Arterial Traffic Estimation Using Vehicular Probe Data

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Motivation

- Is it possible to estimate arterial traffic information from a low-frequency probe vehicle data feed?

Data Feed

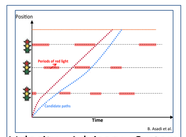
- A public probe vehicle data sent from transit buses in the city of San Francisco.

Aggregated plot of all bus updates for a period of 24 hour in the city of San Francisco.

Applications

- It is successfully shown here that it is possible to use probe data to estimate:
  - Signal Phase and Timing (SPaT)
  - Travel time statistics along the road
  - Queue patterns
  - Vehicle trajectory

with applications in:



Velocity Advisory System uses SPaT data to calculate velocity trajectories that reduce idling time at red.

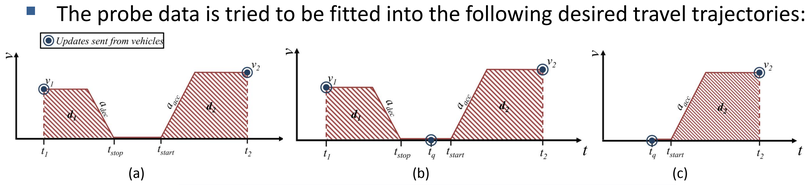
Start-stop system can use SPaT to deactivate the system during very short red light intervals.

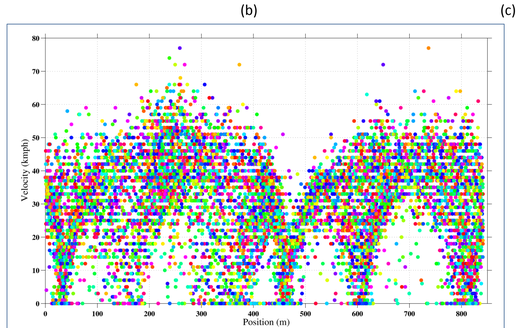
Active Safety System can use SPaT data to warn the driver if the light will turn to red in few seconds.

Arterial Performance Measurement methods can use the estimated travel time as input.

Signal Phase and Timing (SPaT) Estimation

- The probe data is tried to be fitted into the following desired travel trajectories:





The scatter plots of San Francisco Route 28 bus updates over one month correctly depicts the location of intersections and bus stops.

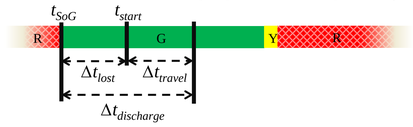
- The key feature of the proposed SPaT estimation approach is estimating the delay between green-initiations (t_{SoG}) and the moment that a stopped vehicle in queue starts moving at green. This delay is called lost time in queue (Δt_{lost}):

$$t_{SoG} = t_{start} - \Delta t_{lost}$$

Queue Flow Statistics

- We assume the discharge time of a N-sized queue consists of two parts:
  - The interval that it takes the vehicle N to start moving after green-initiation (Δt_{lost})
  - The interval that it takes that vehicle to travel all the way up to the stop-bar (Δt_{travel})

$$\Delta t_{discharge} = \Delta t_{lost} + \Delta t_{travel}$$

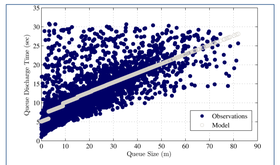


- An analytical solution for the queue discharge time ($\Delta t_{discharge}$) is proposed as given in:

$$\Delta t_{discharge} = \sum_{n=1}^{N} Headway(n) = h.N + l.\sum_{n=1}^{N} e^{-n+1}$$

which is a linear combination of :
- saturation headway (h)
- marginal headway (l)

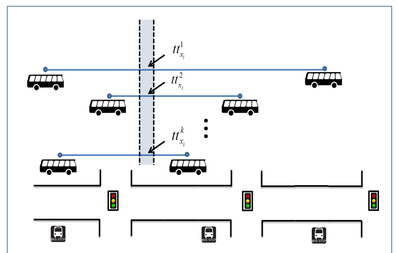
The Multiple Linear Regression model (MLR) is used to estimate these parameters based on the observational data.



Comparing the MLR estimation of Queue Discharge Time to the observational data

Trajectory Estimation

- We present a method of generating the most likely trajectory based on segment travel time statistics.
- We use EM algorithm to obtain segment travel time with maximum likelihood:
  - E step: Find the mean and standard deviation of travel time for each segment
  - M step: Segment travel times are reallocated such that the sum of the log likelihood function for each update pair (observation) is maximized. It is a Constrained Quadratic Programming (CQP) problem.



Schematic of segment travel time

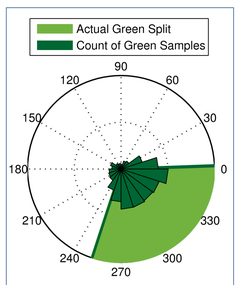
$$\underset{y}{\operatorname{argmin}} J = \frac{1}{2} y^T Q y + c^T y$$

$$s.t. \sum_{i=a_1}^{a_n} tt_{x_i}^k = tt_{[x_{a_1}, x_{a_n}]}^k$$

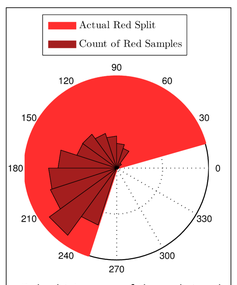
$$y = \begin{bmatrix} tt_{x_{a_1}}^k \\ tt_{x_{a_2}}^k \\ \vdots \\ tt_{x_{a_n}}^k \end{bmatrix}, Q = \begin{bmatrix} \frac{1}{\sigma_{x_{a_1}}^2} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sigma_{x_{a_2}}^2} & \cdots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & \frac{1}{\sigma_{x_{a_n}}^2} \end{bmatrix}, c = -\begin{bmatrix} \frac{\mu_{x_{a_1}}}{\sigma_{x_{a_1}}^2} \\ \frac{\mu_{x_{a_2}}}{\sigma_{x_{a_2}}^2} \\ \vdots \\ \frac{\mu_{x_{a_n}}}{\sigma_{x_{a_n}}^2} \end{bmatrix}$$

- We can predict trajectory by assuming a bus follows mean segment travel time. If there is delay, we use the same method to allocate delay into each segment.

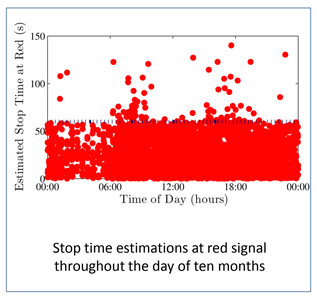
Results



Green times mapped to one circular cycle interval in polar histograms (ten months data)

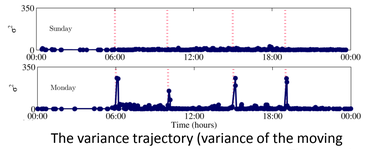


Polar histogram of the red signal timestamps compared to the actual red splits (ten months data)

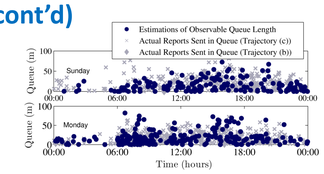


Stop time estimations at red signal throughout the day of ten months

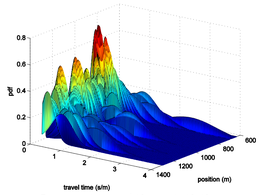
Results (cont'd)



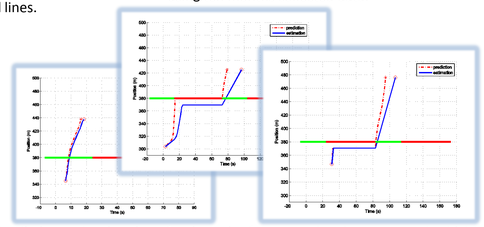
The variance trajectory (variance of the moving average) of estimated green-initiations. The actual schedule-changes happen at the dashed vertical lines.



Observable Queue length estimation using ten months collected data.

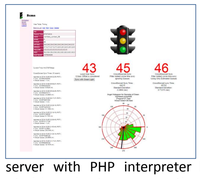


Segment travel time statistics

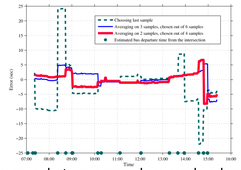


Prediction and estimation of trajectories for stopped and non-stopped vehicles

Validation



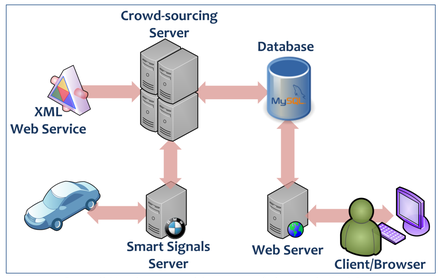
A web server with PHP interpreter has been implemented in order to compare the estimates with real-time signal states at the intersections.



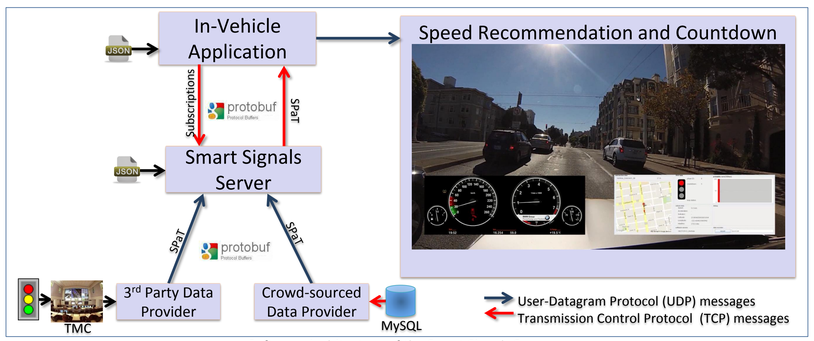
The error between crowd-sourced and actual start of greens for one sample intersection.

Validation via Implementation

- An experimental validation is presented for using the estimated traffic light information in a Velocity Advisory System of a modified test vehicle.



Overall Hardware Architecture of the Back-End System



Software Architecture of the Smart Signals Server

Conclusion

- We demonstrated that it is possible to estimate, fairly accurately, arterial traffic information by observing statistical patterns in sparse probe vehicle data feeds. A successful experimental implementation is also presented for using parts of the estimated arterial traffic information in a modified test vehicle. This implementation is an important step in utilizing this technology in future vehicles.

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