2011 IEEE Forum on Integrated and
Sustainable Transportation Systems
Vienna, Austria, June 29 - July 1, 2011

Real-Time Roadway Emissions Estimation using Visual Traffic Measurements

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Abstract—**Monitoring the state of our roadways has become increasingly important in order to better manage traffic congestion. Sophisticated traffic management systems are being developed that are able to process both static and mobile sensor data that provide traffic information for the roadway network. In addition to typical traffic data such as flow, density, and average traffic speed, there is now strong interest in environmental factors such as greenhouse gas and pollutant emissions from traffic. It is now possible to combine real-time traffic data along with instantaneous emission models to estimate these environmental measures in real-time. In this paper, we describe a system that can more accurately determine average traffic fuel economy, CO_2, CO, HC, and NO_x emissions using a computer vision-based methodology that also incorporates energy/emission profiles from the comprehensive modal emissions model CMEM and EPA's MOVES emission factor database. The vision system provides information not only on average traffic speed, density, and flow, but also on individual vehicle trajectories and recognized vehicle categories. The vehicle trajectories for the specific identified categories are used by the emissions model to predict environmental parameters. This estimation process provides far more dynamic and accurate environmental information compared to static emission inventory estimation models.**

Keywords: computer vision; traffic surveillance; emissions modeling; CMEM; MOVES

I. INTRODUCTION

As our roadways become increasingly congested, it is becoming increasingly critical that we monitor the state of our roadway network through a variety of means. In the last decade, there has been a tremendous amount of research in Intelligent Transportation Systems (ITS) in the field of Advanced Traffic Monitoring and Management Systems (ATMMS). Traffic management centers are becoming increasingly sophisticated around the world where traffic data from a variety of sensors are brought in, analyzed, and then used to better manage overall traffic. A good example of this type of system is the California Traffic Performance Monitoring System (PeMS) [1] which collects link-based traffic data such as traffic flow, density, and average speed across California's freeway network.

In addition to standard traffic measures, there is also a strong interest now is traffic emissions in terms of 1) pollutants such as carbon monoxide (CO), hydrocarbons (HC), oxides of nitrogen (NO_x), and particulate matter (PM); and 2) greenhouse gases such as carbon dioxide (CO_2). Estimating an emissions inventory for mobile sources (i.e., vehicles traveling on the roadway network) is an active field due to requirements from the U.S. Environmental Protection Agency (EPA) and the California Air Resources Board (CARB). Most of the roadway planning must undergo detailed emissions modeling to determine the impacts of future activity. To support these emissions inventory estimates, both the U.S. EPA and CARB have sophisticated emission models that can be used to determine emissions for specific scenarios.

Transportation policy makers are now beginning to see the value of combining both real-time transportation data and emissions modeling so that instantaneous emissions can be predicted for a roadway network on a link-by-link basis. There have been a few attempts to simply take link-based traffic volumes and average speeds and then use a speed-emissions curve to estimate link-based emissions. This approach lacks sensitivity in that it does not capture an instantaneous profile of vehicle types and their instantaneous activity. To estimate real-time link-based emissions (and fuel economy), we have developed a computer vision-based methodology that also incorporates energy/emission profiles that have been derived from a comprehensive modal emissions model (CMEM) [2-6] and EPA's MOVES emission factor database. In Section II, we describe the computer vision-based monitoring system that is capable of estimating not only traffic parameters of flow, density, and speed, but can also extract vehicle velocity trajectories as well as perform rough vehicle categorization. Section III describes the emissions and energy models and how they are interfaced with the results from the computer vision traffic monitoring system. Section IV describes the experimental setup and initial results from this innovative real-time energy/emissions traffic monitoring system.

II. VISION-BASED TRAFFIC MONITORING SYSTEM

Highway traffic management is an important field requiring up-to-date data delivered in real time along with historical data on traffic conditions to design effective control strategies. In California, inductive loop sensors deliver counts (number of vehicles to cross a loop) and occupancy (average fraction of time a vehicle is over a loop) every 30 seconds from locations all over the state, providing a large data infrastructure. Unfortunately, only about 60% of California's loop detectors supply usable data and the system is costly to maintain. Video monitoring offers an attractive alternative for loop sensor data with the advantage that cameras can be unobtrusively deployed on roadsides and that video monitoring has several potential monitoring applications in addition to vehicle counts and traffic measurements. Video monitoring can be used to track individual vehicles in a scene, revealing additional information which is difficult to obtain using loop detectors alone such as trajectory information and vehicle classification. This added information provides a more complete picture of highway traffic then can be obtained from loop detector data alone.

The VECTOR system [7] is a visual traffic monitoring system which detects and tracks every vehicle in view. Highway congestion statistics are accumulated by analyzing vehicle trajectories to mimic the measurements obtained with loop detectors. In addition, the appearance of each detection is used to determine vehicle type.

A. Vehicle Detection and Tracking

A single camera is used to monitor both directions of a busy 4 lane highway. Moving vehicles are detected using background subtraction. Vehicles are tracked using a global nearest neighbor optimization which accounts for dynamics using a Kalman filter and appearance similarity. Detections are matched to existing tracks if they appear where expected based on the Kalman motion model and if the appearance is consistent to help deal with occlusions. As vehicles are tracked, their current lane number is determined using position information described in [7] to mimic the output of inductive loop sensors.

B. Traffic Flow Measurement

Using trajectory information, the time series of fundamental highway usage parameters, analogous to those obtained from conventional loop detectors, is collected in real-time. This system delivers flow (# vehicles/time), density (# vehicles/distance), and average speed (MPH) in 30 second intervals. The primary traffic measure of flow counts the number of vehicles every 30 seconds and indicates link usage. The VECTOR flow statistic is generated by counting the number of passing vehicles in the 30 second update interval. The vehicles are counted as they exit the camera field of view to simulate a spot sensor.

Density is the average number of vehicles in the camera view normalized by the roadway length and measures highway crowding. The speed is the average velocity of all tracked vehicles in the 30 second interval which is difficult to obtain using loops. Fig. 1 through Fig. 3 give examples of the accumulated statistics in the north and south bound directions of US Interstate 5 (I5) on a Friday evening. Density greatly increases in the southbound direction between 15:00-16:00 with an accompanying increase in flow. But, the increased usage leads to a large reduction in link speed. Once the evening commute is in full swing, between 16:00-18:00, the speed is only 20 MPH, density is capped at approximately 175 vehicles per mile, and the flow follows a downward trend after reaching its limit of 60 vehicles per 30 seconds.

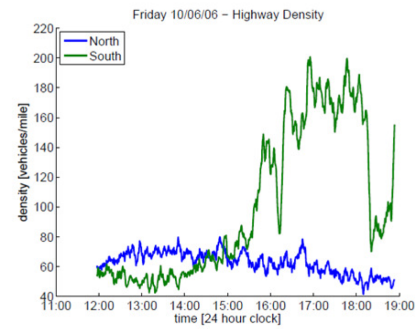


Fig. 1. Density for north and southbound directions of I-5.

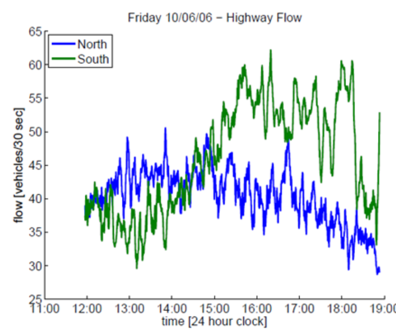


Fig. 2. Flow for north and southbound directions of I-5.

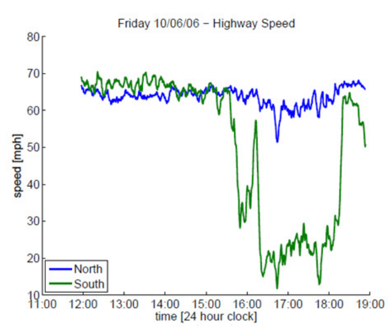


Fig. 3. Speed for north and southbound directions of I-5.

Fig. 4 through Fig. 6 show the south bound statistics for different lanes to highlight lane level congestion effects. In Fig. 4 it is evident lane 4 (the slow lane) is occupied by more vehicles. During the commute hours this difference is greatly increased from 30 vehicles/mile to 80 vehicles/mile which causes congestion. This is revealed in Fig. 5 by noting the increased flow and density until a sudden flow drop shortly after 16:00. The congestion in the slow lane spills over into the adjacent lanes causing a comparable loss in speed over all the lanes as is evident in Fig. 6. This phenomenon demonstrates the need for on and off ramp management to control the slow lane as well as the entire highway link itself.

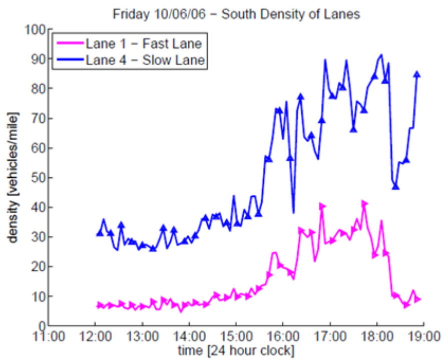


Fig. 4. Lane density for north and southbound direction of I-5.

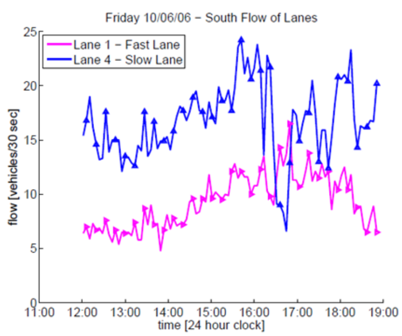


Fig. 5. Lane flow for north and southbound direction of I-5.

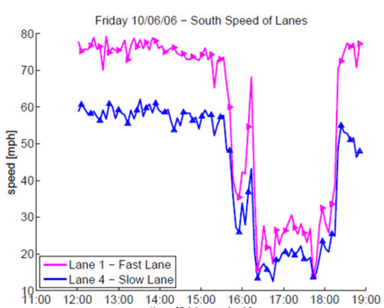


Fig. 6. Lane speed for north and southbound direction of I-5.

C. *Vehicle Classification*

The **VE**hicle **C**lassifier and **T**raffic fl**O**w analyze**R** (VECTOR) classifies vehicles into the eight different vehicle types (Sedan, Pickup, SUV, Van, Semi, Truck, Bike, Merged) seen in Fig. 7. These vehicles were selected because they were the most often occurring vehicle types from the 2001 National Household Travel Survey conducted by the U.S. Department of Transportation [8].

The block diagram depicting the VECTOR classification scheme is in Fig. 8. After a vehicle is detected, a set of blob measurements are calculated to describe the object. The blob measurements consisted of 16 features obtained using morphological operations, $m_t = [n_0, \ldots, n_{15}]^T =$ {area, breadth, compactness, elongation, perimeter, convex hull perimeter, length, long and short axis of fitted ellipse, roughness, centroid, the 4 first and second image moments} [9]. The extracted features are transformed into a lower dimensional space that better separates the vehicle types using Fisher's linear discriminant analysis (LDA) [10]. For each frame a vehicle is tracked, its transformed features are used to generate a single frame classification using a weighted K nearest neighbor (wkNN) technique. Information redundancy, in repeated vehicle images, during tracking is exploited to generate an improved vehicle type classification for the track. The track-based refinement scheme reduces uncertainty and noisy measurements from a single frame through maximum likelihood estimation [7].

Fig. 7. Sample images from VECTOR vehicle classes.

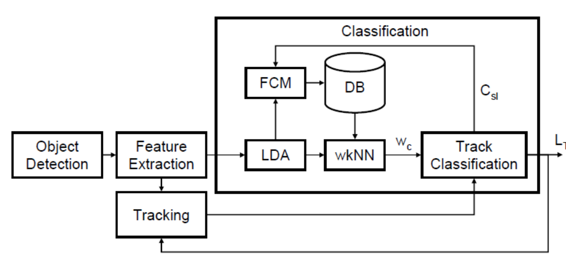
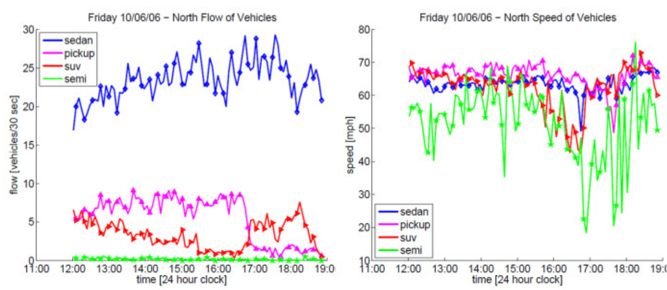


Fig. 8. Block diagram for the VECTOR classification scheme.

Using vehicle type information, VECTOR provides rich contextual traffic measurements in addition to reproducing loop detector data. Traffic parameters are compiled for each type of vehicle based on the vehicle classification. This information is useful for understanding how roads are being utilized. Fig. 9 plots the flow and speed of different vehicle types on a weekday. In Fig. 9a 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. One may speculate that this occurs because contractors and other workers (construction or landscaping) who need pickups start and end their work earlier than the more typical 9-5 day. In Fig. 9b 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 intuition.



(a) Flow: Distribution of highway usage by vehicle type. (b) Speed: Semi trucks travel at noticeably lower speeds.

a) b)

Fig. 9. Traffic highway statistics separated by vehicle type.

III. ENERGY/EMISSIONS MODEL AND INTERFACE

A. Vehicle Emission Modeling

In order to more accurately determine the amount of emissions or fuel usage from a particular vehicle, it is necessary to know certain vehicle characteristics such as weight, fuel type, engine displacement, aftertreatment technology and vehicle age as well as how the vehicle is being operated (the driving profile). Unfortunately, it is not possible to determine many of these vehicle characteristics using conventional traffic cameras. The resolution of these setups along with the vast number of vehicles on the road with varying characteristics makes this level of data collection almost impossible without the use of other identifying techniques such as RF-tags or license plate recognition. As shown earlier, it is however possible to distinguish between different classes of vehicles using conventional traffic cameras. Each class of vehicles has different emission properties which are generally related to vehicle size and type. In the current implementation, an instantaneous emission value (E_{pol}) for pollutant (*pol)* is estimated for each vehicle based on vehicle class and Vehicle Specific Power (VSP)

$$E_{pol}(t) = f(vehicle\ class, VSP) \qquad (1)$$

where *vehicle class* represents the VECTOR categories discussed in Section II and VSP is Vehicle Specific Power, used by several, e.g., Jimenez-Palacios [11]. The emission value is updated and recorded for each vehicle at each time frame *t* that is observed in the camera field of view. The bounding box surrounding a detected vehicle is color coded to indicate the current emission score with more red indicating a higher score.

B. Vehicle Specific Power Approach

There are various approaches to estimating vehicle emissions depending on the scope of the analysis and the available data. By tracking the state of each vehicle in each video frame, the VECTOR system provides velocity, acceleration and vehicle category identification information for each vehicle in the monitored area at a frequency of 1 Hz or greater.

Traditional emission modeling techniques are limited to utilizing average congestion level and average speed based emission rates to estimate emissions. One of the fundamental drawbacks of this modeling approach is that a given speed under various levels of acceleration will results in a wide range of emissions. Acceleration is an important factor in the estimation of vehicle load, which is well correlated with fuel use and consequently emissions. In order to take advantage of this significantly greater level of detail, VSP was used as the basis for emission rates.

VSP is defined as the instantaneous power to move a vehicle per the mass of the vehicle. The calculation for VSP in kW/metric tons is based on the following equation, simplified from the power demand terms for a moving vehicle:

$$\mathrm{VSP} = v(1.1a + \mathrm{g}\sin(\theta) + \mathrm{g}\mathrm{C}_r) + \frac{\rho_a \mathrm{C}_d \mathrm{A}_f v^3}{2\mathrm{M}} \qquad (2)$$

where

- v = vehicle speed in m/s
- a = vehicle acceleration in m/s^2
- g = gravity (m/s^2)
- θ = grade
- C_r = coefficient of rolling resistance
- ρ_a = density of air (kg/m^3) (~1.2 kg/m^3 at sea level and 20 °C)
- C_d = coefficient of aerodynamic drag
- A_f = frontal area of vehicle (m^2)
- M = mass of vehicle (kg)

The values in Table 1 are used to approximate VSP for seven of the VECTOR vehicle classes. The merged vehicle class is excluded.

Table 1. Approximations for VECTOR vehicle category vehicle characteristics.

Type	Mass (kg)	Frontal Area (m^2)	C_r	C_d
Sedan	1360	2.0	0.0135	0.34
Pickup	2340	3.3	0.0135	0.43
SUV	3035	3.44	0.0135	0.41
Van	2270	3.46	0.0135	0.38
Bike	230	0.65	0.0250	0.9
Truck	11360	6.6	0.0094	0.7
Semi	27300	10.0	0.0094	0.85

Using the values from Table 1, equation 2 was reduced, for ease of use, to the equations found in Table 2 for 7 of the VECTOR vehicle classes.

Table 2. VSP equations for VECTOR vehicle classes.

Type	VSP Equation (kW/metric ton)
Sedan	$VSP = v(1.1a + g\sin(\theta) + 0.1323) + 0.000300v^3$
Pickup	$VSP = v(1.1a + g\sin(\theta) + 0.1323) + 0.000364v^3$
SUV	$VSP = v(1.1a + g\sin(\theta) + 0.1323) + 0.000279v^3$
Van	$VSP = v(1.1a + g\sin(\theta) + 0.1323) + 0.000348v^3$
Bike	$VSP = v(1.1a + g\sin(\theta) + 0.24500) + 0.001526v^3$
Truck	$VSP = v(1.1a + g\sin(\theta) + 0.09212) + 0.000244v^3$
Semi	$VSP = v(1.1a + g\sin(\theta) + 0.09212) + 0.000187v^3$

C. Emission Table Generation

Emission tables developed for this project provide instantaneous emission rates for VSP values between 0 and 40 kW/tone and can be conveniently applied both in real-time and in post processing. For each vehicle and at each time step, a VSP value is calculated using the equations in Table 2 and corresponding emission values are determined from the emission table for that specific vehicle class.

1) Comprehensive Modal Emissions Model

The VSP based emission tables for this project were primarily generated from modeling results from the Comprehensive Modal Emission Model (CMEM) which was developed at CE-CERT, University of California at Riverside [2]. CMEM is a modal emissions model intended primarily for use with microscale transportation models that typically produce second-by-second vehicle trajectories. CMEM is capable of predicting second-by-second fuel consumption and tailpipe emissions of carbon monoxide (CO), carbon dioxide (CO_2), hydrocarbons (HC), and nitrogen oxides (NO_x) based on different modal operations from an in-use vehicle fleet. CMEM consists of nearly 30 vehicle/technology categories covering light-duty vehicles and Class-8 heavy-duty diesel trucks. With CMEM, it is possible to predict energy and emissions from individual vehicles or from an entire fleet of vehicles, operating under a variety of conditions.

One of the most important features of CMEM (and other related models) is that it uses a physical, power-demand approach based on a parameterized analytical representation of fuel consumption and emissions production. In this type of model, the fuel consumption and emissions process is broken down into components that correspond to physical phenomena associated with vehicle operation and emissions production. Each component is modeled as an analytical representation consisting of various parameters that are characteristic of the process. These parameters vary according to the vehicle type, engine, emission technology, and level of deterioration. One distinct advantage of this physical approach is that it is possible to adjust many of the physical parameters to predict energy consumption and emissions of future vehicle models and applications of new technology (e.g., aftertreatment devices). For further information on the CMEM effort, please refer to [2-6].

VSP and emission values are calculated for each CMEM vehicle category for both cycles. Vehicle population data from CARB's EMFAC model for San Diego County and calendar year 2010 is used to approximate fleet distributions for CMEM categories. CMEM categories are further grouped into the VECTOR vehicle classes for compositing. Fig. 10 shows compositing results for the VECTOR pickup class. In this figure the light blue lines show VSP emission results for individual CMEM vehicle categories within the VECTOR pickup class and the red line shows the weighted composited VSP based emission values for the VECTOR pickup class.

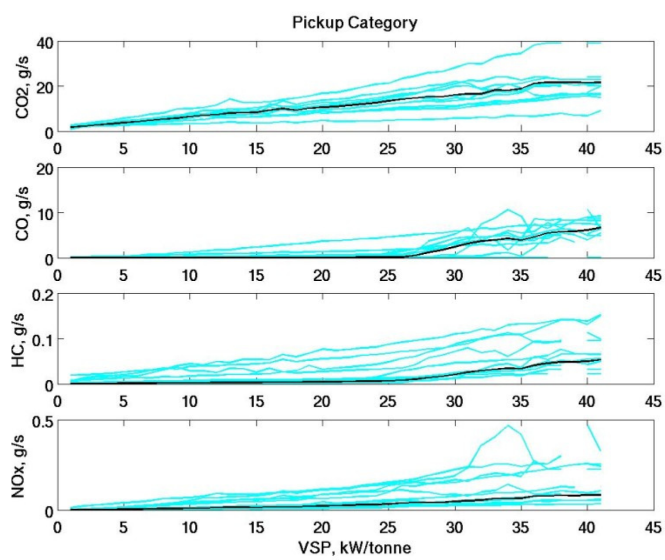


Fig. 10. VSP based emission rate values for the VECTOR pickup class generated from weighted CMEM categories.

In addition to the VECTOR sedan, pickup and semi classes, the CMEM model was used to determine the van and SUV categories as well even though there are no specific van or SUV categories in the CMEM model. In order to determine van and SUV emissions more directly, individual van and SUV vehicles from the NCHRP database from the original CMEM project [2] were identified (20 SUV vehicles and 37 vans) and modeled using CMEM. The VSP based emissions from these vehicles were averaged to create emission tables for those two categories specifically.

2) VSP Emission Rates from EPA's MOVES Model

The VECTOR vehicle classes consist of 7 different vehicle classes not counting the merged category. The car, pickup, van, SUV and semi categories are determined from the CMEM model; the remaining two VECTOR categories, truck and motorcycle, are not supported by the CMEM model.

The VECTOR truck category is a broad category and encompasses a range of visually similar vehicle types such as busses, garbage trucks, and medium heavy trucks. For the most part, these vehicles are large diesel engine driven vehicles and for this application this class was approximated as an urban bus according to EPA's approximation for 1996-2006 class 48 vehicles from heavy-heavy duty (HHD) vehicles [12].

The motorcycle class is modeled using base emission rates found in the 2010 MOVES database. MOVES stands for Motor Vehicle Emissions Simulator and is EPA's latest mobile source emission model. The MOVES modeling methodology is based on VSP binned emission rates. It is applicable at the microscale level and can be integrated upwards for mesoscale and macroscale applications. The core of the MOVES modeling suite is a MySQL database which is referenced by the MOVES software and GUI to run elaborate analysis at various temporal and spatial resolutions. At the fundamental level, the MOVES model, is a database of emission and energy use tables binned by VSP operating mode. VSP operating mode bins are VSP bins split not only by VSP, but also by mode such as acceleration, deceleration, braking, and speed range. MOVES VSP operating mode bins are divided into 3 distinct speed ranges in an effort to separate emission speed effects. For this analysis, MOVES VSP operating mode bins with matching VSP ranges were combined across vehicle speeds to create approximate VSP emission tables. Motorcycle emission rates were extracted from the MOVES database by query using the appropriate sourceBinID for the motorcycle regulatory class and the 2006 model year group. The appropriate polProcessIDs for CO, HC, NO_x and total energy were used as well as ageGroupIDs for 0-3 and 4-5 years. VSP operating mode bins between 11 and 40 were used. Pollutant emission factors were queried from the emissionratebyage table and total energy was queried from the emissionrate table. Total energy was converted to CO_2 using an oxidation factor of 1 and carbon content of 0.00196 g/kJ as discussed in the MOVES documentation[12].

IV. Evaluation Setup and Results

A. Visual Vehicle Type Classification

Total classification accuracy for a sample of 6,500 test tracks was found to be 78.4% and the performance of the system by vehicle type is presented in the confusion matrix in Table 3.

Table 3. Confusion matrix for all test hours. Total classification accuracy of 78.4% over 6,500 test tracks.

	sedan	pickup	suv	van	semi	truck	bike	merged
sedan	2726	127	202	55	0	0	1	0
pickup	40	374	52	24	0	14	0	4
suv	411	113	1147	172	0	3	0	4
van	15	11	54	83	0	6	0	7
semi	0	0	0	0	26	1	0	1
truck	1	5	1	2	11	36	0	0
bike	1	0	0	0	0	0	18	0
merged	7	7	6	10	3	31	2	677
total	3201	637	1462	346	40	91	21	693
% correct	85.2	58.7	78.5	24.0	65.0	39.6	85.7	97.7
% correct	85.2	58.7	80.1		56.5		85.7	97.7

With the vision based monitoring system, vehicle type distribution data can easily be obtained for a given location in real-time from the data presented in Fig. 9. Distribution data for 5 minute samples every hour over the course of 10 hours is presented in Fig. 11. This data compares reasonably to 2010 EMFAC vehicle distribution data for San Diego County which is presented in Fig. 12.

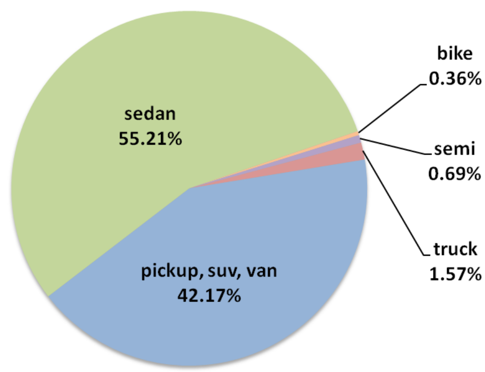


Fig. 11. Measured VECTOR vehicle class distribution for 5 minute samples per hour over 10 hours.

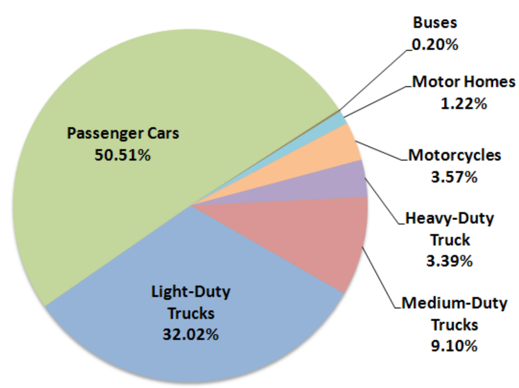


Fig. 12. EMFAC 2010 vehicle distribution for San Diego County.

B. Real-Time Vehicle Emission Aggregation

The VSP emission equations and emission tables described in Section III allow real-time estimation of vehicle emissions using the velocity, acceleration and category identification provided by the VECTOR system. Vehicle emission values are updated for each new video frame acquired, which is at a rate of 30 times per second. The traffic flow and emission are plotted to show the current emission values along with a short history as seen in Fig. 13. To the right of the moving plots are two bars which indicate the current emission load in the north and south bound directions of the highway. The height and color of the bars denote the magnitude of the emission score with red indicating high emissions.

These diagnostic plots provide immediate up-to-date measurements but are quite variable due to the traffic congestion conditions. Similar to the standard loop detector measures used for traffic management, the emission score is accumulated and archived over 30 second increments to aggregate the data into more stable and meaningful timescales. Emission statistics could then be used in the same way that the traditional highway measures of flow, occupancy, and speed are utilized through traffic measurement database systems such as Berkeley's (and now Caltrans) Performance Measurement System (PeMS) [1]. Fig. 14 through Fig. 17 show the variability and trend of cumulative predicted CO_2 , HC, NO_x and CO emission over a more than 9 hour time period. In Fig. 18, a simple map application provides a color coded view of the highway emissions in a particular roadway segment. Darker more red colors indicate a higher emission score in the past 30 seconds. This map is similar to navigation speed colored maps which display the highway speed based on loop (or floating car) measurements. The map can display the historical emissions at a location over time to demonstrate how commutes affect air quality.

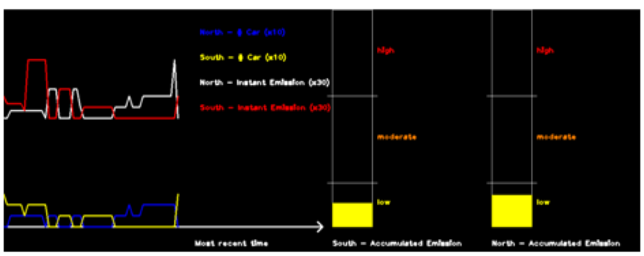


Fig. 13. Real-time plot of vehicle counts and emission measurements.

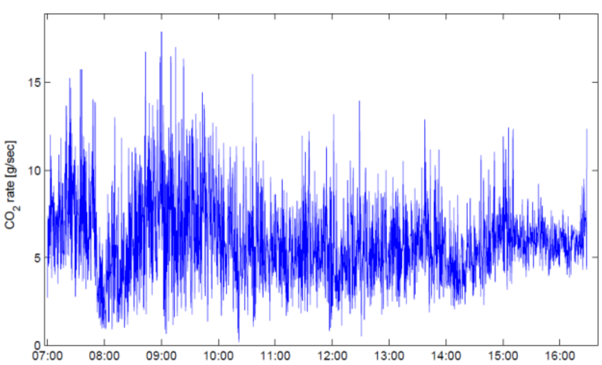


Fig. 14. Cumulative predicted CO_2 emissions for southbound I-5.

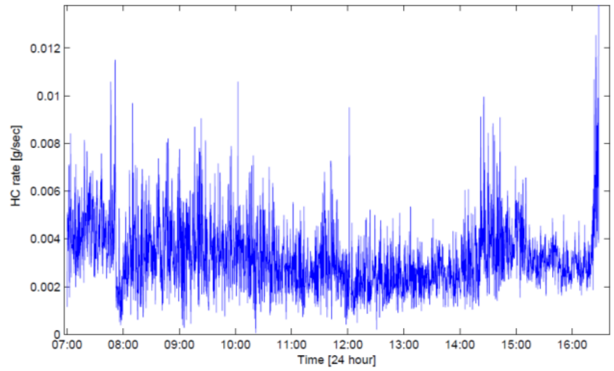


Fig. 15. Cumulative predicted HC emissions for southbound I-5.

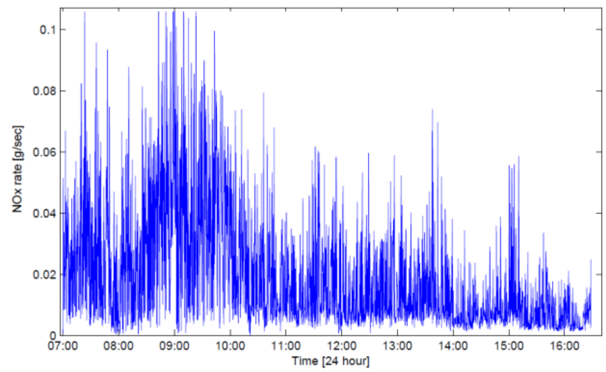


Fig. 16. Cumulative predicted NO_x emissions for southbound I-5.

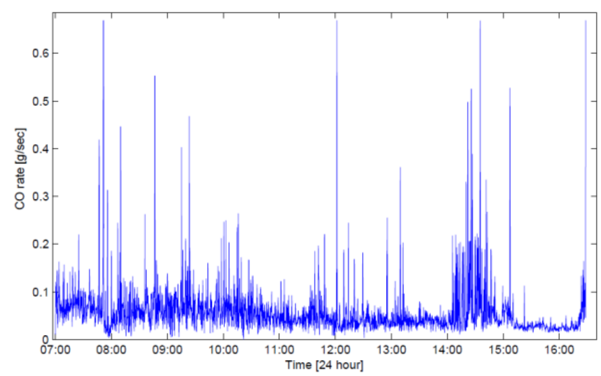


Fig. 17. Cumulative predicted CO emissions for southbound I-5.

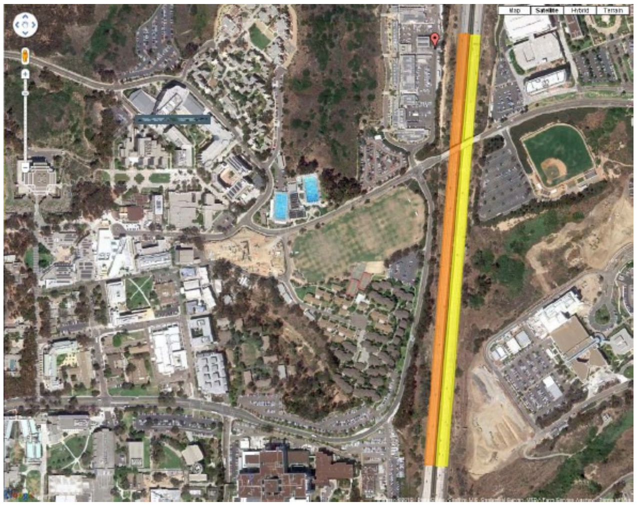


Fig. 18. Google map with highway color-coded based on transportation emission measurement updated in 30 second intervals.

V. Conclusions and Future Work

A computer vision-based system for traffic monitoring was integrated with a VSP based emission modeling approach to develop an innovative system for estimating real-time traffic emissions accounting for vehicle velocity, acceleration and type. A set of VSP based emission profiles was developed from CE-CERT's microscale emission model CMEM and additional categories were supplemented with data from EPA's latest emission model MOVES. The method for processing both of these emission modeling data sources is presented. Using this system, real-time vehicle distribution statistics that are generally comparable to EMFAC vehicle population data were observed and real-time estimated emissions for a sample period were shown.

This study was performed on a level section of road, but can easily be extended to include road grade as an additional input for emission modeling. Future work will be to develop this for additional areas of interest to verify operation in a wide variety of differing conditions.

VI. References

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