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Quickest Freeway Accident Detection Under Unknown Post–Accident Conditions

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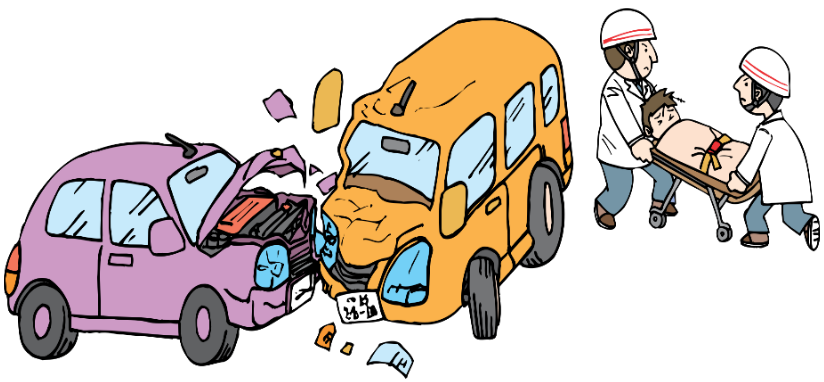
Motivation

- Around 40,100 people died due to road accidents in 2017, a 6% increase from 2015 [NationalSafetyCouncil2017]
- Traffic accidents cause also tremendous loss in time and energy [TTInstitute2015]
- Two **key practical issues** in traffic accident detection thus far remain unaddressed:
  - Low delay in detection
  - Low probability of false alarm



Goal: detect accidents **as quickly as possible**, while keeping **false detection of accidents low**

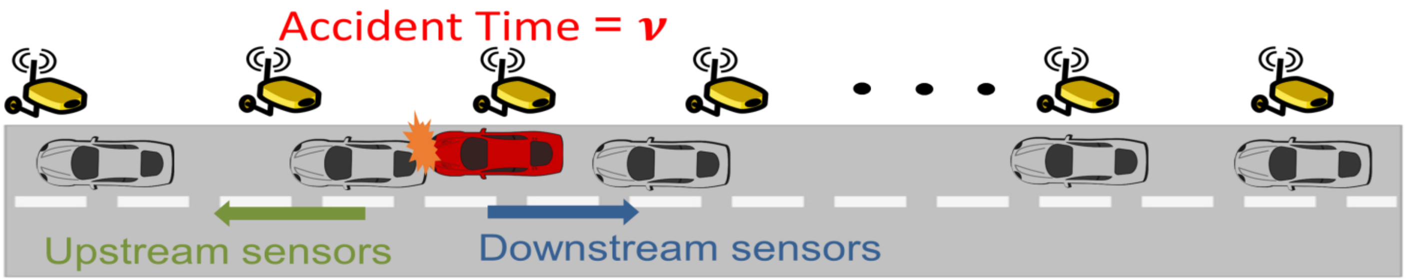
Related Work

- Mostly focused on **intersections** using **image**, **video**, and **sound features** (e.g., [Ki2007])
- **Does not explicitly model** detection delay and/or false alarm rate (e.g., [Yue2016])
- Makes **explicit assumptions** about the expected behavior of the time–series using well–known models (e.g., ARIMA) [Laptev2015]

- We generalize our prior work [Liyanage2018] to
  - accommodate **unknown parameters**
  - **estimate unknown parameters over time** using maximum likelihood principles

Problem Description

- Freeway with set $\mathcal{L}$ of spatially distributed sensors
  - Average speed readings $\{Y_k^i\}, k \in \{0, 1, \ldots\}, s_i \in \mathcal{L}$ are generated
  - Accident sensitive features $\{Z_k^i\}, k \in \{0, 1, \ldots\}, s_i \in \mathcal{L}$ are extracted
- At an unknown time ν, an accident occurs
  - Pre–accident features $Z_1^i, Z_2^i, \ldots, Z_{\nu-1}^i \Rightarrow f_0(Z_k^i) \sim \mathcal{N}(\mu_0, \sigma_0^2)$
  - Post–accident features $Z_\nu, Z_{\nu+1}, \ldots \Rightarrow f_1(Z_k^i) \sim \mathcal{N}(\mu_1, \sigma_1^2)$



- Model accident time ν as a **zero–modified geometric** random variable

$$P(\nu = j) = \begin{cases} \pi & \text{if } j = 0 \\ (1-\pi)\rho(1-\rho)^{j-1} & \text{if } j = 1, 2, \ldots \end{cases}$$

Optimization Problem

- **Goal:** select a stopping time τ to stop reviewing features and declare an accident

average detection delay

$$\boxed{\begin{aligned} & \min_{\tau} \quad d_a(\tau) \\ \text{s.t.} \quad & P_{\text{FA}}(\tau) \leq \gamma \end{aligned}}$$

probability of false alarm

  - $d_a(\tau) \triangleq \mathbb{E}\{(\tau - \nu)^+\}$, where $x^+ = \max(0, x)$
  - $P_{\text{FA}}(\tau) \triangleq P(\tau < \nu)$

Optimal Solution

- Lagrangian relaxation of the optimization problem

$$J_L = \min_{\tau} \left[\mathbb{E}\{(\tau - \nu)^+\} + \lambda P(\tau < \nu) \right]$$

Lagrange multiplier λ

- Optimal solution via **infinite horizon dynamic programming**

$$\tau_{\text{optimal}} = \inf \left\{ k \geq 0 \mid \pi_k \geq (1 - \gamma) \right\}$$

sufficient statistic

$$\pi_k \triangleq P(\nu \leqslant k | Z_1^i, Z_2^i, \ldots, Z_k^i)$$

Unknown Post–Accident Distribution Parameters

- We focus on the case where **known μ_0** changes to **unknown μ_1**, while variance σ^2 remains unaltered
- The likelihood ratio $\varpi_k = \dfrac{\pi_k}{1-\pi_k}$ is computed as

$$\varpi_k = \frac{\sum_{j=0}^{k} \lambda(j) \prod_{l=j}^{k} \frac{f_1(Z_l^i)}{f_0(Z_l^i)}}{\sum_{j=k+1}^{\infty} \lambda(j)}$$

- Maximizing the lower bound of likelihood with respect to μ_1

$$\hat{\mu}_{1,k} = \frac{\sum_{j=0}^{k} \lambda(j) \sum_{l=j}^{k} Z_l^i}{\sum_{j=0}^{k} \lambda(j)(k-j+1)}$$

Optimal Solution Implementation

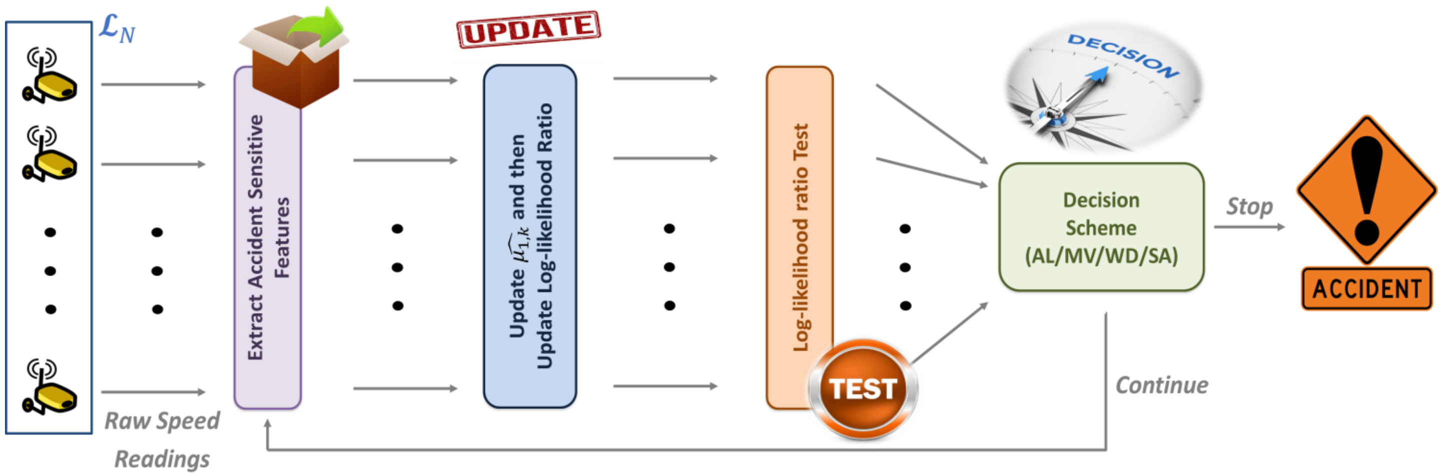
- For implementation convenience, **log–likelihood ratio** $g_k \triangleq \log(\varpi_k)$ is used

$$g_k = \log(\rho + e^{g_{k-1}}) - \log(1-\rho) + \frac{(2Z_k^i - (\hat{\mu}_{1,k} + \mu_0))(\hat{\mu}_{1,k} - \mu_0)}{2\sigma^2}$$

- Optimal stopping strategy becomes

$$\tau_{\text{optimal}} = \inf\left\{k \geq 0 \mid g_k \geq \delta^*\right\}, \quad \delta^* = \log(\delta)$$

ATTAIN-ML: Accurate and Timely Traffic AccIdent DetectioN using ML principles



- Accident sensitive feature
  - **Speed ratio** computed at each timestep $k, \forall s_i \in \mathcal{L}_N$ via:

$$Z_k^i = \frac{(Y_k^i - \overline{Y_k^i})}{\overline{Y_k^i}}$$

$\overline{Y_k^i}$: Historical average speed

- Decision Schemes
  - **AL (At Least one):** one sensor in $\mathcal{L}_N$ detects
  - **MV (Majority Vote):** majority sensors in $\mathcal{L}_N$ detects
  - **WD (Weighted Distance):** decisions are weighted by sensor distance
  - **SA (Sensor Accuracy):** decisions are weighted by sensor accuracy

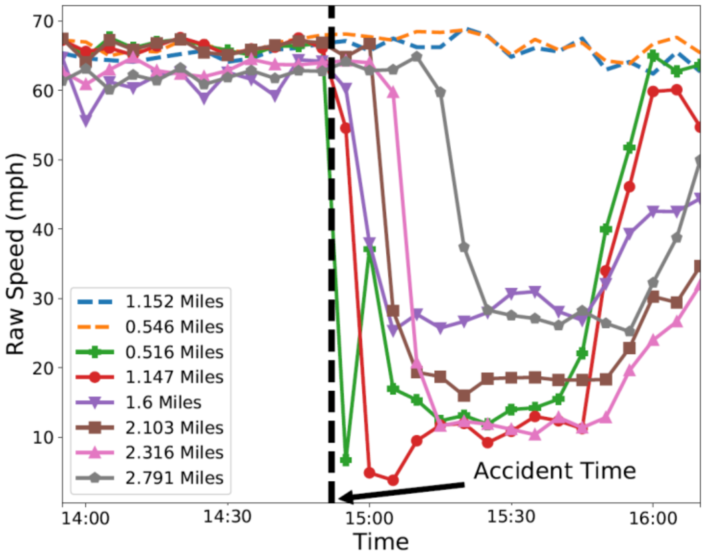
Experiments

- Dataset
  - I405 freeway in Los Angeles County
  - 822, 049 speed readings
  - 1, 158 accident reports

October 2013

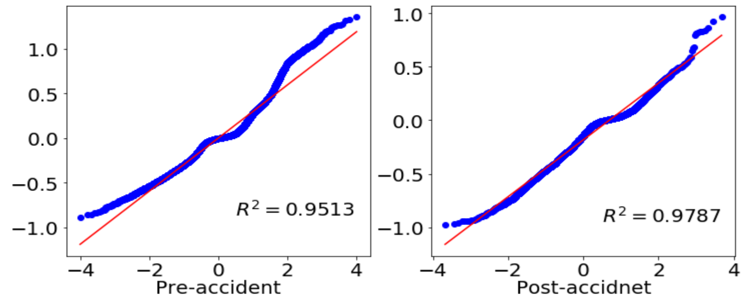
- Speed readings
  - Measured in mph
  - Every 5 minutes from 6am to 9pm everyday
  - 223 sensors placed approximately 0.5 miles apart in both north and south directions

Accident on north lane of I405 at 2.52pm on October 1st, 2013



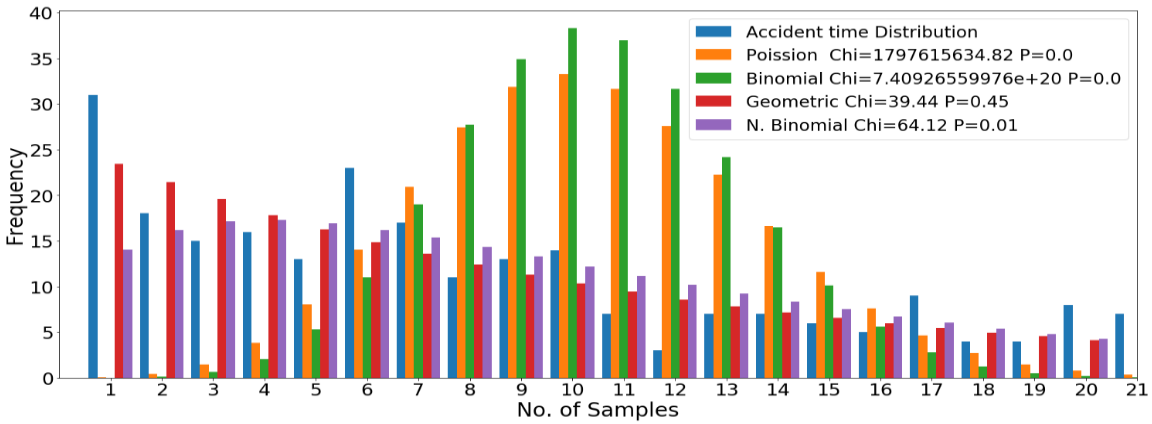
Validation of Model Assumptions

- **Gaussian assumption:** Pearson's correlation coefficient from Q-Q plots



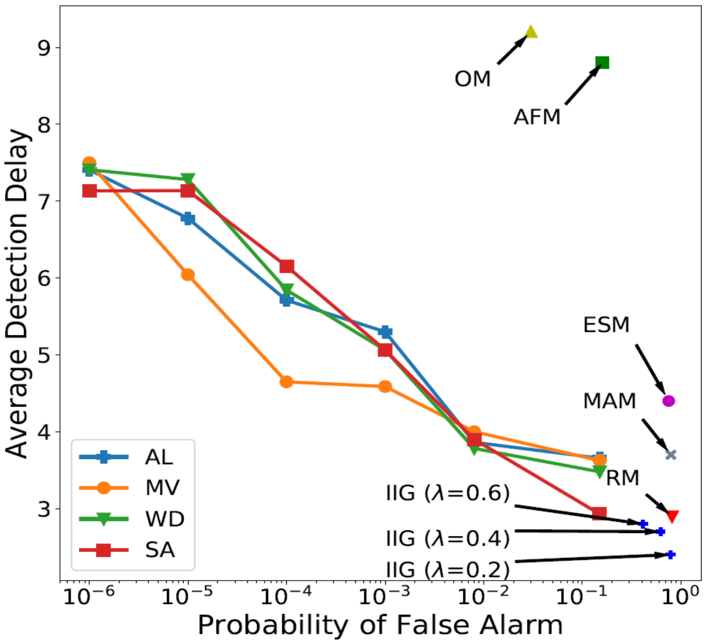
  – Both distributions pass the Gaussianity test with confidence level > 0.95

- **Geometric prior** for accident time: χ^2 goodness of fit test



Results

- Baselines:
  - Interval Grouping (IIG) algorithm with "Nearest Center" grouping heuristic [Yue2016]
  - Change point detection methods (EGDAS) for time–series data [Laptev2015]
- ATTAIN–ML achieves
  - **81.5% improvement** in **false alarm rate** compared to EGADS–RM
  - **58.9% improvement** in **average detection delay** compared to EGADS–OM



- Compared to our prior work [Liyanage2018], **average detection delay improvements** range from **4.6%** to **19.7%** for same false alarm rate

Contributions & Future Directions

- Contributions
  - **Bayesian quickest change detection framework** to optimize trade–off between average detection delay and false alarm rate
  - **Recursive ML method** to track unknown parameters over time
- Future directions
  - Devise optimal aggregation schemes to improve robustness of decision–making process
  - Jointly estimate accident time and location
- Questions?

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