Real-Time Traffic Incident Detection Using Probe-Car Data on the Tokyo Metropolitan Expressway

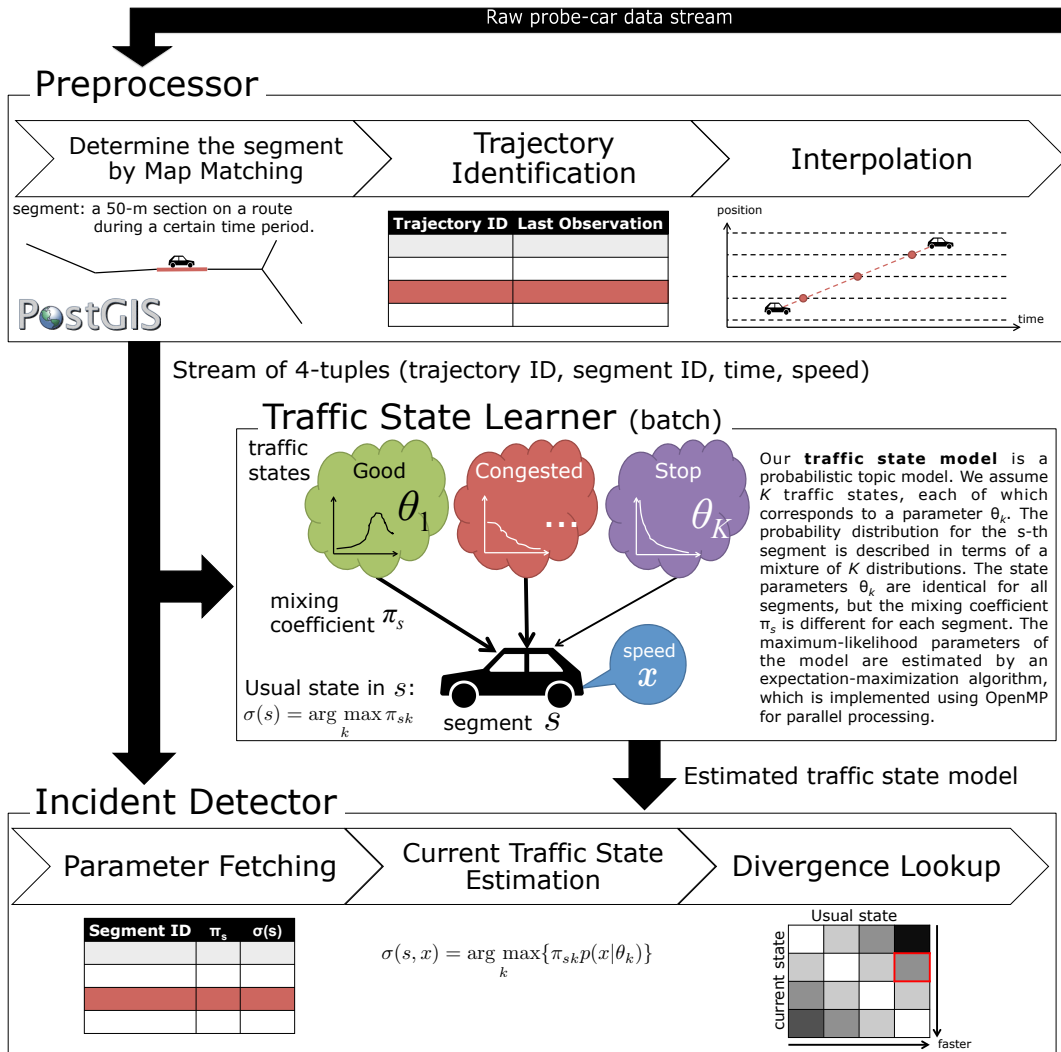Akira Kinoshita[1,2], Atsuhiro Takasu[2], and Jun Adachi[2]
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Objective

Developing a real-time traffic incident detection system for the Tokyo Metropolitan Expressway, using our detection algorithm [1].

System Architecture & Implementation

Raw probe-car data stream

Preprocessor

| Determine the segment by Map Matching | Trajectory Identification | Interpolation |

segment: a 50-m section on a route during a certain time period.

PostGIS

Trajectory ID	Last Observation

position

time

Stream of 4-tuples (trajectory ID, segment ID, time, speed)

Traffic State Learner (batch)

traffic states

Good θ_1 Congested $\cdots$ Stop θ_K

mixing coefficient π_s

Usual state in s:
$$\sigma(s) = \arg\max_k \pi_{sk}$$

speed x

segment s

Our **traffic state model** is a probabilistic topic model. We assume K traffic states, each of which corresponds to a parameter θ_k. The probability distribution for the s-th segment is described in terms of a mixture of K distributions. The state parameters θ_k are identical for all segments, but the mixing coefficient π_s is different for each segment. The maximum-likelihood parameters of the model are estimated by an expectation-maximization algorithm, which is implemented using OpenMP for parallel processing.

Estimated traffic state model

Incident Detector

| Parameter Fetching | Current Traffic State Estimation | Divergence Lookup |

Segment ID	π_s	$\sigma(s)$

$$\sigma(s,x) = \arg\max_k \{\pi_{sk} p(x|\theta_k)\}$$

Usual state

current state

faster

2-tuples (trajectory ID, estimated divergence)

Monitoring Sliding Windows

Trajectory ID	Divergences

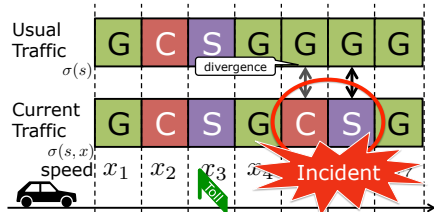

Incident

OpenLayers 3

Tokyo Metro. Expwy.

Total length: 301.3 km
Traffic: approx. 1M vehicles/day
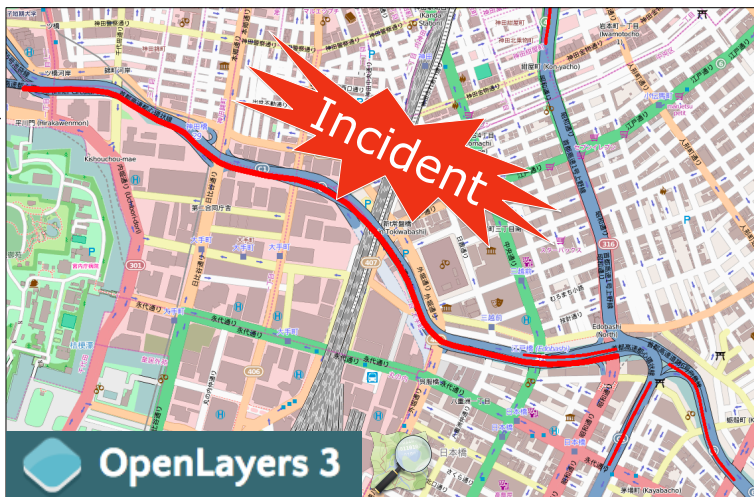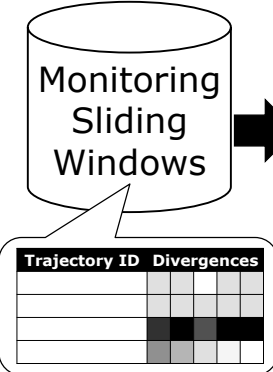Route map (red lines) [2]:

Detection Algorithm

Our detection algorithm [1] measures the degree of anomaly for each probe car's trajectory. Assume a probe car travels along a route and observes values x for each segment that it passed through.

Usual Traffic $\sigma(s)$

| G | C | S | G | G | G | G |

divergence

Current Traffic $\sigma(s,x)$

| G | C | S | G | C | S | G |

speed x_1 x_2 x_3 ... Incident

The usual traffic state $\sigma(s)$ and the current traffic state $\sigma(s,x)$ are estimated using the estimated traffic state model. Then we measure the difference between the two states in terms of the Kullback–Leibler (KL) divergence of the two distributions. The KL divergences are stored in a sliding window for each trajectory to calculated the divergence of the trajectory as the sum of the last N KL divergences. When the divergence of the trajectory is sufficiently large, the algorithm detects it as an incident, i.e., a sudden and unusual traffic event.

Future Work

- Introducing parameter-tuning functions to improve the detection accuracy.
  The parameters include the length of road segments, the number of traffic states, the length of sliding windows. They should be updated adaptively for a real-time application.
- Reducing memory usage.
  Memory is used to hold hash tables and a lookup table. The usage is approximately proportional to the number of segments.
- Evaluating & improving throughput for each process.

References

[1] A. Kinoshita, A. Takasu, and J. Adachi. Traffic Incident Detection Using Probabilistic Topic Model. In *Proceedings of the Workshops of the EDBT/ICDT 2014 Joint Conference*, 2014, pp. 323–330.
[2] tokorozawa22 and Widehawk. Available at http://commons.wikimedia.org/wiki/File:Tokyo_Metropolitan_Expressway_map–en.svg