Abstract—It has become increasingly important to monitor the state of roadways in order to better manage traffic congestion. Sophisticated traffic management systems are in development to process both the 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 gases, pollutant emissions, and fuel consumption from traffic. It is now possible to combine high resolution real-time traffic data with instantaneous emission models to estimate these environmental measures in real-time. In this paper, a system is described that estimates average traffic fuel economy, CO$_2$, CO, HC, and NO$_x$ emissions using a computer vision-based methodology in combination with vehicle specific power based energy and emission models. The CalSentry system provides not only the typical traffic measures, but also gives individual vehicle trajectories (instantaneous dynamics) and recognizes vehicle categories which are used in the emission models to predict environmental parameters. This estimation process provides far more dynamic and accurate environmental information compared to static emission inventory estimation models.

I. INTRODUCTION

With increased roadway congestion, it has become critical to monitor the state of the roadway network through a variety of means. Over the last decade, there has been a tremendous amount of research in intelligent transportation systems (ITS) for advanced traffic monitoring and management. Traffic management centers (TMC) around the world are becoming increasingly sophisticated. They bring in data from large networks of sensors for analysis in order to better manage overall traffic. Efficient operation of these centers requires both an up-to-date view of current conditions, for speedy response, as well as historical data for modeling, planning, and prediction.

A prime example of such a system is California’s Performance Measurement System (PeMS) [1] which gathers measurements from 30 thousand inductive loops embedded in the highway and distributed across the state in addition to police incident reports and lane closure information. PeMS has been a great success because it has made the fundamental flow, occupancy, and speed data along with basic traffic calculations accessible to the research community, thus inspiring novel new traffic management outcomes.

More recently, video cameras have become popular in TMCs for human monitoring and verification to augment ITS data elements such as loops. Cameras provide complementary analysis difficult to manage using traditional sensors. Vision-based systems have been developed in the past decade to allow real-time traffic flow, vehicle classification, tracking, and trajectory analysis [2]–[5]. Cameras have also been integrated in multi-modal frameworks for structural health monitoring and event detection [6].

While capacity and congestion have historically been the major motivating factors of transportation management, new performance metrics have recently garnered attention. In addition to standard traffic metrics, there is a strong interest in traffic-related emissions now in terms of

1) pollutants (e.g. carbon monoxide (CO), hydrocarbons (HC), nitrates of oxygen (NO$_x$), and particulate matter)
2) greenhouse gases (e.g. carbon dioxide (CO$_2$))
3) and energy (fuel consumption).

Estimating the emissions inventory for vehicles traveling on the roadway network is an active field due to emission requirement from government institutions such as the U.S. Environmental Protection Agency (EPA) and the California Air Resources Board (CARB). Both the EPA and CARB have sophisticated emission models [7], [8] that can be used to determine emissions for specific scenarios and most roadway planning must utilize these models to determine the impacts of future activity. The transportation community is now beginning to see the value of combining both real-time transportation data and emissions modeling to predict instantaneous emissions or energy usage on a road network on a link-by-link basis. Unfortunately, there is no PeMS-like system for accurate roadway emissions measurements. Attempts have been made to utilize link-based traffic volumes and average speeds along with speed-emissions curves for estimation [9] but these approaches lack sensitivity. They do not account for vehicle profiles, the differences between different vehicle types and instantaneous activity, which drastically affect emissions.

In order to provide real-time link-based emissions (and fuel economy), this work has developed the CalSentry system which combines the VEHICLE Classifier and Traffic Flow analyzeR (VECTOR) [10] system, a computer vision-based highway measurement system, with vehicle specific power (VSP) [11] based energy/emission profiles derived from the the Comprehensive Modal Emission Model CMEM [12] and the MOtor Vehicle Emissions Simulator (MOVES) [7]. This
system provides subtle vehicle dynamics (instantaneous speed and acceleration) through visual tracking along with categorization of the type of vehicles on the road in order to accurately estimate vehicle-specific emissions. The system could be deployed within a larger sensor network to provide a streaming data source for traffic management system such as PeMS. Thus providing useful real-time information for policy makers, planners, and health officials and facilitating further transportation related emissions research.

II. RELATED STUDIES

The world’s rapidly growing and expanding population has led to traffic congestion even in the best planned road networks. This congestion results in a loss of time and productivity and contributes a high economical cost. In order to tackle the congestion problem, without continual road construction projects, traffic management and control approaches have been adopted to better utilize the existing roadway infrastructure. However, in order to develop effective management or control strategies, data is needed. Historical data is needed to learn and develop models while real-time measurements can provide up-to-date indicators of performance for prompt response. In addition, this data is needed over large coverage areas with varied conditions. Effective monitoring systems must therefore be scalable, provide distributed and cooperative sensing, be robust to a wide range of environmental conditions, and have efficient transmission and storage.

The dominant sensor for traffic management has been the inductive loop sensor which is able to detect the presence of a vehicle based on an induced magnetic field. This simple spot detector provides the count of vehicles that have passed over it (flow) as well as the amount of activation (occupancy) in a time period. By collecting the loop readings from many sensors, traffic researchers have built complex models for analysis. PeMS [1] which was developed at UC Berkeley (and is now in Caltran’s control) provides raw loop readings as well as fundamental traffic performance measures. PeMS collects and stores the data from over 34,000 inductive loops on California’s highways making it indispensable for researchers.

However, inductive loops are limited because they are costly to install and maintain (only 62% of California’s PeMS loop sensors are in working order), making the search for alternative sensing solutions [?] or augmentation schemes [?] appealing. Video cameras have emerged as a popular ITS device because of large spatial coverage or field of view (FOV) which allows capture of higher order dynamics in vehicles and traffic, rich information content for more complex analysis (e.g., classification), and many TMC have already installed them for human observation.

A. Visual Traffic Monitoring

Highway monitoring has been one of the oldest applications for vision researchers. The inherent structure of roads coupled with a vehicle’s rigid body constrains the vision processes. Early vision-based traffic monitoring researchers looked to mimic the popular inductive loop sensor counts by manually defining virtual loops in the camera FOV [13]. While easy to manage and effective, the virtual loops did not take advantage of the spatial coverage afforded by the camera, reducing the wide FOV into several small point sensors. Subsequently, most researchers began to focus on moving object detection and tracking [14]. In this paradigm, a count is generated for every tracked vehicle [10], [15].

The spatial sensing and wide area coverage which makes video an attractive monitoring sensor also provides the greatest difficulty. In order to properly count vehicles, each and every vehicle must be detected with a single sensor. Camera placement and view are critical for successful deployment. Imaging provides roadway coverage over long distances but also causes perspective distortion which greatly affects the apparent size of vehicles and leads to occlusion. Significant effort has gone into developing detection methods which can resolve occlusion such as feature grouping in the image plane [15] or in 3D space using multiple homography transformations [16].

Cameras also have difficulties dealing with changing environmental conditions. The sun’s normal course during the day causes challenging illumination conditions due to cast shadows. Researchers have attempted to distinguish cast shadows on the roadway from vehicles using shadow detection and suppression techniques [17]. In addition to shadows caused by lighting, it is quite difficult to operate vision systems at night, reducing the effective operating time. Major efforts have begun to develop techniques to detect and track vehicle headlights [18] to avoid use costly low light sensitive or infrared cameras.

B. Vehicle Classification

The switch to video-based traffic monitoring is particular useful for vehicle classification because of the appearance information contained in an image. Loop-like sensors only generate a one dimensional signature which makes it difficult to resolve differences between vehicles (large and fast moving vs. small and slow). Generally, these systems count the number of axels to only distinguish between large and small vehicles.

The review by Buch et al. [19] devotes two large sections to top-down (object-based) and bottom-up (part-based) visual classification techniques for urban traffic. It is noted that often times classification degenerates into a detection problem because the techniques are designed for matching. In fact, even a recent vehicle classification paper only makes a distinction between two different classes of vehicles based on stable features [16]. Early work by Gupte et al. [20] classified vehicles by their length. However, length measurement precision was found to be low and not flexible to camera views. More detailed classification has been tackled using shape and appearance techniques [10], using a linearity feature [21], or explicit vehicle models. Edge matching techniques have been designed using 3D wire-frame vehicle models [22]. Though the 4 models were quite simple and had low resolution, they only operated at 5Hz. More generic and adaptive 3D models have been explored to provide a deformable vehicle model with higher resolution [23]. Results were shown up to a difficult 5 class problem where a distinction was made between 2 and 4 door sedans. Despite these efforts, it is still difficult to leverage high resolution imaging while maintaining the computational efficiency required for real-time monitoring.
C. Emissions/Energy

Environmentalists and health officials have long been concerned with the effects of air pollution on air quality, but only recently has there been a major shift in focus to the transportation sector. Traditionally, monitors which measure pollutants in the air in parts per million and parts per billion are used to evaluate air quality. Unfortunately, the number of monitoring sites is limited and existing sites provide sparse spatial data that does not necessarily express traffic emissions specifically since contributions from other pollutant sources may be included. Monitoring sites cannot accurately depict the spatial distribution of pollutants or target area for focused surveys, nor can they attribute emission contributions to individual vehicles. Mobile measurement systems have been employed and have shown that high levels of pollutants are found near highways which significantly exceed maximum values reported by fixed measurement monitors [24].

In order to isolate the effects of transportation emissions, a wide range of modeling techniques have been adopted [9]. The simplest models are easy to calculate and rely on average speed, but do not account for real world driving characteristics [25]. More complex modal models operate at a higher time resolution (seconds) and account for more detailed vehicle and traffic characteristics such as specific engine operation and vehicle movements. The modal models have gained traction recently because supporting data can more easily be obtained via GPS [26] and they can be integrated into microscopic traffic simulation models [27]. While promising, these techniques are difficult to scale to large areas. Communication networks must be established and there must be high penetration rate for GPS-based emission calculations. Microscopic traffic and emissions simulation is computationally expensive for large networks because trajectories and emissions must be calculated for each vehicle at each simulation time step over the entire network and are affected by errors in the traffic models themselves.

Currently, there is no tool available to calculate transportation related emissions in real-time for a large number of vehicles. In addition, there is no way to present this information to stakeholders in order to manage or plan future decisions.

III. CALSENTRY HIGHWAY EMISSION MANAGEMENT SYSTEM

This manuscript presents CalSentry, the first real-time integrated highway transportation measurement and management system for emission/energy estimation. This vision-based system combines four major components as shown in Fig. 1:

1) visual traffic measurement,
2) dynamics-based emission estimation,
3) real-time visualization,
4) and a database for record keeping.

The elements in purple comprise the parts of the VECTOR highway monitoring module [10] which is a visual tracking and analysis system suitable for distributed traffic understanding [5]. The emissions modeling and estimation block in green utilizes VECTOR analysis in order to estimate the amounts of pollutants produced by vehicles on the roadway using real-time emission modeling [7], [12]. Adhering to a framework designed for thematic contextualization [28], measurements and model estimations are stored and utilized for appropriate visualization of system output (orange block). As a testament to its robustness, the CalSentry system has been in continuous daily operation at a single site since early 2011, collecting...
highway data during the daylight hours (approximately 5:00 - 19:00).

At the host site, a traffic operator can view live highway video feeds; both in raw and processed form. Fig. 2a presents the output of the VECTOR system. The highway video is processed in real-time to display object detection and tracking results. Tracked vehicles have a color-coded bounding box to indicate the current emission score (based on dynamics and vehicle type) with red indicating a higher score. In addition, on the left of Fig. 2b in red and white are moving time-series plots of of highway flow. The plots are updated every video frame to give the instantaneous count of vehicles traveling either north or south while providing a short 30 second history. Using the VSP approach [11] (described in Section V-B), the roadway emissions are estimated based on tracking information and vehicle type (determined by visual processing). Similar to the moving flow plots, the instantaneous VSP value with 30 second history is displayed in yellow and blue. The time-series plots are intended to show the evolution of conditions on the road. On the right of Fig. 2b are two bins representing the total accumulated emissions in the north and south directions in a sliding 30 second window. The bins are color-coded, yellow, orange, and red, to indicated low, medium, and high amounts of greenhouse emissions.

The diagnostics plots of Fig. 2b provide immediate up-to-date measurements but are quite variable due to traffic congestion conditions. The emission score, which includes the four greenhouse gases and pollutants \{CO_2, CO, HC, NO_x\}, is accumulated and aggregated over 30 second increments for more stable and meaningful time scales. By adopting the standard loop detector aggregation scheme, emission statistics can be directly correlated and used in the same way as the traditional highway measures of flow, occupancy, and speed. In fact, they could be combined not only with VECTOR highway measurements but also any loop data, such as those warehoused by PeMS.

The final output component in the CalSentry system is a remote user interface. A public website, utilizing the Google Maps API, was constructed to provide interested parties access to the emission measurements. Fig.2c shows the map with a color-coded view of a highway link. Using the same color scheme as the bins above, \{yellow, orange, red\} = \{low, medium, high\}, the highway is colored to indicate the 30 second aggregate emission value for the link. In this snapshot, the northbound direction is colored yellow indicating a low emission level while the southbound is orange indicating a medium emission level. The map is similar to the more familiar navigation maps that have been color-coded for speed. Similar emission coverage could be provided with more CalSentry nodes to give a better sense of the current emission conditions in a city or region.

Although not visualized, an important part of the CalSentry system is the database for historical record keeping. With increased coverage and data, the database will be valuable for displaying trends (e.g., the evolution of emission “hotspots” in a city over the course of a day) and as input to support larger scale emission modeling. This data will help transportation engineers and policy makers understand how commutes affect air quality and determine how to best manage or build future roads.

The following sections describe the two main computational components in the CalSentry system. Section IV highlights the VECTOR modules and the emission/energy modeling is presented in Section V.

IV. VECTOR TRAFFIC MONITORING

The following section describes highway traffic monitoring with VECTOR [10]. The camera-based system is able to detect, track, and identify the type vehicles on the roadway. In addition, it produces traffic measurements, similar to traditional loop detectors, in real-time.
A. Vehicle Detection and Tracking

Unlike a loop detector which is a spot sensor, cameras observe a vehicle over a period of time while it travels through the camera’s FOV. Each video frame, every 33 msec, provides a new view which is used to describe the appearance of a vehicle as well as its dynamics.

The VECTOR systems utilizes a single camera to monitor both directions of a busy, 4-lane, highway. Vehicles are detected as moving regions using background subtraction and tracked using a global nearest neighbor optimization which accounts for both the dynamics as well as appearance. The trajectory of vehicle $i$,

\[ F_i = \{f_1, \ldots, f_t, \ldots, f_T\}, \quad \text{with} \quad f_t = [x, y, u, v]^T, \]

is the sequence of positions and velocities that describes the vehicle dynamics. The morphological appearance vector

\[ M_i = [\eta_0, \ldots, \eta_{15}]^T = \]

\{area, breadth, compactness, elongation, perimeter, vertex hull perimeter, length, long and short axis of fitted ellipse, roughness, centroid, the 4 first and second image moments\}

encodes the shape appearance of the particular vehicle.

B. Vehicle Classification

Using the appearance vector $M_i$, VECTOR classifies each vehicle into one of the 8 different types, \{Sedan, Pickup, SUV, Van, Semi, Truck, Bike, Merged\}, seen in Fig. 3. The classification scheme is depicted in the block diagram of Fig. 4. At a particular instant, $M_i$ is transformed using linear discriminant analysis (LDA) and compared with a vehicle database using a weighted K nearest neighbor (wkNN) technique to produce class weights. The final vehicle label $L_i$ of a track is determined after iterative refinement with each new video frame.

1) Feature Transformation: Appearance features were projected using LDA [29] in order to separate vehicle classes and provide a lower dimensional space to reduce computational complexity for real-time implementation.

Let $D_c = \{x_1, \ldots, x_{N_c}\}$ be a set of $N_c$ training vectors for class $c$, each of dimension $d$, with mean $\mu_c = \frac{1}{N_c} \sum_{i=1}^{N_c} x_i$. The full training set, $D = \{D_1, \ldots, D_C\}$, is composed of the training samples from all classes and has mean $\mu = \frac{1}{N} \sum_{i=1}^{N} x_i$, where $N = \sum_c N_c$. The LDA projection is given by the maximization problem

\[ P_{LDA} = \arg\max_w \frac{|w^T S_B w|}{|w^T S_W w|} \]

where $S_B$ is the between class scatter matrix and $S_W$ is the within class scatter matrix.

\[ S_B = \sum_{i=1}^{C} N_i (\mu_i - \mu)(\mu_i - \mu)^T \]

\[ S_W = \sum_{i=1}^{C} \sum_{x_k \in D_c} (x_k - \mu_i)(x_k - \mu_i)^T \]

The solution to this maximization leads to the generalized eigen problem

\[ S_B w = \lambda S_W w \]

The top $M = 5$ eigenvectors are retained to obtain the LDA projection matrix,

\[ x_{LDA} = P_{LDA} x = [w_1, \ldots, w_i, \ldots, w_M]x \]

2) Detection Classification: The wkNN rule is a modification of the NN classifier for robustness to noise and outliers that uses a soft assignment rule rather than a binary class membership. The soft membership is denoted by the class weight

\[ w_c = \frac{1}{\sum_{x_t \in D_c} \|x_t - x_i\|} \]

where a larger weight indicates a higher likelihood of a sample belonging to class $c$ based on the similarity to the $K = 5$ closest training examples. In (7), $x_i$ is a new test sample to classify given the training set consisting of all samples $x_t$. To completely specify the weights of the $C = 8$ vehicle types, $K \times C = 40$ comparisons must be made.

3) Track-Based Classification Refinement: Information redundancy contained in sequential frames can be exploited to improve vehicle type classification. A track-based refinement scheme is used to overcome measurement noise inherent in a single image. Given $T$ images of a vehicle during tracking, the track classification is found by maximum likelihood

![Fig. 3: Sample images from each vehicle class.](Image)

![Fig. 4: Block diagram for the VECTOR classification scheme.](Image)
density is inferred based on occupancy and traffic flow. Traffic directly measure density because it is a spot sensor, instead normalized by the roadway length. A loop detector cannot

5a) indicates how crowded a roadway is and is computed

and average speed (MPH) in 30 second intervals, averaged

over a 5 minute window as shown in Fig. 5.

C. Traffic Statistics

Using trajectory information, the time series of fundamental highway usage parameters, analogous to those obtained from conventional loop detectors, is collected in real-time. The VECTOR system delivers density (vehicles/mile), flow (vehicles/30 sec), and average speed (MPH) in 30 second intervals, averaged over a 5 minute window as shown in Fig. 5.

1) Directional Measurements: The highway density (Fig. 5a) indicates how crowded a roadway is and is computed by counting the number of vehicles in the camera view normalized by the roadway length. A loop detector cannot directly measure density because it is a spot sensor, instead density is inferred based on occupancy and traffic flow. Traffic flow (Fig. 5b) is a count of the number of passing vehicles in a 30 second time interval. VECTOR produces the flow statistic by counting vehicle tracks as they exit the camera field of view in a manner similar to loop detectors. The highway speed measure (Fig. 5c) is the average velocity of all vehicles seen in the 30 second interval. The roadway is calibrated based on ground plane homography to convert pixels/sec image tracking into MPH. VECTOR provides direct measurement while loop detectors often rely on algorithms based on flow and occupancy to estimate speeds [1].

2) Lane-Level Measurements: In Fig. 5 the traffic in north and southbound directions are compared during daylight hours. In this section of road, the southbound traffic is affected during the evening commute hours of 14:00-16:00. The causes can be further investigated by focusing on the lane level traffic measurements presented in Fig. 6. During tracking, the lane number is determined based on position in the image. The density of vehicles in the fast lane (lane 1) dramatically increases during evening and results in a significant drop in driving speed.

3) Vehicle-Level Measurements: Since VECTOR is based on video technology, rich contextual information not obtained with loop detectors can be extracted to further study traffic conditions. The loop-like traffic statics are further categorized based on the vehicle type as shown Fig. 7. Fig. 7a shows the proportion of vehicles on the road over the course of a day.
The speeds, shown in Fig. 7b, of sedans are greatest during congestion while SUV and pickup drivers are required to slow more with large commercial semi-trucks always traveling slowest.

V. EMISSION/ENERGY ESTIMATION

Current emphasis on environmental issues such as air pollution, greenhouse gases and energy consumption has fueled research in areas such as “green” vehicle technologies, alternative fuels and ITS. This has resulted in the commercial success of hybrid automobiles and the re-introduction of consumer electric vehicles as a way to curb emissions and energy consumption. In the area of ITS, advances in traffic monitoring and data collection help improve traffic characterization and management, however, it is still unclear exactly how the transportation network really affects emissions and how emissions contributions can be characterized by location, time or mobile source.

It is generally difficult to measure pollution from specific mobile sources under real-world conditions due to the mixing and dispersion of emissions as well as contributions from additional sources such as other vehicles, nearby factories and secondary pollutants. These issues are further influenced by environmental factors such as meteorological conditions and topographic features. Some methods of emission measurements, such as tunnel studies, remote sensing, and portable emission monitoring systems, address these problems to some extent. These methods, however, either do not isolate emissions from specific vehicles, are very limited in testing locations or can not be practically applied to large sets of vehicles. A method to better estimate emissions attributed to transportation and even specific vehicle classes in real-time is useful for traffic management and policy makers as well as health organizations.

Using a vision based traffic management system, which is able to accurately track individual vehicles (collecting dynamic driving patterns) and determine their type, it is possible to estimate the emissions and energy consumption from specific vehicles on the road. By accumulating emissions data over time, a real-time map can be formed to indicate the level of pollutants on our roadways.

A. Vehicle Class Emission Modeling

In order to 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, after-treatment technology, vehicle model year 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.

At the current time \( t \), an instantaneous emission value \( E_{pol}(t) \) for pollutant \( pol \) can be estimated for each vehicle based on the vehicle class, \( L \), and dynamic profile, \( F(t) \)

\[
E_{pol}(t) = h_F(L, F(t)).
\]  

The functional mapping, \( h_F \), specifies how emissions are obtained from the vehicle information and must be specified or modeled.

B. Vehicle Specific Power Approach

There are various approaches to estimating vehicle emissions depending on the scope of the analysis and the available data. Traditional emission modeling techniques utilize average speed based emission rates for estimation. One of the fundamental drawbacks of this modeling approach is that speed alone is not a good predictor of emissions since 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 additional level of detail, VSP [11] 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,

\[
V_{SP}(t) = v(t)(1.1a(t) + g \sin(\theta) + gC_r) + \frac{\rho_a C_d A_f v^2(t)}{2M}. \tag{10}
\]

\[v = \text{speed [m/s]}
\]
\[a = \text{acceleration [m/s}^2\text{]}
\[g = \text{gravity} = 9.8 \text{ [m/s}^2\text{]}
\[\theta = \text{grade [radians]}
\[C_r = \text{coefficient of rolling friction}
\[\rho_a = \text{density of air} = 1.2 \text{ [kg/m}^3\text{] at sea level and } 20^\circ \text{C}
\[C_d = \text{coefficient of aerodynamic drag}
\[A_f = \text{frontal area [m}^2\text{]}
\[M = \text{mass [kg]}
\]

The vehicle dynamic information \([v(t), a(t)]\) are encoded in the trajectory \(F(t)\). The parameter values in Table I are the approximate values used for the seven VECTOR vehicle types (merged is excluded) based on the NCHRP 25-11 [30] data set and values found in literature.

Using the VSP approach, emissions are estimated by modifying (9) as

\[E_{pol} = h(L, V_{SP}(t)) \tag{11}\]

where class \(L\) represents the VECTOR vehicle type categories \(8\) and \(V_{SP}(t)\) encodes the vehicle emission-dynamics relationships. The mapping, \(h\), to produce emission values [31], is modeled based on CMEM and MOVES as described in the next section.

C. Vehicle Specific Emission Tables

After accounting for the vehicle type and driving dynamics with the VSP, the mapping \(h\) from VSP to a particular pollutant emissions is found. The VSP mapping is generated using two different simulation models, CMEM [12] and the EPA’s MOVES [32]. Emission tables developed for this project provide instantaneous emission rates for VSP values between 0 and 40 kW/tonne 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 equation (10) with vehicle class specific constants of Table I. An alternative, more computationally intensive approach to estimating real-time vehicle emission would be to use individual vehicle trajectories directly as input to CMEM.

1) Comprehensive Modal Emissions Model (CMEM): The VSP based emission tables for this project were primarily generated from modeling results from CMEM [12] which was developed at CE-CERT, University of California at Riverside. CMEM is a modals 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 (CO₂), hydrocarbons (HC), and nitrogen oxides (NOₓ) 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 these physical parameters to predict energy consumption and emissions of future vehicle models and applications of new technology (e.g., aftertreatment devices).

VSP and emission values are calculated for each CMEM vehicle category using the US06, FTP and MEC [30] driving schedules. 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. 8 shows compositing results for the VECTOR pickup class. In this figure the light green lines show VSP emission results for individual CMEM vehicle categories within the VECTOR pickup class and the black line shows the weighted composited VSP based emission values for the VECTOR pickup class. The emission values are binned in 1 kW/tonne bins and in the figure the first bin represents VSP values between 0 and 1 kW/tonne.

In addition to the VECTOR sedan, pickup and semi classes, specific van and SUV categories were developed to model emissions from these two vehicle types with the CMEM model. In order to determine van and SUV CMEM categories, individual van and SUV vehicles from the NCHRP 25-11 database from the original CMEM project were identified (20 SUV vehicles and 37 vans), calibrated and modeled using CMEM. The VSP based emissions from these vehicles were composited to create emission factors for those two vehicle types specifically.

2) EPA MOVES Model: The remaining two VECTOR categories, truck and motorcycle, are not supported by the CMEM

<table>
<thead>
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<th>Type</th>
<th>(M) [kg]</th>
<th>(A_f) [m²]</th>
<th>(C_r)</th>
<th>(C_d)</th>
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<td>0.43</td>
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</tr>
</tbody>
</table>
model and are instead modeled using the 2010 MOVES database which is the EPA’s latest mobile source emission model. The VECTOR truck category is a broad category and encompasses a range of visually similar vehicle types such as buses, garbage trucks, and medium heavy trucks. For the most part, these vehicles are large diesel engine driven vehicles and for this project 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 [32]. The motorcycle class is taken directly from the motorcycle base emission rates found in MOVES.

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 set 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. An alternative approach is to use the MOVES VSP operating bins with the speed ranges. Emission rates were extracted from the MOVES database by query using the appropriate sourceBinID for the regulatory class and a sample model year group. The appropriate polProcessIDs for CO, HC, NOx and total energy were used as well as ageGroupIDs for 0-3 and 4-5 years. VSP operating modes 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 CO2 using an oxidation factor of 1 and carbon content of 0.00196 g/kJ [32].

VI. EXPERIMENTAL EVALUATION

The combination of real-time tracking and emissions modeling present in the CalSentry system gives rise to a completely new type of performance measurement system. In order to assess the performance, first the vehicle classification scheme is evaluated followed by a comparison with PeMS loop-based emission output.

A. Visual Vehicle Type Classification

The vehicle classifier was only evaluated during the daylight hours of a single day because the detection and tracking does not work at night due to poor lighting and headlight reflection on the road surface. Each hour, with sufficient sunlight, a 5 minute video clip was saved for manual annotation of each observed vehicle. Both the type of vehicle and the lane of travel were recorded, resulting in 6491 total tracks. 78.44% of the tracks were classified into the correct vehicle type. The full-day confusion matrix is presented in Table II. The classifier has difficulties with the Van and Truck classes because they are quite similar in appearance to SUV and Semi respectively. Table III gives the classification accuracy for each hour of the experiment. The results from a single 5-minute clip is generally in the 80% range, except between 08:00-11:00. There is a significant performance drop during these morning hours due to adverse lighting conditions which caused large cast shadows from the vehicles. This typically caused larger detections which resulted in misclassification into the SUV type. Lighting issues are not new to visual monitoring and shadow suppression techniques [17], [33] could help improve classifier performance.

B. Vision-based Traffic Statistics

Although real-time data is needed to understand current conditions, historical measurements provide the data for modeling and provides a deeper understanding of higher order effects. The observed flow and speed over a given week are shown in Fig. 9. The differences between weekday and weekend traffic patterns are quite clear. During the weekdays, there is a large increase in demand between the evening commute hours of 15:00 and 17:00. The increased flow rate causes congestion and results in a large drop in speed. On the weekdays, there is a 50% decrease in average speed during the commute hours.
TABLE II: Confusion matrix for all hours of test. Total classification accuracy of 78.4% over 6491 test tracks

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<th>suv</th>
<th>van</th>
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<th>truck</th>
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TABLE III: Percentage Accuracy for Hourly Test Clips

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<td>0</td>
<td>100</td>
<td>-</td>
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</table>

while the weekends show no significant speed difference. By storing measurements in a database, they can be utilized to learn and model variations in traffic patterns and behavior. During the daylight test, 98% of vehicles traveling south (closest to the camera) were identified in the correct lane. The northbound direction, which is much further away and suffers more perspective distortion, only had 93% accuracy in lane assignment with the 3-lane performing worst at 84.4%. This implies lane level accuracy is only possible with the proper camera-road configuration. However, link direction measurements are reliable even at sub-optimal camera configurations.

C. Real-Time Vehicle Emission Aggregation

Using Table I along with VSP-based emission profiles (highlighted in Fig. 8), the emissions from each vehicle were calculated at 10 Hz and archived. The 10 Hz update rate was chosen as a compromise between VECTOR’s high video frame rate of 30 fps and the natural 1 Hz operation of the microsimulation model. This compromise was necessary because at 30 Hz the vehicle dynamics are noisier but at 1 Hz much of the trajectory profile would be lost. Emission measurements were aggregated into 30 second increments before archival to provide more stable and meaningful timescales which match PeMS loop detector rates.

Fig. 10a presents the emissions (CO₂, CO, HC and NOₓ) rates [g/sec] in the southbound direction of the highway. The HC and NOₓ rates are scaled 50x and CO by 2x for plotting purposes since the CO₂ rate is much higher. The time-series plots have a number of spikes which should not come as a surprise because of the nature of traffic. During a particular 30-second time interval, the number of and types of cars and driving style, which greatly impacts emission production, is variable. In Fig. 10b the emissions are aggregated over a longer 5 minute time period. The emission measurements are significantly more stable at this time scale and provides a better indication of the daily patterns. Around the 16:00-17:00 time period there is a drop in emissions due to congestion. At this time vehicles move slower and the VSP is greatly influenced by speed (0 speed results in no VSP output). Further work will need to take into account idling emissions.

The emissions measurements generated by CalSentry are compared with loop detector based estimates, shown in Figs. 10c, 10d. These plots were generated by using the PeMS speed measurement (no acceleration) in (10). The PeMS flow value was divided into the VECTOR vehicle classes based on registration distribution resulting in fixed ratios of all vehicles at all times. The 5 minute aggregates are of similar scale and have the drop off during the evening commute, but the average speed version has a lower floor. As with CalSentry, the 30 second aggregate is quite a bit more noisy (Fig. 10c) than the 5 minute version.

CalSentry results are generally more variable and result in slightly higher estimated emission rates than the loops estimates based on average speed.

D. Future Work

Future work is needed to evaluate the validity of the emission estimates, which will require more sophisticated techniques such as tunnel measurements or instrumented vehicles. Although it is expected that the accuracy of emission estimates with the CalSentry system will be better than loop-based estimates and that the CalSentry system will significantly improve the quality of on-road vehicle emission estimates, there are several factors which impact prediction accuracy. These factors include misclassification of vehicle categories, lumping of certain vehicle types (e.g. truck category), un-
known vehicle operating weights (especially for heavy duty vehicles), unknown vehicle conditions (bad catalysts, tampered emission controls, engine malfunctions, age of the vehicle), and the representativeness of emission factors which will vary based on the test vehicle sample size used to develop them. However, these same factors impact loop-based estimation and loops typically do not benefit from driving profiles or diverse vehicle classification.

VII. CONCLUDING REMARKS

This paper introduced the first vision-based system for traffic monitoring and emission/energy measurement called CalSentry. CalSentry integrates live video processing, emissions modeling, and historical data archival into a visualization framework for providing real-time emissions. An innovative system for real-time estimation of traffic emissions was developed using a VSP-based approach which accounted for the class of vehicle as well as the dynamic driving profile of velocity and acceleration. Using the CMEM and MOVES emission models, VSP-based emission profiles were generated to convert the real-time vision tracking and VSP into CO\textsubscript{2}, CO, HC, and NO\textsubscript{X} emission estimates. A public website is provides a map that is color-coded based on the current emission conditions on a highway link which could be extended for wider area coverage and used for policy decisions and real-time traffic management.

REFERENCES


Brendan Tran Morris received his B.S. degree from the University of California, Berkeley in 2002 and his Ph.D. degree from the University of California, San Diego in 2010. His dissertation research on “Understanding Activity from Trajectory Patterns” was performed under Professor Mohan Trivedi and was awarded the IEEE ITS Best Dissertation Award in 2010.

Morris’ research focus has been in real-time sensing and processing for understanding environments and situations. His interests include unsupervised machine learning for recognizing and understanding activities, real-time measurement, monitoring, and analysis, and driver assistance and safety systems.

Cuong Tran is a Ph.D. candidate at the Computer Vision and Robotics Research Laboratory, University of California San Diego. His research interests include vision-based human pose estimation and activity analysis for interactive applications, intelligent driver assistance, human-machine interfaces, and behavior prediction. Tran received the B.S. in computer science from Hanoi University of Technology, Vietnam in 2004 and the M.S. in computer science from UC San Diego in 2008. He is a Vietnam Education Foundation (VEF) Fellow.

Mohan Manubhai Trivedi is a Professor of electrical and computer engineering and the Founding Director of the Computer Vision and Robotics Research Laboratory and Laboratory for Intelligent and Safe Automobiles (LISA) at the University of California, San Diego. He and his team are currently pursuing research in machine and human perception, machine learning, human-centered multimodal interfaces, intelligent transportation, driver assistance and active safety systems. Trivedi serves as a consultant to industry and government agencies in the U.S. and abroad, including the National Academies, major auto manufactures and research initiatives in Asia and Europe. Trivedi is a Fellow of the IEEE (“for contributions to Intelligent Transportation Systems field”), Fellow of the IAPR (“for contributions to vision systems for situational awareness and human-centered vehicle safety”), and Fellow of the SPIE (“for distinguished contributions to the field of optical engineering”).

George Scora earned a B.S. degree in Environmental Engineering in 1996 and an MS degree in Chemical and Environmental Engineering (CEE) in 2007 from the University of California, Riverside (UCR) where he is currently pursuing a PhD degree in CEE. He has over ten years of experience working at UCRs College of Engineering Center for Environmental Research and Technology as a development engineer in the Transportation Systems Research group.

Mr. Scoras areas of interest include vehicle emission modeling and transportation related air quality issues. He has been heavily involved in the development of UCRs Comprehensive Modal Emissions Model (CMEM). As a student, Mr. Scora was also involved in work with the U.S. EPA Office of Transportation and Air Quality in Ann Arbor, Michigan, which focused on analyzing emission data sets and helping to develop emission factors of both light-duty and heavy-duty vehicles for the MOVer Vehicle Emission Simulator (MOVES) model.
**Matthew J. Barth** received his B.S. degree in Electrical Engineering/Computer Science from the University of Colorado in 1984, and M.S. (1985) and Ph.D. (1990) degrees in Electrical and Computer Engineering from the University of California, Santa Barbara. Dr. Barth joined the University of California-Riverside in 1991, conducting research in Electrical Engineering and the Center for Environmental Research and Technology (CE-CERT), where he is currently director.

Dr. Barth’s research focuses on applying engineering system concepts and automation technology to Transportation Systems, and in particular how it relates to energy and air quality issues.

Dr. Barth is a member of the Institute of Electrical and Electronic Engineers (IEEE), Air and Waste Management Association (AWMA), Transportation Research Board’s Transportation and Air Quality Committee, New Technology Committee, and ITS America’s Energy and Environment Committee. He has also served on several National Research Council (NRC) committees. Current research interests include Intelligent Transportation Systems, Transportation/Emissions Modeling, Vehicle Activity Analysis, Electric Vehicle Technology, and Advanced Sensing and Control.
Fig. 11: 5-Minute highway emission comparison between CalSentry and PeMS.