracted traffic parameters were compared over a longer period of time using loop detector measurements available from the PeMS website. The PeMS data accumulates flow and average speed in 5 minutes windows rather than the 30 second intervals used for by the Flow Analysis module. Fig. 13 plots the south bound PeMS data along with the 5 minute corrected Flow Analysis module estimates. There is generally good consistency with PeMS, but there are noticeable differences in speed, as seen in Fig.




(a) Lane 1 - Error of 56.9 vehicles/30 mins (b) Lane 4 - Error of 28.5 vehicles/30 mins

Fig. 12. True lane flows, 5 minute average truth, and Flow Analysis module flow comparison.




(a) Flow (b) Speed

Fig. 13. Comparison between PeMS data and the Flow Analysis module shows strong agreement.

13(b). There is an early morning drop in PeMS speed and conversely there is a significant evening slowing of traffic in the VECTOR plot. Visual inspection of the video stream confirmed the VECTOR speed pattern. The discrepancy in speed measurements come from the differing sensor configurations.The PeMS detectors are on the opposite side of Genesee Ave., approximately 0.4 miles from our camera setup. The differences in speed can be attributed to vehicles exiting (PeMS) and entering (Camera) the highway on the southbound Genesee ramps.

The true flow and PeMS comparison results show the Flow Analysis module can accurately estimate traffic parameters making it as useful as inductive loop sensors.

## VII. Conclusion

Effective highway traffic management requires up-to-date traffic data delivered in real-time along with historical patterns. The VECTOR system offers a video based alternative to inductive loop sensors. In addition to providing traffic measurements equivalent to loop detectors, the use of cameras allows more diverse vehicle classification into 8 major types and live event analysis. VECTOR tracks vehicles in real-time and uses those tracks to accumulate traffic statistics, density, flow, and speed. These statistics comprise a highway model that allows for speed profiling based on average daily behavior. The delivery of accurate highway measurements and real-time implementation make it possible to integrate VECTOR into larger advanced highway traffic monitoring and management systems.

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