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TRAFFIC STATE ESTIMATION USING FLOATING CAR DATA

Abhinav Sunderrajan, Vaisagh Viswanathan, Wentong Cai and Alois Knoll

Presented by: Abhinav Sunderrajan

Agenda

1. Background and motivation
2. Methodology
3. Experiments
   - Traffic Simulation
   - The simulated environment
   - Simulation parameters and Simulation scenarios
4. Results
5. Conclusions and Future Work

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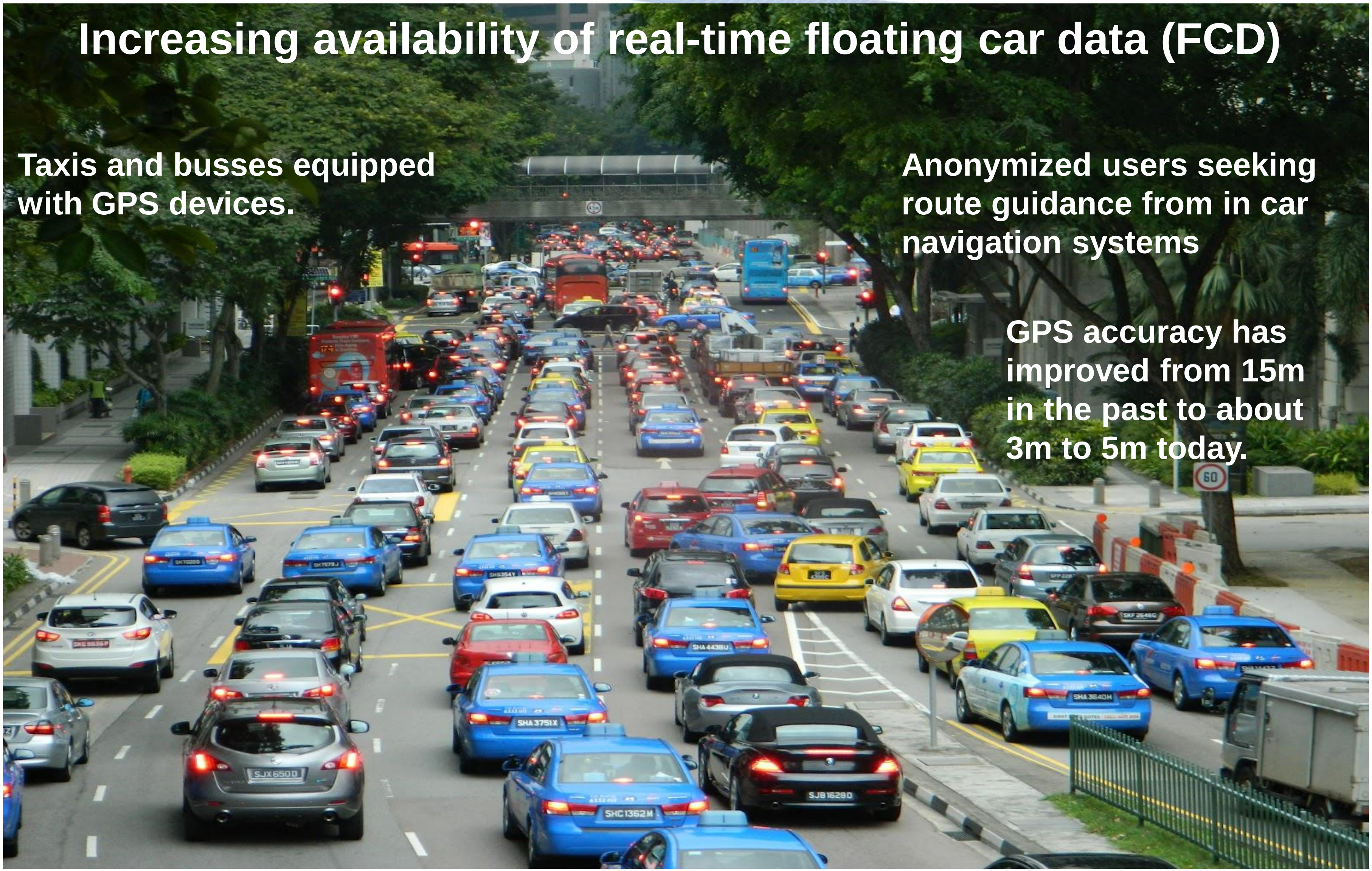
Background and Motivation



Increasing availability of real-time floating car data (FCD)

Taxis and busses equipped with GPS devices.

Anonymized users seeking route guidance from in car navigation systems

GPS accuracy has improved from 15m in the past to about 3m to 5m today.

Background and Motivation

Next generation ERP could be Global navigation satellite system based.

Thus most vehicles will have GPS receivers emitting data such as location and speed at fixed time intervals.

Background and Motivation

Can we leverage this real-time data stream (along with the data from traditional fixed sensors) for current traffic state estimation?

Traffic state is defined in terms of the macroscopic quantities constituting density, average speed and flow.

Background and Motivation

What are the benefits of estimating traffic state in real-time?

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Background and Motivation

Data driven adaptive traffic flow prediction and control

Data from smart phones, GPS receivers and fixed sensors.

Data stream processing

Predict and evaluate different control actions

Short term prognosis of traffic flow

Suggest the best control measure for dynamic traffic flow optimization.

Background and Motivation

Data driven adaptive traffic flow prediction and control has enormous potential in several advanced traffic management strategies.

- Dynamic ramp metering
- Congestion aware routing
- Variable speed limits in expressways

Contributions

- A methodology for obtaining aggregated macroscopic (speed, density and flow) quantities from the microscopic floating car data (FCD) represented by the tuple *{vehicle-id, speed, latitude, longitude}.*
- An estimation of the minimum percentage of probe vehicles (of total traffic) required for the macroscopic traffic state reconstruction under different traffic flow regimes. This is also referred to as *probe vehicle penetration*.

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Methodology

We employ *agent-based microscopic traffic simulations* of 13 km stretch of a real world expressway for determining a methodology for spatial aggregation of FCD and to determine the minimum probe vehicle penetration.

Image courtesy http://gamma.cs.unc.edu/HYBRID_TRAFFIC/

Methodology

- Traffic simulations were employed owing to the lack of real world data.
- Microscopic models describe traffic from the perspective of individual driver-vehicle units (DVUs).
- These high fidelity simulations help capture the heterogeneities in traffic in terms of different vehicles classes (e.g. cars, trucks) and driver behaviors (e.g. intelligent, aggressive).
- The movement of driver-vehicle units are characterized by acceleration models for longitudinal motion and lane change models for lateral movement along the road.

Methodology

Algorithm for determining the aggregate values of traffic speed, density and flow from FCD

Naively divide the expressway into 13 segments of length 1.0 km each

Make use of the topology of the expressway to divide into sections between on/off ramp pairs

Recursive binary splitting

RECURSIVE BINARY PARTITIONING OF EXPRESSWAY FOR SPATIAL AGGREGATION OF FCD

- Divide expressway into J segments such that variance of speeds within all segments is minimized.
- Formally, the goal is to find sections $S_1 \ldots S_j$ such that the total variance of speeds given by $\sum_{j=1}^{J} \sum_{i \in Sj} (vi - \widehat{v_{Sj}})^2$ is minimized for all sections.
- This is a computationally hard problem due to the infinite number of ways in which the expressway can be split into J sections.
- We use the top down greedy approach called the *recursive binary partitioning* to solve this problem.

Methodology

RECURSIVE BINARY PARTITIONING OF EXPRESSWAY FOR SPATIAL AGGREGATION OF FCD

- Identify the region along the expressway from (0.0m, 13000m) which minimizes

$$\sum_{i \in R_1} (vi - \widehat{v_{R1}})^2 + \sum_{j \in R_2} (vj - \widehat{v_{R2}})^2$$

v_i and v_j are speeds of vehicle i and vehicle j in regions R_1 and R_2 respectively. $\widehat{v_{R1}}$ and $\widehat{v_{R2}}$ represent the average speed in regions R_1 and R_2 respectively.

- Recursively Split both R_1 and R_2 until there are minimum of 10 GPS readings in each segment.

- To ensure that there is no overfitting modify the algorithm using *cost complexity pruning*

$$\sum_{t=1}^{T} \sum_{i \in Rt} (vi - \widehat{v_{Rt}})^2 + \alpha T$$

The above modifications ensures that the number of final segments the road is divided into has minimal variance for a given traffic scenario. T represents the final number of segments the expressway is divided into and $\widehat{v_{Rt}}$ represents the average speed of each of these segment $t \in T$

Methodology

- The efficacy for spatial aggregation is determined based on the best model fit that can be obtained for traffic density ρ as a function of mean speed $\widehat{V}$.
- To quantify the reliability of the model, we make use of the R^2 Statistic commonly used in linear regression.
- The R^2 Statistic is a measure of model fit in the form of a proportion of variance explained by the model.

$$R^2 = 1 - \frac{\sum(yi - \widehat{y})^2}{\sum(yi - \bar{y})^2}$$

- It takes a value between 0.0 and 1.0 and a value close to 1.0 indicates that a large proportion of the variability in the density is explained by the predictor, which in this case is the mean speed $\widehat{V}$.

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Traffic Simulation

- The microscopic simulation is based on the SEMSim platform.
- SEMSim uses the Intelligent Driver Model as the acceleration model for moving the agent/vehicle forward every time-step of the simulation.
- The IDM is an accident free model which ensures that a vehicle attains the desired velocity at free flow and maintains the safe bumper to bumper distance to the leading vehicle.

Treiber, M. and Kesting, A., 2010. An open-source microscopic traffic simulator. *Intelligent Transportation Systems Magazine, IEEE*, *2*(3), pp.6-13.

Traffic Simulation

The differential equation of IDM for moving a vehilce/agent is

$$\frac{dv}{dt} = a\left[1 - \frac{v}{v_0}^{\delta} - \left(\frac{s^{*}(v, \Delta v)}{s}\right)^{2}\right] \quad \text{where} \quad s(v, \Delta v)^{*} = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$$

- v_0 free flow speed of vehicle
- s_0 safe distance to lead vehicle.
- T desired safe time-gap
- b is the comfortable breaking deceleration.
- δ is the acceleration constant

- v is the velocity of vehicle
- s is the distance to the lead vehicle
- Δv is speed difference with respect to the lead vehicle $(v - vl)$
- **a is the acceleration of vehicle.**

IDM ensures that a vehicle's acceleration

1. Is a decreasing function of its speed.
2. An increasing function of the distance to the leading vehicle.
3. An increasing function of the speed of the leading vehicle

Traffic Simulation

- SEMSim uses MOBIL as the lane change model.
- MOBIL ensures that the resultant accelerations and decelerations for a vehicle and its followers in the old and new lanes does not exceed a safe threshold.
- A lane change is done only if a vehicle gains speed without violating the safety and inconvenience (to the old and new followers) criteria.

Kesting, Arne, Martin Treiber, and Dirk Helbing. "General lane-changing model MOBIL for car-following models." *Transportation Research Record: Journal of the Transportation Research Board* (2007).

Traffic Simulation

- The traffic simulation takes as input a road network consisting of links nodes and the lanes constituting each link.
- Road links that do not have a preceding link are considered sources and those without a subsequent link are sinks.
- Traffic thus flows from the sources to the sinks.
- Vehicles are created at each source as a Poisson process with a constant mean inter-arrival time (IAT).
- The route taken by each DVU is determined based on static turn ratios specified at each intersection.

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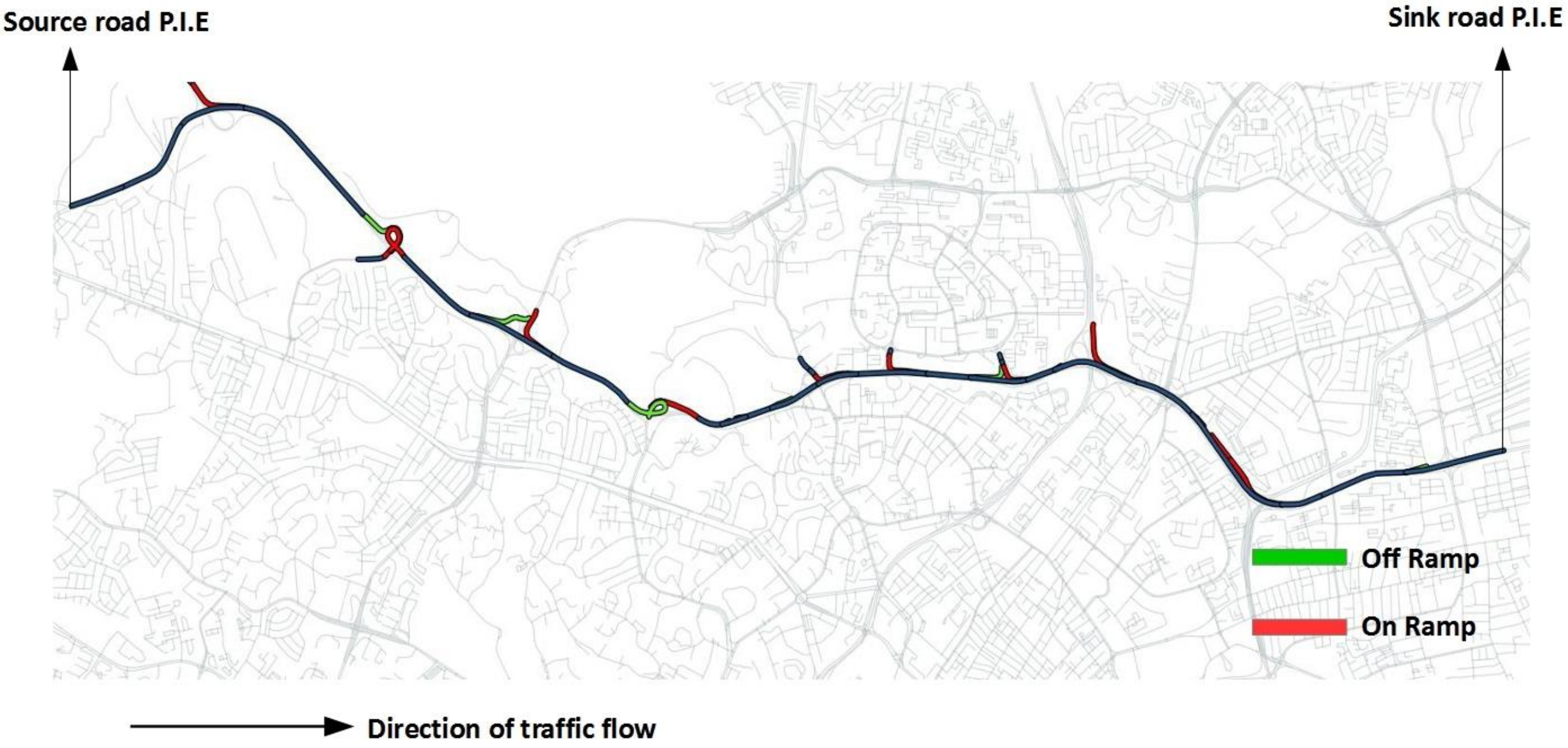
Simulated Environment



13 km stretch of P.I.E (Pan Island Expressway) in central Singapore with all on ramps and off ramps.

Simulated Environment

- The on ramps and the first P.I.E link are sources for the vehicles/agents entering the simulation.
- The off ramps and the last link on P.I.E are sinks through which the vehicles exit the simulation.
- The turn ratios for all off-ramps is kept constant at 0.25. This implies that 25% of all vehicles exit at a given o ramp while the remaining 75% of the vehicles continue to travel on the main expressway.
- The number of lanes in the simulated stretch of the expressway varies between 3 and 6.

Simulated Environment

DISTANCE (m)	RAMP TYPE
583.98	On Ramp
1973.35	Off Ramp
2489.87	On Ramp
3261.27	Off Ramp
4071.9	On Ramp
4834.84	Off Ramp
5531.18	On Ramp
5743.11	Off Ramp
5965.29	On Ramp
6207.74	Off Ramp

DISTANCE (m)	RAMP TYPE
7025.15	On Ramp
7658.4	On Ramp
8040.83	Off Ramp
8554.28	On Ramp
8807.94	Off Ramp
9591.84	On Ramp
10148.24	Off Ramp
11286.2	On Ramp
11637.04	On Ramp
12438.23	Off Ramp

Location of all on and off ramps along the expressway

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SEMSim Parameters

Simulation parameter	Description	Value
ST	Simulation time	7200 sec
s_0	Minimum bumper-to-bumper distance to the front vehicle.	2.0 m
T	Time gap to preceding agent	1.4 sec
l_i	Vehicle length	Normal distribution with $\mu = 3.0$ m and $\sigma = 0.1$ m
V_0	Desired speed of agent	20 m/s
a	Maximum acceleration term for IDM	Uniform distribution between 1.2 and 1.6 m/s^2
b	Maximum deceleration term for IDM	Uniform distribution between 1.8 and 2.2 m/s^2
p_0	Politeness factor for MOBIL	0.3
Δa_{th}	Lane change threshold for MOBIL	0.3 m/s^2

SEMSim parameters initialized at the beginning of each run

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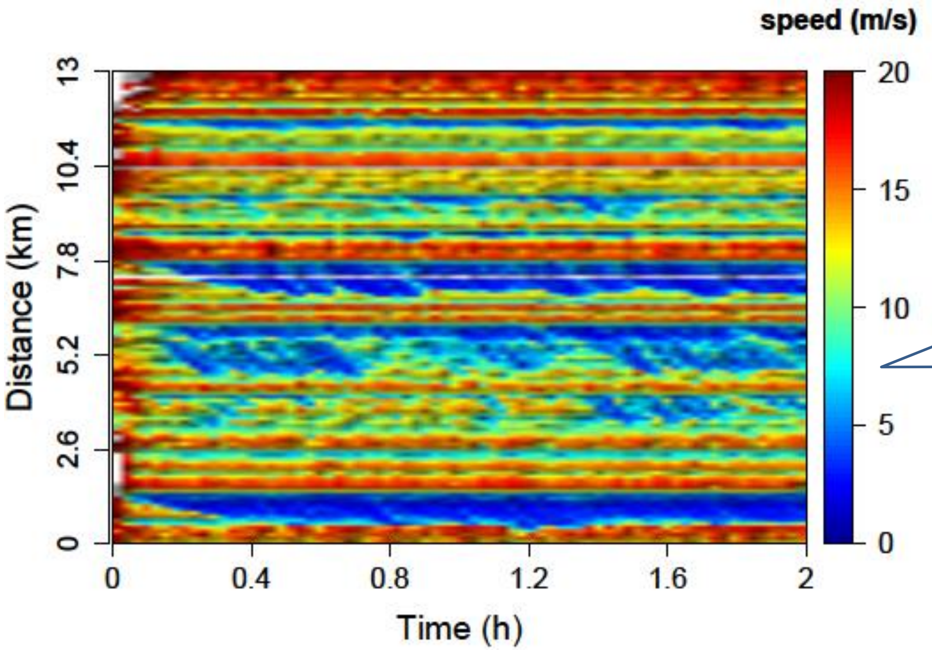
Simulation Scenarios

- The traffic density in number of vehicles/km across the expressway is controlled by varying the average inter-arrival rates at all sources along P.I.E.
- To simulate heavy congestion along P.I.E the mean IAT for all on-ramps was set to a uniform random number between 2.0 sec and 2.5 sec (representing a flow of 1800-1440 vehicles/hour) while the mean IAT for the first and only source link of P.I.E was set to 1.0 sec (3600 vehicles per hour)



The average traffic density (computed at the end of simulation) is 110 vehicles/km

The heat map represents the speed profiles of all the agents averaged over space and time intervals of 50 meters and 1 minute.

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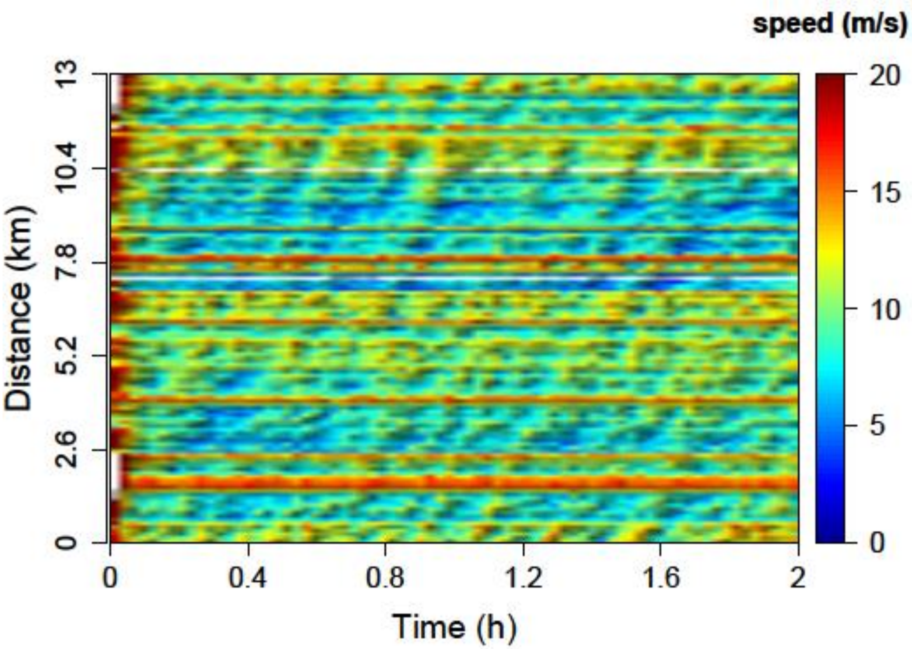
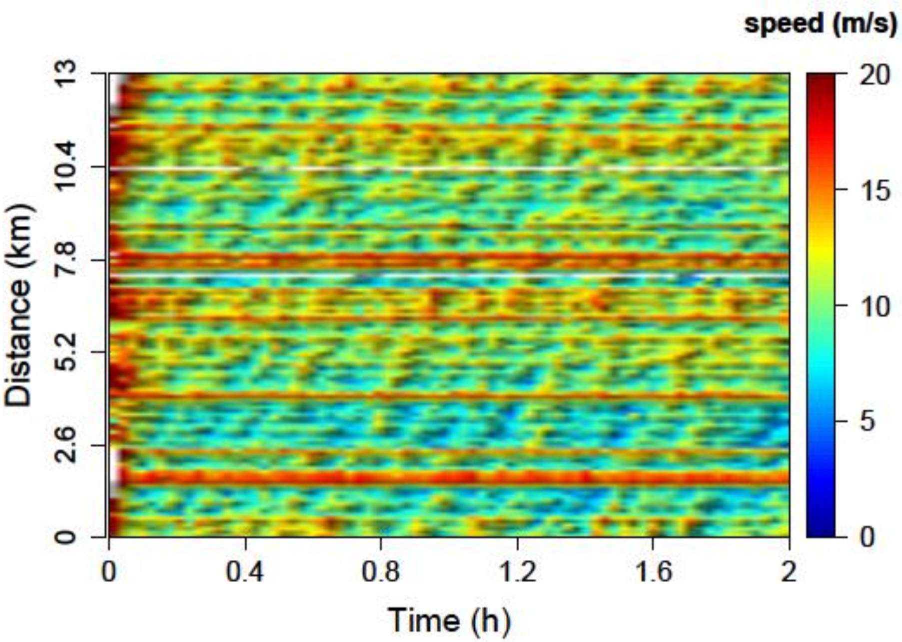
Simulation Scenarios

- The spatiotemporal state of P.I.E during partial congestion.
- The average vehicle density is 78 vehicles/km.



- The spatiotemporal state of P.I.E during non peak traffic.
- The average vehicle density is 65 vehicles/km.



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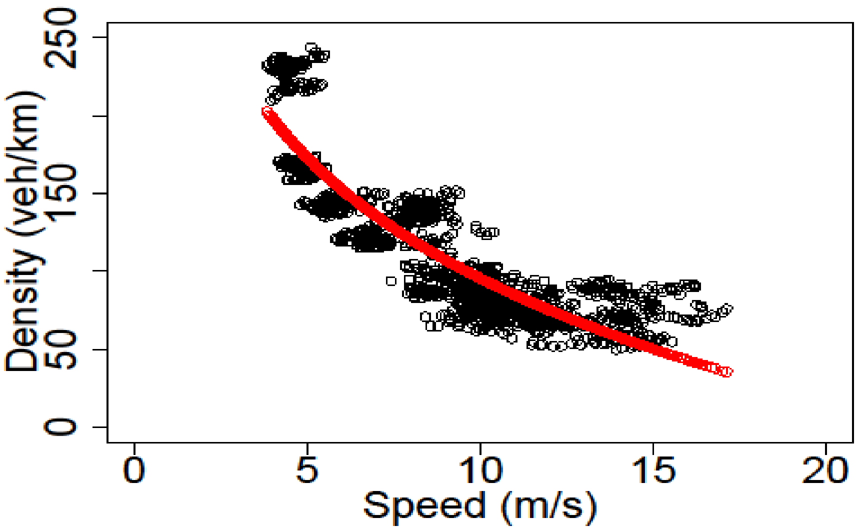
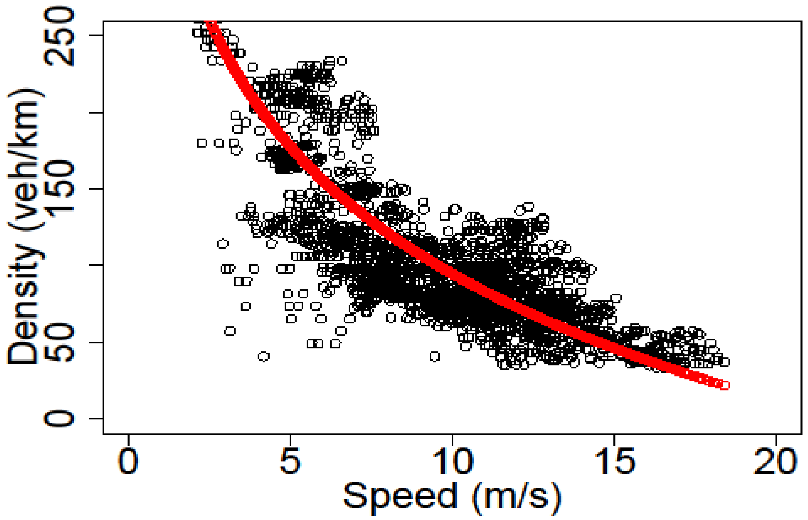
Results



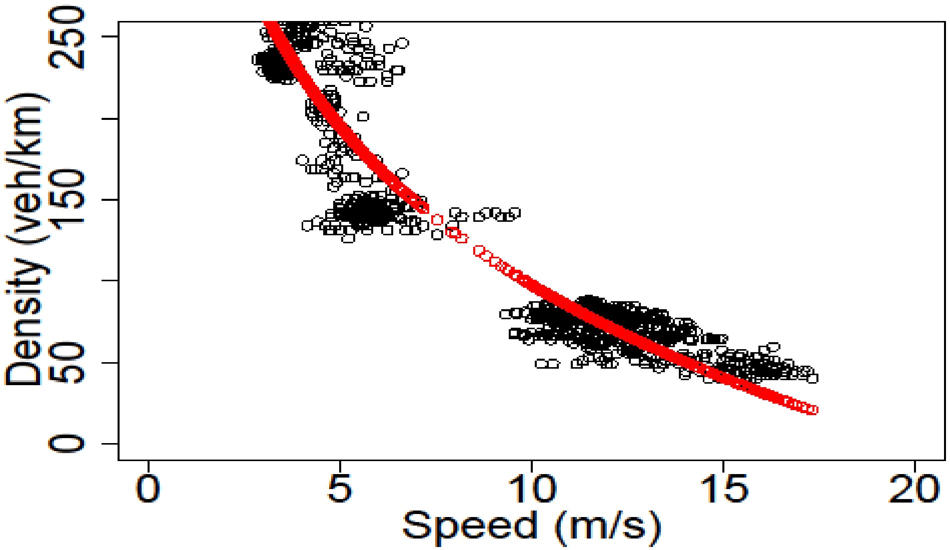
Density vs Average speed for
13 uniform partitions of length 1.0 km
(100% probe vehicle penetration)



Density vs Average speed for
25 P.I.E road segments used as
partitions (100% probe vehicle
penetration)

Both the figures clearly establish an exponential relationship (based on the linear regression fit) between average speed and density despite significant bias.

Results



Density vs Average speed for 12 segments using recursive binary splitting (100% probe vehicle penetration)

- The exponential relationship between average speed and density is of the form

$$\rho = \beta_0 + \beta_1 * \log(\hat{V})$$

- The coefficients β_0 and β_1 are the least squares coefficient estimates for linear regression.

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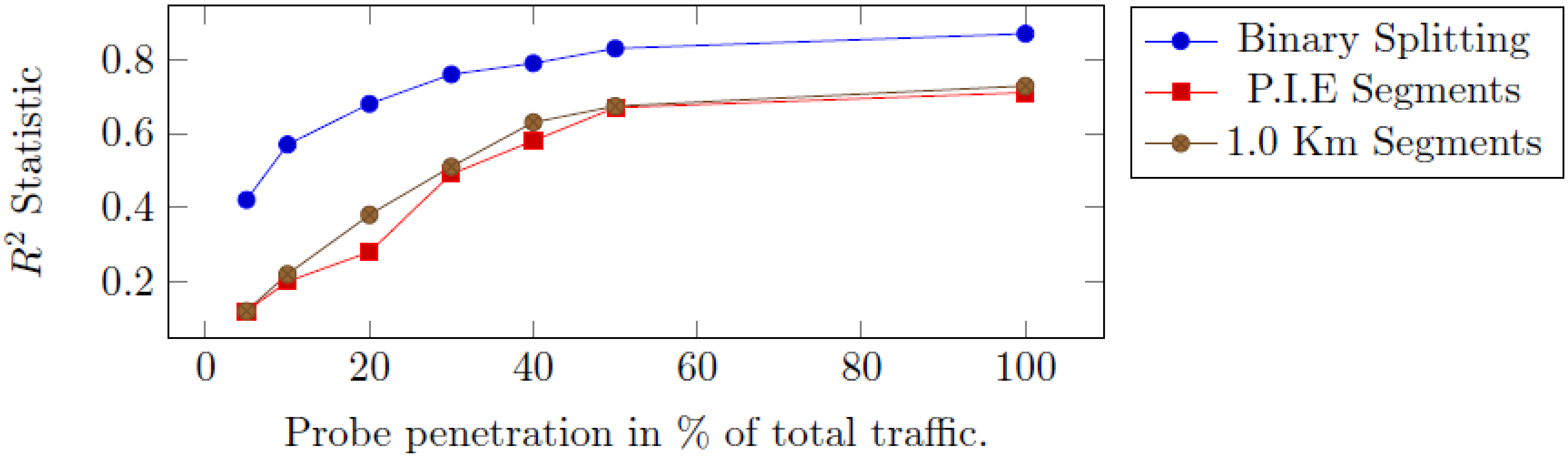
Probe Penetration for Effective Density Estimation



R^2 Statistic vs probe penetration for heavily congested traffic

- The plot shows the averaged R^2 Statistic for five different two minute sub intervals of the two hour simulation of the heavily congested traffic flow regime.
- The R^2 Statistic expectedly shows a downward trend as probe penetration decreases for all three aggregation methodologies.
- <u>The plot clearly shows binary splitting to be a superior approach for spatial aggregation enabling a reasonable estimate of traffic density even at a probe penetration as low as 5%.</u>

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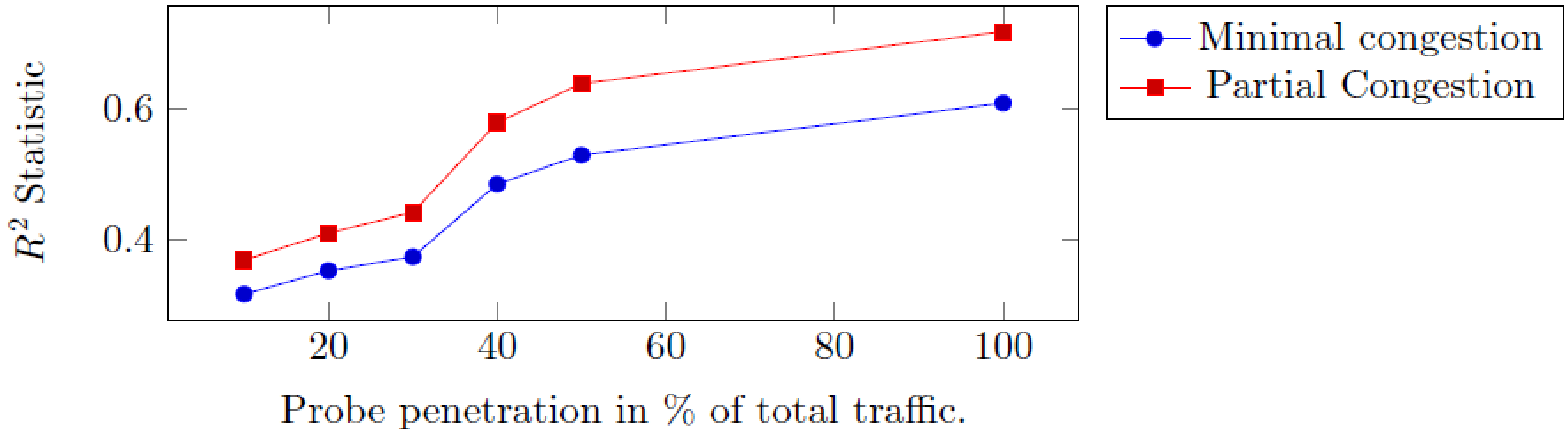
Results



- The above plot shows the R^2 Statistic (of the exponential model fit) for recursive binary partitioning approach as a function of probe penetration for the traffic conditions corresponding to the average traffic densities of 78 vehicles/km and 65 vehicles/km.
- Note that the accuracy of the model decreases as the level of congestion decreases.
- This can be explained by the fact that vehicles generally travel at uniform speeds during heavy congestion and during free flow resulting in minimum variance of speeds across lanes.
- While partially congested traffic regimes generally tend to have a far greater variance in speed due to vehicles traveling at varying speeds in different lanes.

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Conclusions & Future Work

CONCLUSIONS

- In this work we have established that reliably estimating traffic state and more specifically density (and thereby flow) on an expressway can be achieved with a minimum of 5% to 10% probe vehicles depending upon the prevailing traffic conditions.
- Microscopic traffic simulations reveal that recursive binary partitioning can be used to subdivide a stretch of road to identify relatively homogeneous regions of flow, density and average speed.

FUTURE WORK

- Future work will involve optimizing the minimum variance partitioning of the road network to automatically detect onset of congestion and anomalous events such as accidents based on statistical learning methods.
- Accurate estimation of speed, density and flow along important roads can help initialize data driven simulations for short term predictions of traffic flow.
- Predictive simulations will play a major role in enhancing the capabilities of dynamic control strategies such as ramp metering and routing for traffic ow optimization.

Thankyou for your attention!

Questions?