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Publication Date

2013-04-01

UCI-ITS-WP-13-4

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April, 2013

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Word Count: 6,691
Tables: 3
Figures: 9
TOTAL: 9,691

ABSTRACT

This paper presents a new method for estimating traffic density on freeways, and an adaptation for real-time applications. This method uses re-identified vehicles and their travel times estimated from a real-time vehicle re-identification (REID) system which attempts to anonymously match vehicles based on their inductive signatures. The accuracy of the section-based density estimation algorithm is validated against ground-truth data obtained from recorded video for a six-lane, 0.66-mile freeway segment of I-405N in Irvine, California, during the morning peak period. The proposed density estimation algorithm results are compared against a g-factor based method which relies on inductive loop detector occupancy data and estimated vehicle lengths from the Caltrans Performance Measurement System (PeMS) as well as a selected REID method which uses a sparse REID algorithm based on long vehicle detection and volume counts at detector stations. Although the g-factor approach produces real-time density estimates, it requires seasonally calibrated parameters. In addition to the calibration effort to maintain overall accuracy of the system, the g-factor approach will also produce errors in density estimation if the actual composition of vehicles yields a different observed g-factor from the calibrated value. In contrast, the proposed method uses an existing vehicle re-identification model based on the matching of inductive vehicle signatures between two locations spanning a freeway section. This approach does not require assumptions on the vehicle composition, hence does not require calibration. The proposed algorithm obtained section-based density measures with a mean absolute percentage error (MAPE) of less than four percent when compared against groundtruth data and provides accurate density estimates even during congested conditions, improving upon both the PeMS and selected alternative REID based methods.

Key words: traffic density, vehicle re-identificationg-factors, real-time estimation

INTRODUCTION

Density is a measure of the concentration of vehicles, defined as the number of vehicles per lane per unit distance. Density is an important dimension in determining the level of service (LOS) of a freeway segment, and is, in fact, designated in the Highway Capacity Manual 2000 (HCM 2000) as the primary variable by which to distinguish LOS *(0)*. While other traffic measures such as volume and speed can be used as surrogate indicators of congestion, density is the most valuable parameter for doing so *(20)*. Problems arise, however, in measuring traffic density from existing point-based traffic monitoring devices such as widely deployed inductive loop detectors (ILDs) which collect measurements of volume and occupancy. However doing so is desirable due to the existing communications and system architectures that are in place to support these devices.

Theoretically, traffic density can be determined from point-based flow and space-mean speed measures according to the fundamental equation of traffic flow, *density = flow / space-mean-speed*. For freeways, flow measurements can be readily obtained from ILDs but space-mean-speed measures cannot be directly measured. Instead, point measures of time aggregated occupancy coupled with an assumption of vehicle length have been used to estimate density from ILDs. Nevertheless, density is a spatial measure and to estimate it accurately, information about the section, rather than a point, is needed. Hence, density estimation from point sources such as ILDs can be broken into two broad methods delineated by the spatial characteristics of the measured data:

1) *Point-based estimates* of vehicle lengths and loop occupancy
2) *Section-based estimates* of travel time and coarse vehicle trajectories derived from point sources

Point-Based Estimation

Traditional operational measurements from ILDs include volume and occupancy (defined as the percentage 'on-time' of the detector), both of which represent point measures but are often used in conjunction with an assumption or measurement of effective vehicle length (defined as the length of roadway traversed by the vehicle during the 'on-time' of the detector and sometimes referred to as the *g-factor*) to estimate traffic density, speed, and/or travel time *(1)*. Thus, since conventional ILDs produce volume and occupancy at *a point in space over time*, they cannot directly capture traffic density, which represents a measurement *over space within a snapshot in time*. Where double loop configurations are installed, vehicle length and speed can be measured directly, this however would still represent a point measure and therefore estimates of density from this approach may still be inaccurate.

In order to use the widely deployed ILDs where single loops are installed to measure traffic density, assumptions need to be made regarding the average length of vehicles sampled, which are typically estimated from historical data, and cannot be directly obtained in real-time *(2-6)*.. As pointed out by Jia et al. *(7)*, average effective vehicle lengths vary significantly over time, station, and lane and should therefore not be set as static values and doing so would result in density estimates that are not sensitive to temporal changes in vehicle mix which would affect the actual average vehicle length represented. This would be of special concern if density estimates are required at short time intervals to capture traffic instability, since vehicle mix would vary to a greater degree in smaller sampling periods. This generally results in poor estimates of traffic density during peak periods when traffic conditions are unstable, such as from the initial onset until the final dissipation of traffic congestion, which corresponds to the period when accurate measures of traffic density are most desired. Although the inaccuracies of estimating density from point-based occupancy and either measured or estimated effective vehicle length are apparent, this method represents the state-of-the-practice *(7).*

The Performance Measurement System (PeMS) managed by Caltrans, gathers occupancy and volume data from over 25,000 single and double inductive loop detectors throughout California *(8)*. To estimate speed PeMS employs an adaptive g-factor approach which is based on the assumption that an initial g-factor can be estimated when traffic is under free-flow conditions *(7)*. Although they do not estimate density as part of their performance measures, it can be derived from occupancy and the adaptive g-factor for any time, *t*, and lane, *l*, for which occupancy data is available according to Equation 1:

$$k_{gfactor}(t,l) = \frac{occupancy(t,l)}{gfactor(t,l)} \qquad \text{Eq. 1}$$

Density estimated from this equation represents a point-based estimate from which estimates at two adjacent stations can be averaged together to estimate section-density. This approach for averaging point densities to obtain section estimates neglects the detailed geometry changes within a section, such as the lane drops, however, given the complexities of estimating a section density from point estimates, there is no clear average that would fare better. In general and for the purpose of this paper, the inclusion of PeMS density estimate is used to show its inadequacy in estimating link conditions, even when considering ‘real-time’ estimates of g-factors.

Section-Based Estimation

Considering that section-based measures are required for accurate density estimation, methods for obtaining section measures from existing ILDs have been developed by several researchers *(9-15)* in order to overcome the limitations presented by point-based ILD measurements. In general, these methods attempt to uniquely match vehicles as they traverse a section of roadway bounded by upstream and downstream ILDs and are referred to as ‘vehicle re-identification’ (REID) techniques. After re-identifying a vehicle over a section, one can determine whether the vehicle is in the section at any time, and by aggregating all vehicle pairings, one can determine the number of vehicles in the section at any given time, thus producing an estimate of density under the theoretically correct interpretation. Thus, vehicle REID is ideally suited for density estimation.

TABLE 1 provides a brief summary of REID methods along with implementation status, total match rate (the percent of vehicles matched over the total number of vehicles detected), and correct match rates (the total number of vehicle correctly matched over the total number of vehicles detected). Each of the REID methods listed in

TABLE **1** is capable of estimating travel time with minimal error and the results vary more significantly in their total and correct match rates. Total match rate becomes important for density estimation since it is essential to obtain an accurate count of the number of vehicle in a section at any time, meaning that a high percent of the vehicle population must be matched. Further, traffic management agencies operate in real-time and thus rely on accurate real-time estimates of traffic conditions so real-time implementation is an essential characteristic of a vehicle REID method for this purpose.

TABLE 1 Summary and Comparison of Vehicle REID Methods

Author and Year *(Ref.)*	Summary of approach	Implementation Status	Total Match Rate	Correct Match Rate
Coifman, 2003 *(16)*	Two algorithms are deployed to match vehicles based on measured lengths from dual loop detectors outputting bivalent signals: 1) for congested conditions, all vehicles are attempted to be matched based on platoons patterns, 2) for uncongested conditions, only long vehicles are attempted to be matched.	-Dual loop detector sites capable of reporting individual vehicle lengths; -Real-time application and implementation; -Running on a freeway segment in Oakland, CA, as part of the Berkeley Highway Lab; -Published method for density estimation using this reidentification method	-75% in congested conditions -7% in uncongested conditions	-98.4% for congested conditions (see ref. *9*) -Not reported for uncongested conditions
Tawfik, 2004 *(11)*	Applied a decision tree approach using vehicle length, speed, lane assignment, travel time, and inductive signature spatiotemporal pattern differences to inductive signature data to identify matched vehicle pairs.	-Dual loop detector sites capable of reporting individual vehicle inductive signatures; -Real-time application possible but not currently implemented	81%	90%
Jeng, 2006 *(12)*	Data compression and transformation techniques were applied to raw inductive signatures prior to applying a vehicle reidentification method. The reidentification method is based on temporal-spatial search space reduction and computation of summed differences between the compressed data points.	-Dual or Single loop detector sites capable of reporting individual vehicle inductive signatures; -Real-time application and implementation coupled with real-time vehicle classification -Running on a freeway segment in Irvine, CA, as part of CTM Labs[1]	98%	80%
Kwon, 2006 *(13)*	Focused on processing raw signatures via a signal restoration approach prior to applying pattern recognition algorithms to obtain matched vehicle pairs. Pattern matching relied on calculating the minimum difference between processed signature features of candidate signature identified by the upstream station estimated speed.	-Dual or Single loop detector sites capable of recording inductive signature output stream; -Real-time application developed but not currently implemented	~90% for small test dataset, not reported for all datasets used	~89% for test datasets
Cetin, 2009 *(15)*	Two stage approach: 1) Bayesian method for matching similar vehicles based on detector attributes, 2) Assignment problem for restricting possible assignment to single vehicle pairs.	-Implemented with weigh-in-motion (WIM) and automatic vehicle classification (AVC) system data but can be applied to ILD signatures; -Offline algorithm, historical application	Not reported; Only FHWA classes 4-13 included in analysis, passenger vehicles not included	97% AVC data 99% WIM data
Nyode, 2011 *(14)*	Focused on pre-processing of inductive/magnetic signals via signal processing techniques. Matched signals based on finding the maximum cross correlation coefficient.	-Dual sensors required but may be inductive loops or magnetic sensors -Real-time application and implementation possible but does not currently exist	Not reported, test data gathered from one lane of a multilane facility	95% on a sample data set of front and rear loops at same station

[1]The real-time Inductive Signature Performance Evaluation project can be found through the CTM Labs website: http://www.ctmlabs.net/projects/inductive-signature-performance-evaluation

Due to the current real-time implementation and high total and correct match rates compared to the other algorithms, the real-time inductive signature based REID method developed by Jeng et al. *(12),* referred to as RTREID-2, is used as the basis for the density estimation algorithm presented in this paper. In addition to providing real-time matched vehicle data, unlike all other listed REID algorithms, the selected algorithm also classifies vehicles into the five detailed classes shown in TABLE 2 with 97.6% accuracy *(18)*. The reader is directed to *(12)* and *(18)* for further detail on the selected REID and classification algorithms.

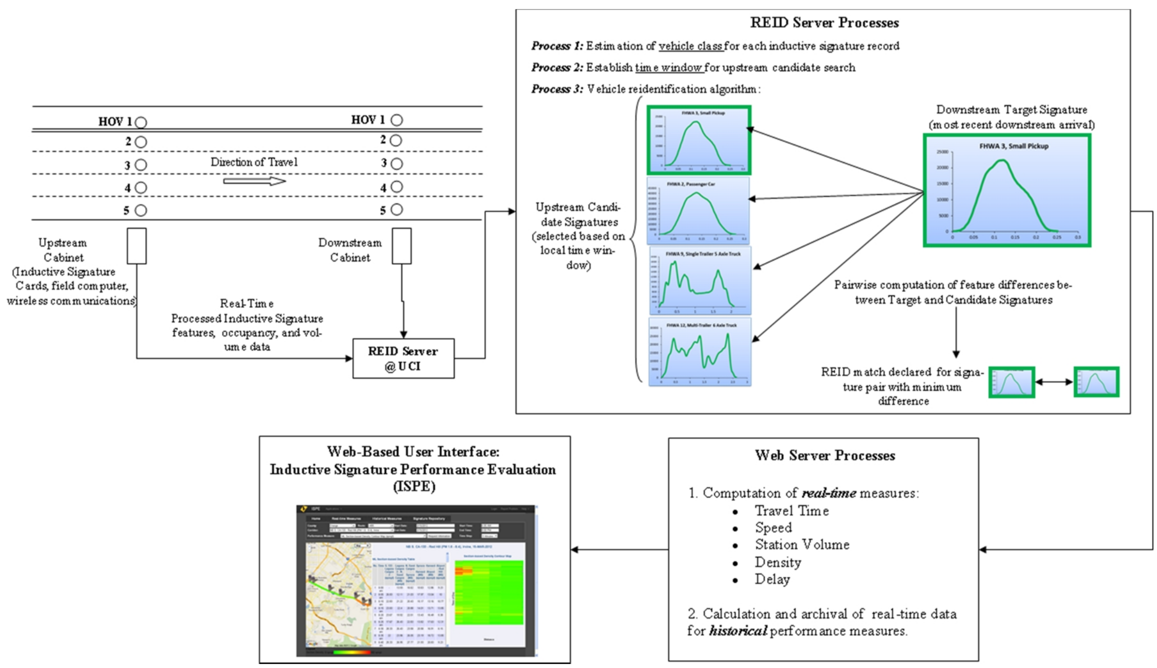


FIGURE 1 Overview of selected vehicle REID algorithm, RTREID-2 *(12)*.

TABLE 2 Vehicle Classes from Liu et al. *(18)* following the MOVES Vehicle Classification Scheme *(19)*

Vehicle Type	Class	Vehicle Class
Motorcycle	0	Motorcycle
Passenger Car	1	Passenger Car
Passenger Truck	2	4-tire single unit vehicle
Light Commercial Truck	2	
Intercity Bus	3	Buses and 4+ tire single unit Trucks
Transit Bus	3	
School Bus	3	
Refuse Truck	3	
Single Unit Short-haul Truck	3	
Single Unit Long-haul Truck	3	
Motor Home	3	

Combination Short-haul Truck	4	Multi-unit trucks
Combination Long-haul Truck	4	

Additionally, the REID and density estimation methods proposed by Coifman *(16)* represent the first attempt in obtaining spatially derived density estimates from ILDs and have been shown to be operational with purportedly low error rates. For these reasons, this method was also selected for analysis in this paper. A description of the density estimation approach proposed by Coifman *(16)* is provided later in the paper.

PROPOSED METHOD

As mentioned in the introduction, incorporating information about a vehicle's trajectory over space and time into density estimation would significantly improve the accuracy of the estimate. In this section, the theoretical framework for the density estimation algorithm is presented, followed by a description of the inductive signature REID and classification based density estimation method. Further, an explanation of how the proposed method is adapted to work in real-time is provided. And finally, a comparison between the proposed signature based density estimation algorithm and the selected alternative method by Coifman *(16)* is provided.

Theoretical Framework

Intrinsically, vehicle trajectories over a section of roadway can provide a direct count of the number of vehicles in that section at any given time and therefore provide an accurate density measure. In more detail, for a closed section of a multi-lane roadway where all vehicles are matched at the entry and exit points, assuming that no vehicles can go in reverse, the trajectory of each vehicle is represented by non-decreasing functions as shown in FIGURE 1. The intersecting trajectories in FIGURE 1 illustrate that arrival and departure order is not preserved in multi-lane facilities, since vehicles may change lanes. Trajectories crossing the horizontal lines which represent the up and downstream stations give the corresponding entry and exit times of each vehicle.

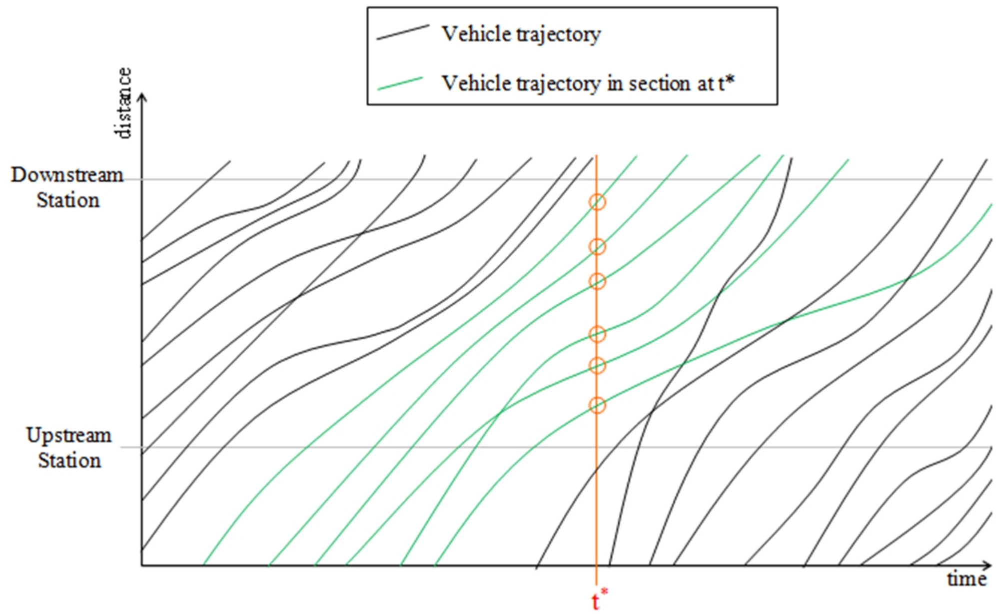


FIGURE 2 Trajectory diagram for a section of roadway identified by an upstream and downstream station in which all trajectories are known

At any given time (t*), the number of vehicles within the section can be obtained by finding the number of trajectories that intersect the vertical line, shown in orange in FIGURE 1, at t* between the upstream and downstream stations. Since each trajectory is a non-decreasing function, a vehicle is within the section if and only if it crosses the entry point before t* and exits after t*. Hence, even if vehicles cannot be directly observed within the section, the number of vehicles within the section at t* can be determined by summing the number of vehicles which meet the following two criteria: (1) the time crossing the entry point is earlier than t*, and (2) the time cross the exit is greater than t*.

Since the number of lane-miles within the section is readily obtainable as the sum of the length of each lane found within the section (for lanes without drops, the length would be equivalent to the length of the section), the density of the section at t* can be expressed as the number of vehicles in the section at t* divided by the number of lane-miles as shown in Equation 1.

$$k(t^*) = \frac{\sum_{i=1}^{N} f(n_i)}{\sum_j l_j} \quad \text{Eq. 1}$$

where

$k(t^*) = density\ at\ t^*$

$f(n_i) = \begin{cases} 1 & if\ t_{i1} < t^* and\ t_{i2} > t^* \\ 0 & otherwise \end{cases}$

$l_j = length\ of\ lane\ within\ section\ for\ j\ lanes$

This method is referred to as 'theoretical' because existing real-time vehicle REID approaches do not produce trajectory or entry and exit times for *all* vehicles, but rather for some proportion of the vehicle population *(9-14)*. Thus a temporal-spatial search method for estimating coarse trajectory information of unmatched vehicles was developed.

Inductive Signature REID Based Density Estimation Algorithm

Assume that only a sample of vehicles is tracked at the entry and exit points. The density of the section at t^* can still be estimated using the theoretical framework if travel characteristics of the sample of matched vehicles is representative of the overall population that were present in the section at t^*. Hence, FIGURE 3 is adapted from the theoretical framework (see FIGURE 2) such that some vehicle trajectories and entry and exit time pairs remain unknown as a result of the RTREID-2 algorithm. In FIGURE 3, the unmatched vehicles' actual trajectories are shown as grey lines, with short solid lines representing an actuation of the upstream or downstream station sensor. Green lines are partially known vehicle trajectories that result as output of the REID algorithm. These trajectories are considered to be 'partially known' since only the entry and exit times and upstream and downstream lane assignments are known but the full trajectories is unknown. Orange circles indicate the vehicles which contribute to traffic density and thus should be counted during the estimation algorithm. Note that although some trajectories are unknown, crossing times, station volumes, and vehicle class at the upstream and downstream stations are known, though not as pairs.

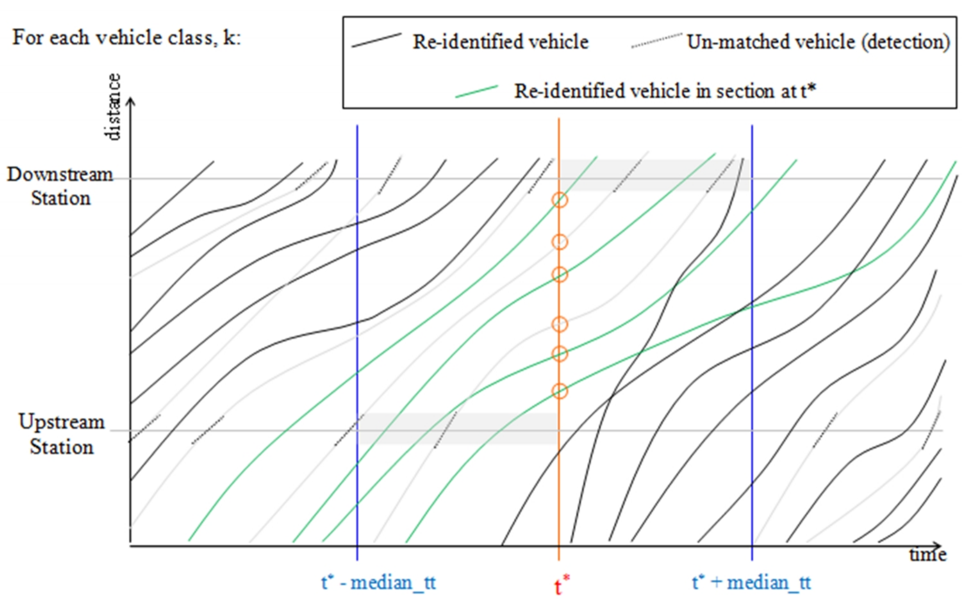


FIGURE 3 Trajectory diagram considering a REID system with unmatched vehicle pairs

In order to capture the presence of the unmatched vehicles, a temporal and spatial aggregation approach is required to count the possible number of unmatched vehicles within the section at t^*. To appropriately count density-contributing unmatched vehicles, knowledge of the vehicle type and lane presence of unmatched vehicles is used. The proposed inductive signature REID based density estimation algorithm which follows from FIGURE 3 is outlined in the flow chart shown in FIGURE 4 and detailed as follows. First, vehicles within the section at *t**, i.e. vehicles with an upstream station crossing time less than *t** and a downstream station crossing time greater than *t**, are counted and referred to as the count of matched vehicles, $V_{matched}$. Second, the set of matched vehicles is used to compute a median travel time, $t_{median,\,k}$, by class and lane facility type (such as single or high occupancy lanes). Third, the upstream set of unmatched vehicles, V_{up}, is determined by counting the unmatched vehicles which passed the upstream station between $t^* - t_{median,\,k}$ and t^* by vehicle class. At the same time, the downstream set of unmatched vehicles, V_{down}, is determined by counting the unmatched vehicles which passed the downstream station between t^* and $t^* + t_{median,\,k}$ by vehicle class. Fourth, the count of matched vehicles known to be in the section at t^*, $V_{matched}$, the upstream and downstream unmatched vehicles possibly in the section at t*, V_{up} and V_{down}, respectively, are combined to get the total count of vehicles in the section at t^*, $N(t^*)$. Lastly, the density of the freeway section, $k(t^*)$, is computed by dividing the total count by the section length, d, as shown in the last step of FIGURE 4.

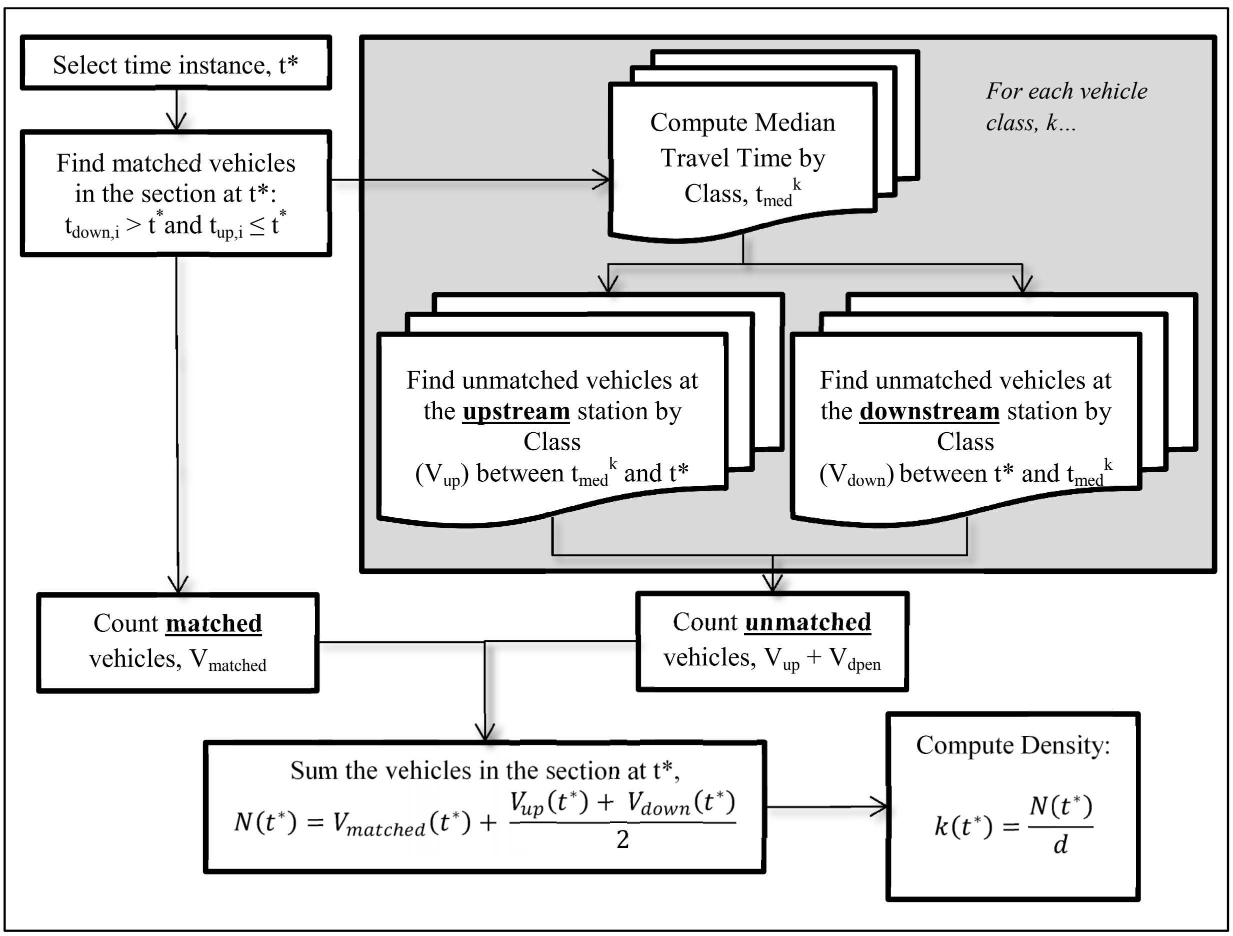
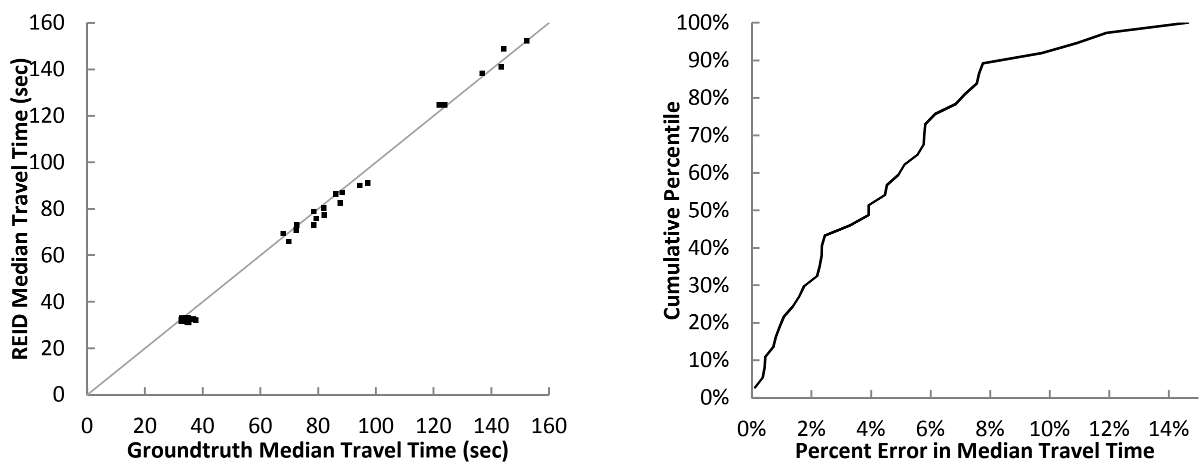


FIGURE 4 Flow Chart of the Inductive Signature REID Based Density Estimation Algorithm

DETAILS REGARDING THE USE OF MEDIAN TRAVEL TIME

The use of median travel time of matched vehicles is able to capture the population of unmatched vehicles that may be in the section and thus contribute to the section density with minimal error with a corresponding mean absolute percentage error (MAPE) of 4.45 percent for all vehicle classes and 2.43 percent for class 1 vehicles only. FIGURE 5 depicts the comparison between median travel times based on all re-identified and groundtruth vehicle pairs found within the section at the same one-minute time instances. The cumulative percentile plot shows that 90% of the REID median travel times have errors of fewer than eight percent. Occasionally, there may be no matched vehicles for a given vehicle class, especially during periods when vehicle of that particular class are severely under-represented. In such circumstances, the median travel time across all vehicle classes is used for that class.

Furthermore, both upstream and downstream unmatched sets are expected to include some fast vehicles that were not in the section as well as miss out on some slow vehicles that were in the section at *t**. However, the use of median travel times in the sampling frame would cause most of these errors to cancel out, since it has been shown that the travel time distribution obtained from the matched set is similar to the unmatched set.



(a) (b)

FIGURE 5 (a) A comparison of average and median travel times for REID and groundtruth data at one minute time slices and (b) cumulative percentile of the MAPE error in median travel time for REID against groundtruth data.

Real-Time Adaptation of the Inductive Signature REID Based Density Estimation Algorithm

The density algorithm presented requires that all vehicles in the section at the sampling instance exit the downstream station before the density can be estimated. Two related issues arise in obtaining real-time measures of density using this approach. Since vehicles can only be determined to be within the section at the sampling instance after they have traversed the downstream station, the density can only be determined after the last vehicle sampled exits the section. More importantly, since it is impossible to know when the last vehicle leaves the section, a large enough lag time needs to be considered before the density estimate can be obtained which limits its ability to provide current density estimates. Hence, a modification to the algorithm is suggested for real-time applications, and is presented in the flow chart of FIGURE 6. In essence, the requirement for all vehicles to exit the downstream station is relaxed in this variation of the original algorithm. This is achieved by modifying the approach used to estimate the median vehicle class travel times as well as the up- and down-stream unmatched set.

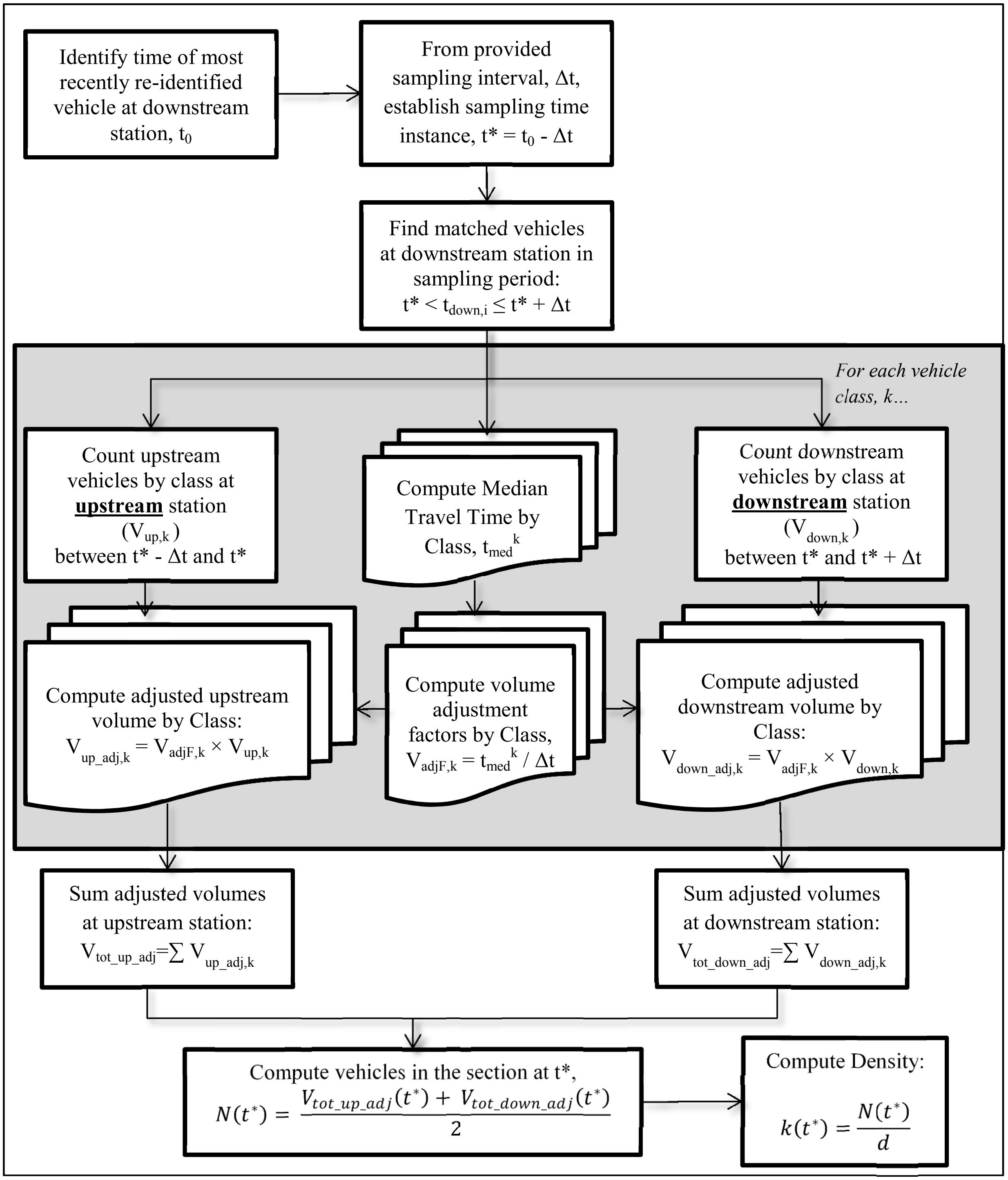


FIGURE 6 Flow Chart of the Inductive Signature REID Based Density Estimation Algorithm adaptation for real-time application

Comparison of the Signature Based REID Based Density Estimation Algorithm to the Selected Alternative Method

As mentioned in the Introduction, a second density estimation method based on an alternate method of vehicle REID which uses bivalent loop outputs, as opposed to inductive signatures, was selected for comparison to the proposed method. Coifman's density estimation method *(16)* combines travel time information with station volumes to derive density by assuming that as a matched vehicle traverses the section all vehicles that passed the upstream station after the matched vehicle entered the section must still be in the section when the matched vehicle exits at the downstream station. Accordingly, all vehicles that crossed the downstream station as the matched vehicle traversed the section would have exited the section by the time the matched vehicle crossed at the downstream station. Thus, for each matched vehicle, two values of density are estimated for the upstream and downstream stations at t_1, and t_2, corresponding to the upstream and downstream traversal time of matched vehicle according Equations 2 and 3.

For each matched vehicle pair $[N_u(t_1), N_D(t_2)]$:

$$k_{CT,U}(t_2) = \frac{N_u(t_2) - N_u(t_1)}{d} \quad \text{Eq. 2}$$

$$k_{CT,D}(t_1) = \frac{N_D(t_2) - N_D(t_1)}{d} \quad \text{Eq. 3}$$

where

t_1 and t_2 = upstream and downstream station traversal time

$N_u(t_1)$ *and* $N_u(t_2)$ = cumulative upstream vehicle number at times t_1 and t_2

$N_D(t_1)$ *and* $N_D(t_2)$= cumulative downstream vehicle number at times t_1 and t_2

$k_{CT,U}(t_2)$ = upstream density at times and t_2

$k_{CT,D}(t_1)$ = downstream density at times and t_1

d = distance between the upstream and downstream stations

Some key differences between the density estimation method proposed by Coifman and the method proposed in this paper are (1) the continuity of density estimates over time and by lane, (2) the reliance on travel times estimates from certain vehicle classes, and (3) assumptions of lane changing behaviors. First, Coifman's model produces two estimates of density, one at each location corresponding to the times a matched truck crosses the upstream and downstream station. The method proposed in this paper samples multiple matched vehicles, and provides a single estimate of density that represents the section at a time instance. Second, Coifman's model identifies the travel time of a truck, then assumes that all vehicles in the traffic stream share the same travel time as the matched truck (which is usually slower than smaller vehicles, especially for multi-lane facilities). The model proposed in this paper establishes the median travel time for each vehicle class to account for their representative travel times to identify unmatched vehicles that may be in the section corresponding to the sampling time instance. Third, Coifman's reidentification model assumes that most vehicles will not change lanes so that platoons of vehicle entries and exits into the roadway section are maintained. Because of these constraints, the usefulness of the method may be restricted to road facilities with single or few lanes where queue discipline is maintained such that vehicles follow first-in-first-out queuing procedures and truck section travel times are similar to general traffic. The REID method used in this paper makes no assumptions about lane assignments in matching vehicles and the density estimation algorithm counts of vehicles in the section are based on matched vehicle pairs.

RESULTS

Density estimated from PeMS adaptive g-factors, Coifman's estimation algorithm based on REID of long vehicles *(16)*, and the proposed inductive signature REID based density algorithms were evaluated for the same study area at one and five minute intervals. Each was compared to groundtruth data captured from video analysis. This section provides details on the study area, groundtruth data process, and comparison of the three density estimation methods.

Study Area

Data was collected from I-405N in Irvine, California. FIGURE 7 depicts the study area. The mainline stations at Laguna Canyon 1 (LC1) and Sand Canyon (SC) comprise a 0.66-mile segment spanning four mainline and two high occupancy vehicle lanes in the northbound direction. The study segment also contains an off-ramp at Sand Canyon (SC Off-ramp) for which data were also collected. Each of the detector locations contains double square inductive loop detectors that are connected to advanced loop detector cards located in the traffic cabinets adjacent to the freeway. The detector cards are connected to the field computer, a small industrial PC running a Linux operating system, via a USB interface. The detector cards process inductance signals at 1200 samples per second as vehicles pass over the loop sensors, while a client program logs these in binary format to the PC hard drive. All PC clocks were synchronized with side-fire video recorders.

Additionally, point data from PeMS was downloaded for the same study section and time period. This data consisted of 30-second loop detector occupancy and five minute g-factor estimates for the mainline and HOV lanes at Laguna Canyon (PeMS VDS ID #1209176 and #1209177) and Sand Canyon (PeMS VDS ID# 1213963 and #1213966). Although loops at these two locations are different from the loops in the Irvine detector testbed described above, they are located within very close proximity as shown in FIGURE 7, and are expected to share similar corresponding g-factor values.

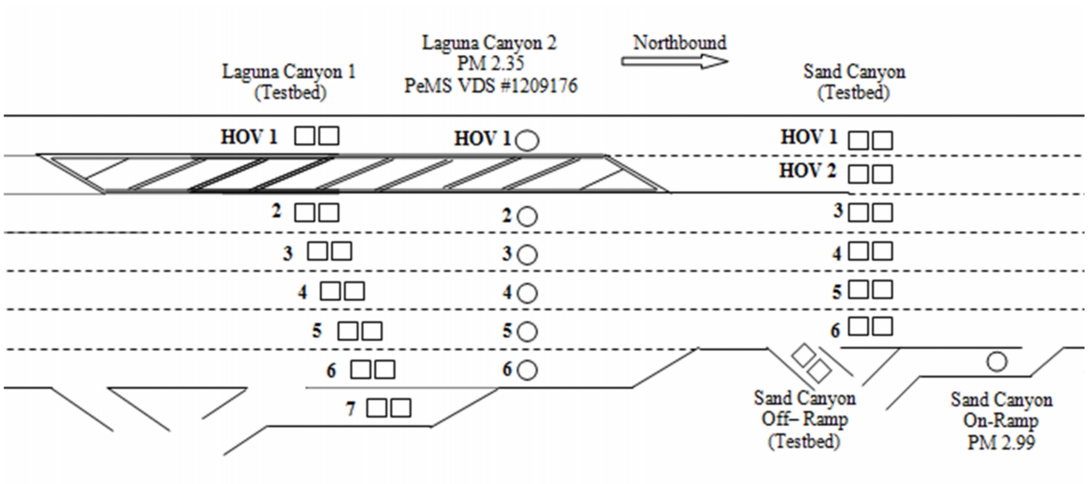


FIGURE 7 Study Area, I-405 Northbound between Laguna Canyon 1 and Sand Canyon in Irvine, California

GROUNDTRUTH DATA

Side-fire camcorders were set up at three locations (LC1, SC, and SC Off-ramp) to record vehicles traversing the entry and exit detector stations. Video and signature data were collected during the morning peak period continuously from 6:35AM to 10:00AM on Tuesday, May 12th, 2009. The vehicles observed in the video were matched to their corresponding inductive signature, and were matched between detector stations spanning the section as well.

The groundtruth dataset of vehicle matches between the upstream and downstream detector stations was obtained for nine distinct non-overlapping three to five minute periods spread throughout the three and a half hour period, capturing both congested and uncongested conditions. The total groundtruth dataset consisted of vehicle matches and classifications of 5,712 vehicle pairs. Groundtruth density was obtained by determining the actual number of vehicles in the section at specific times, then dividing the result by the sum of length of lanes within the section. The number of vehicles within the section was obtained from the set of groundtruth vehicle matches that had crossed the upstream detector prior to each time instance and the downstream detector subsequent to the corresponding time instance.

A NOTE ABOUT DATA AGGREGATION AND ALGORITHM PERFORMANCE

Since PeMS provides only five minute g-factor estimates, the same g-factor value is used over each corresponding one minute sub-interval within the five minute interval, and used with 30 second occupancy measures available from PeMS. PeMS density estimates for each station were averaged together by time of day to produce a density estimate for the section, as shown in Equation 6:

$$k_{PeMS}(t) = \frac{\sum_{lanes_{up}} k_{gfator}(t,l) + \sum_{lanes_{down}} k_{gfactor}(t,l)}{2} \qquad \text{Eq. 6}$$

An attempt to estimate density using the long vehicle REID method *(16)* on the study section yielded poor results. This was likely due to the greater number of lanes and length of the section of the study site used in this study, which would result in less platoon and lane discipline, adversely affecting the ability to obtain matches. Hence, it was decided not to implement the REID procedures proposed in *(16)*, further considering that there are also several parameters which are site specific and would require re-calibration. Instead, the groundtruth dataset of trucks re-identified by video were used in place of the algorithm to ensure that all available truck matches were used for estimating density, all of which were true matches. Note that there is a temporal gap in truck REID between 9:04AM and 9:33AM in which video groundtruth of trucks was not carried out, and was not a consequence of the density estimation technique. This does not affect the results, however, since comparisons between methods are only made for the nine time periods with groundtruth data, which are fully represented using the long vehicle REID based density estimation method. The long vehicle REID based density estimation method produces two density estimates per matched vehicle, one for each station corresponding to two different times (the upstream and downstream traversal times, t_2 and t_1, respectively): $k_{LV,\mathrm{u}}(t_2)$ and $k_{LV,\mathrm{d}}(t_1)$. Therefore, to compare to the proposed section-based method, the two density estimates were averaged by time and reported for the entire section. Equation 7 was applied to aggregate the separate station estimates resulting from the CT-density algorithm.

$$k_{LV}(t^*) = \frac{\sum_{t_2,t_1 \in [t^*, t^*+t^{int}]} k_{LV,u}(t_2) + k_{LV,d}(t_1)}{N} \qquad \text{Eq. 7}$$

where
t^* = time instance for calculating density
t^{int} = time aggregation interval
$k_{LV,u}(t_2), k_{LV,d}(t_1)$ = density estimated for upstream and downstream stations at t_1 and t_2
N = number of re-identified vehicles between t^* and t^{int}

COMPARISON OF DENSITY ESTIMATES

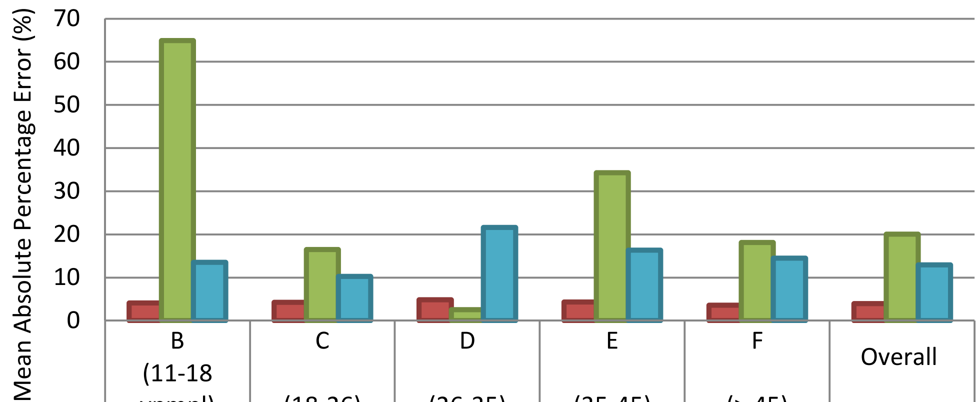
Each method was compared against groundtruth density. Density estimates were evaluated based on the mean absolute percentage error (MAPE), computed by Equation 8:

$$MAPE = \frac{1}{n}\sum_{n}\left|\frac{x_{MODEL} - x_{GT}}{x_{GT}}\right| \times 100\% \qquad \text{Eq. 8}$$

where
x_{MODEL} is the performance measure of the model being compared
x_{GT} is the performance measure of the groundtruthed data
n is the number of samples in the data set

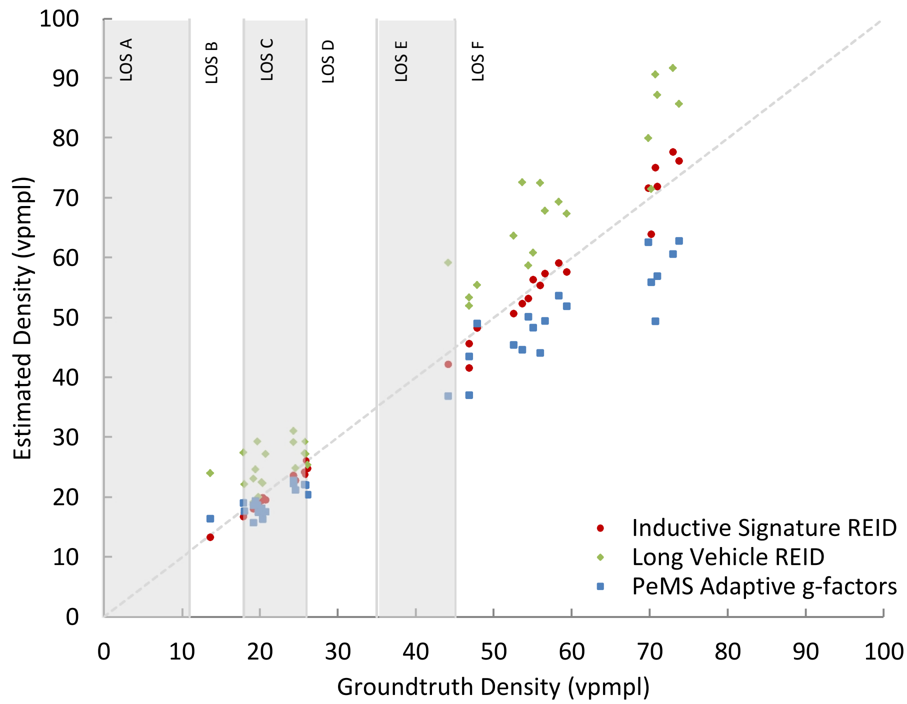
FIGURE 8 depicts the correlation between the inductive signature REID, long vehicle based REID, and PeMS adaptive g-factor density estimates with the groundtruth density for one-minute time aggregation/instance. FIGURE 9 depicts the one-minute time density estimates each of the three algorithms. The overall MAPE for each algorithm is shown in TABLE 3 along with the MAPE by LOS as defined by the Highway Capacity Manual for multilane highways *(1, p. 298)*. Note that during the study period, the freeway section did not experience LOS A.

TABLE 3 MAPE by LOS for the inductive signature REID based density algorithm, the long vehicle REID based density algorithm, and PeMS adaptive g-factor based density estimation methods.

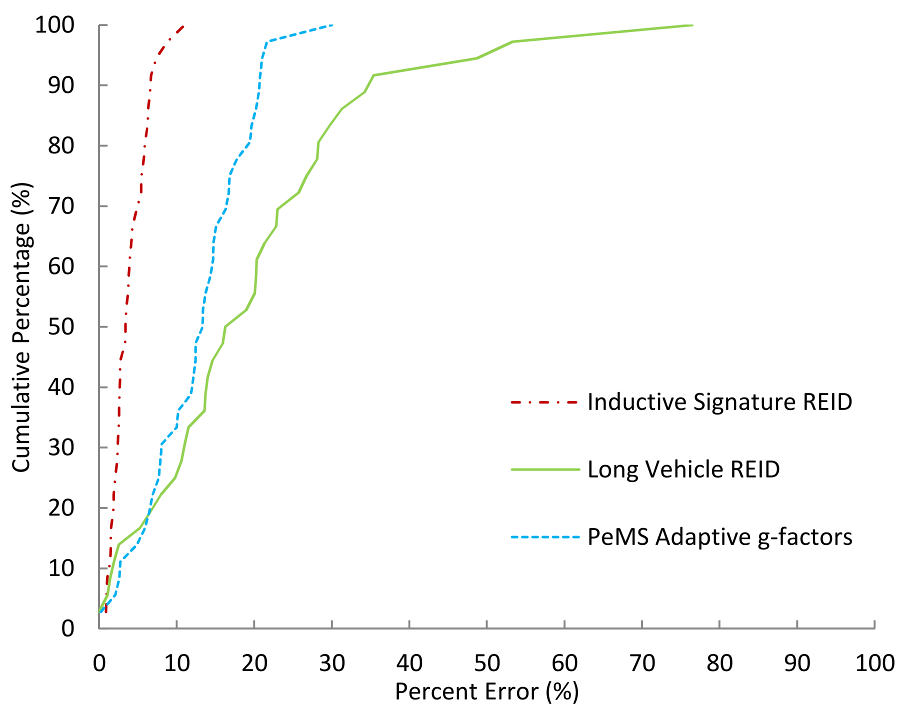


	B (11-18 vpmpl)	C (18-26)	D (26-35)	E (35-45)	F (> 45)	Overall
Inductive Signature REID	4.1	4.3	4.8	4.3	3.6	3.9
Long Vehicle REID	64.9	16.5	2.5	34.3	18.2	20.1
PeMS Adaptive g-factors	13.6	10.3	21.6	16.3	14.5	12.9

Level of Service (LOS)



(a)



(b)

FIGURE 8 Comparison of inductive signature REID based, long vehicle REID based, and PeMS adaptive g-factor based density estimation algorithms to groundtruth data for one-minute aggregation/time instance: (a) correlation comparison and (b) cumulative error distribution.

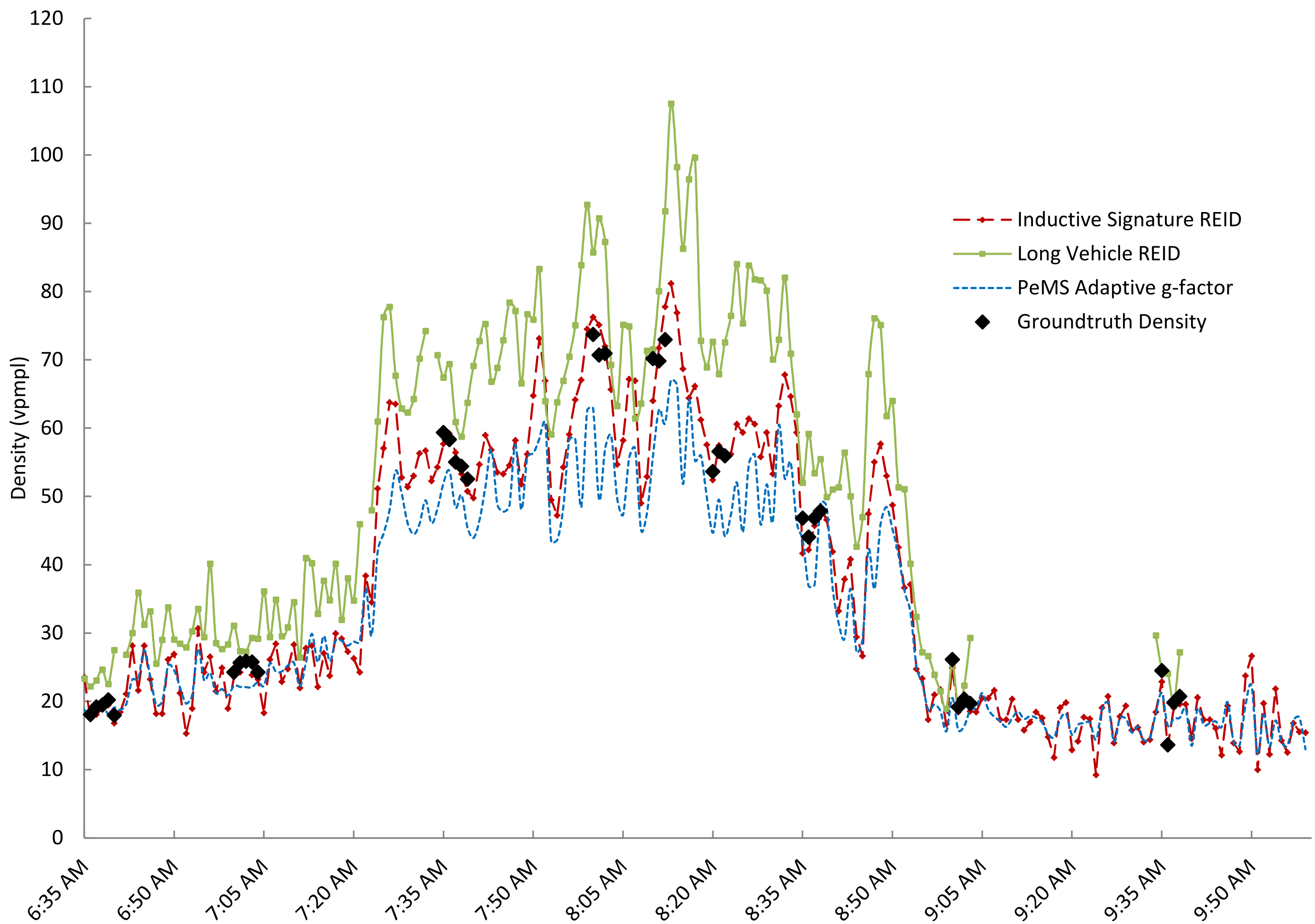


FIGURE 9 Comparison of density estimation methods: inductive signature REID, long vehicle REID, and PeMS adaptive g-factor for **one minute** time instances.

DISCUSSION

The groundtruth dataset used for model comparison contains highly congested and uncongested conditions ranging from around 20 to 75 vehicle per mile per lane (vpmpl). Of the density estimation methods compared in this paper, the inductive signature REID based method provides the most accurate depiction of the section density with under 4 percent MAPE at one minute time intervals.

The point-based method which uses occupancy and adaptive g-factors provided by PeMS at the upstream and downstream stations tends to underestimate the section density during periods of congestion. A possible explanation could be due to the inability of the point-based density estimation approach to account for the traffic condition between detector stations. In addition, it can be observed that the trend of density estimates by PeMS do not follow closely to groundtruth. This may also be explained by the use of a fixed g-Factor value over five-minute periods, which are not sensitive to the changes in proportions of long vehicles present in the section that result in dynamic g-Factors beyond the fidelity provided by PeMS. Additionally, clock synchronization is not guaranteed between the PeMS and study clocks, therefore estimates may be slightly unsynchronized, but as can be seen in FIGURE 9, this is unlikely the cause for most of the large errors. Alternately, to provide a less direct comparison of point to section measures, dual loop vehicle length estimates at the same loop locations as those used by RTREID-2 could be calculated to determine point based density. This was not done for this paper, since a direct comparison to PeMS adaptive g-factors was the main interest.

The long vehicle REID based density estimation method relies on the travel times of a sparse REID set of long vehicles to compute density. This method is employed because long vehicles may be captured from bivalent loop outputs during congested and uncongested conditions. The results show that density estimates based on this method—even with the use of groundtruth set of matched vehicles to obtain section travel travel times—tend to overestimate section density. This can be expected as the algorithm uses the resulting travel time from long vehicles to count cumulative volumes at the upstream and downstream stations. Since long vehicles typically correspond to trucks with longer travel times, the corresponding counts obtained are expected to result in higher estimates of density. Also, temporal and spatial aggregation is difficult considering that two density estimates are provided at different times for each matched vehicle at both the upstream and downstream lanes. It is difficult to estimate density in the presence of a lane drop, such as at the study site, without aggregating the density estimates across all lanes and at specified time intervals, which limits the ability to provide density estimates by lane or lane-type (i.e. HOV or main line). Coifman suggests that the density algorithm is mostly useful for diagnosing periods in which there is detector drift/error and to determine lane-inflows/outflows from ramps or high percentage of lane change maneuvers. Notwithstanding, the long vehicle REID algorithm is expected to yield better results when applied on a shorter section with fewer lanes, since the difference in travel times between trucks and the overall traffic may not be as significant and platoon discipline is expected to be maintained.

CONCLUSIONS

The paper describes a method to estimate traffic density using travel time information from re-identified vehicles and vehicle class counts at the entry and exit stations. The algorithm was compared to a point-based estimated density which relied on occupancy and time adaptive g-factors and an algorithm which used cumulative station counts and travel times from a sparse re-identification system based on matching long vehicles. The results compared against groundtruth data show that the proposed method for estimating density yielded under 4 percent MAPE, and is significantly better than the alternative methods used in comparison.

An adaption to the original algorithm is also presented for real-time applications as well. Since the proposed method does not require calibrated model parameters, it has great potential for spatial transferability. The inductive signature reidentification based density algorithm is currently deployed in the Inductive Signature Performance Evaluation (ISPE) website which demonstrates its ability to provide section density information for a corridor containing six contiguous sections between 0.13 and 2.07 miles in length and spanning a total distance of 6.8 miles.

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