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Anomaly Detection using Microscopic Traffic Variables on Freeway Segments

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Introduction

This study proposes and assesses the effectiveness of monitoring vehicular traffic anomalies using microscopic traffic variables, namely *relative speed* and *inter-vehicle spacing*. In particular, we show that when applied to real-world scenarios, our algorithm can use the *variance* of statistics of relative speed to detect traffic anomalies and precursors to non-recurring traffic congestion [1]. The performance of the proposed algorithm is also assessed using a microscopic traffic simulation environment, where we show that with minimum prior knowledge, the proposed algorithm has comparable performance to an *ideally* placed loop detector monitoring the standard deviation of speed. The algorithm also performs very well even when the microscopic traffic variables are available only from a fraction of the complete population of vehicles.

Motivations & Aims

• The first step to proactively assess the occurrence of traffic incidents is to detect a deviation from normal traffic patterns, which we refer to as traffic anomaly.

• Most existing approaches are based on stationary detectors, e.g. loop detectors, where an anomaly can be missed if it takes place far away from the detectors' locations, especially under low vehicle density.

• Emerging automotive navigation and road-side infrastructure technologies enable the measuring of microscopic traffic variables associated with individual vehicles, which are particularly useful for anomaly detection.

• Aim: develop a methodology that can utilize microscopic traffic variables for anomaly detection even when the information is available only from a fraction of the complete population of vehicles

Analysis Framework

• The microscopic traffic information could be measured by vehicles sharing information through automotive navigation systems and wireless communications, or from road-side infrastructure.

• The statistics are calculated from *PoA* × I_{total} vehicles; *PoA* (Percentage of Availability) denotes the percentage of vehicles whose microscopic information can be measured, and I_{total} is the total number of vehicles on the segment

Anomaly Detection Algorithm

• Anomaly detection is formulated as a variance change point detection by assessing the posterior probability ratio based on Bayes' theorem [1]:

$$\frac{\log\ p(H_0 \mid y_n)}{\log\ p(H_1 \mid y_n)} > 1; \quad p(H_q \mid y_n) = \frac{p(y_n \mid \theta_q)\, p(\theta_q)}{p(y_n)}.$$

• Detection is performed when there are at least ***L*** samples of y_n, where ***L*** is the pre-determined sliding window size.

FIGURE 1: Anomaly Detection on Single Simulated Realizations

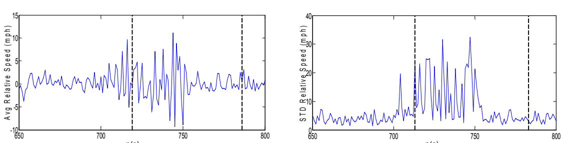

TABLE 1: Evaluations Results using Simulation: DR = Detection Rate, MTTD = Mean Time to Detection, FAR = False Alarm Rate.

Proposed Algorithm (*PoA* = 50 %)	**DR_{n1}**	**$MTTD_{n1}$ (s)**	**DR_{n2}**	**$MTTD_{n2}$ (s)**	**FAR**
Average of Relative Speed	1	31.6	1	34.6	0
Standard Deviation of Relative Speed	1	31.7	1	32.6	0
Average of Inter-vehicle Spacing	1	30.2	1	28.9	0.87
Standard Deviation of Inter-vehicle Spacing	1	30.2	1	28.9	0.87
Benchmark Algorithm [2] (Ideal setting: Using STD Speed from Loop Detectors placed at anomaly location)	**DR_{n1}**	**$MTTD_{n1}$ (s)**	**DR_{n2}**	**$MTTD_{n2}$ (s)**	**FAR**
Sampling Interval = 30s	1	38.0	0	-	0.33
Sampling Interval = 60s	0.9	27.0	0.3	28.0	0.64

Preliminary Analysis using Simulation

• In Figure 1, anomalous condition is simulated from $n_1 = 690$ to $n_2 = 750$.

• Figure 1 shows that the proposed algorithm detects anomalies based on the fact that a short-time transient disruption can exacerbate variation of the relative speeds.

• Table 1 shows that when using relative speed, the proposed algorithm achieves higher detection rate and much lower false alarm rate compared to the benchmark algorithm [2] .

• Table 1 also shows that for this experiment, inter-vehicle spacing is not a good anomalous indicator as the proposed algorithm has high false alarm rate.

• A reduction in false alarm rate is achieved by increasing *PoA* and/or sliding window size *L*, which enables the proposed algorithm to assess more relative speed samples [1].

Performance Evaluations using Real-World Data

• In order to validate and assess the proposed algorithm, a freeway segment is analyzed in which the microscopic traffic variables can also be obtained from a video surveillance camera [3].

• The freeway segment is part of the main route that links Bangkok to the Northern provinces of Thailand.

• As the density of vehicles on the segment can vary with time and the vehicle density can be very low at certain periods, *PoA* = 100% is used to guarantee that there are always enough individual vehicle information for our analysis.

• The real-world cases are classified according to whether they lead to non-recurring congestion; anomaly cases that lead to non-recurring congestion are referred to as ***non-recurring congestion precursors***, otherwise they are simply referred to as ***transient anomalies.***

FIGURE 3: Detection of Variance Change Point of Relative Speed and the Corresponding Video Snapshot

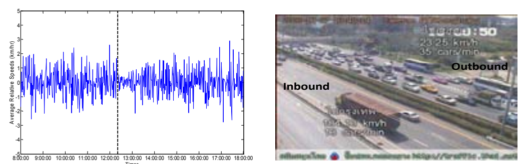

TABLE 2: Evaluation Results from using the Proposed Algorithm with Statistics of Relative Speed in Real-World Data

Transient Anomalies	**Number of Cases**	**Detected Cases**	**MTTD (s)**
Average of Relative Speed	7	7	390
Standard Deviation of Relative Speed	7	7	156
Non-Recurring Congestion Precursors	**Number of Cases**	**Detected Cases**	**MTTD (s)**
Average of Relative Speed	15	12	300
Standard Deviation of Relative Speed	15	14	210

• Table 2 shows that the proposed algorithm can use the variance of statistics of relative speed to detect most traffic anomalies on the real world data with MTTDs less than seven minutes.

• One case that is missed by standard deviation of relative speed alone occurred between two consecutive periods of non-recurring congestions.

• Three cases that are missed by average of relative speed alone occurred under high volume of vehicles (≥ 2000 vehicles/hour), which limit the change of variability of relative speed.

• We also note that there is preliminary evidence that detection times of transient anomalies could be used to estimate the times when the traffic flow and average speed evolve from free-flow to congestion [1].

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