

# Detection and Classification of Traffic Anomalies Using Microscopic Traffic Variables

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**Abstract**—This paper proposes a novel anomaly detection and classification algorithm that combines the spatiotemporal changes in the variability of microscopic traffic variables, namely, relative speed, intervehicle time gap, and lane changing. When applied to real-world scenarios, the proposed algorithm can use the variances of statistics of microscopic traffic variables to detect and classify traffic anomalies. Based on a simulation environment, it is shown that, with minimum prior knowledge and partial availability of microscopic traffic information from as few as 20% of the vehicle population, the proposed algorithm can still achieve 100% detection rates and very low false alarm rates, which outperforms previous algorithms monitoring loop detectors that are ideally placed at locations where anomalies originate.

**Index Terms**—Anomaly classification, anomaly detection, freeway segments, microscopic traffic variables, traffic monitoring.

## I. INTRODUCTION

IT IS WELL known that road traffic congestion is still the cause of billions of dollars in extra hours of travel and extra fuel [1], [2]. Since traffic congestion that may have a big impact on delays in travel time is normally related to traffic incidents, which is usually nonrecurring in nature, it is important to proactively assess the emergence of traffic anomalies as an early warning incident precursor signal, which might prevent or minimize the impact and duration of a traffic incident.

The first step to proactively assess the imminent emergence of traffic incidents is to detect deviations from normal traffic patterns, which we refer to as traffic anomaly in this paper [3], [4]. It is important to note that we are primarily interested in transient anomaly, which is the onset of deviation of traffic patterns. Although this type of anomaly usually receives less attention in the literature, the detection and classification of transient anomalies are challenging and very important as they could be the sign of traffic developing into major traffic incidents.

The characteristics of traffic anomalies that lead to traffic incidents, which are commonly known as incident precursors, have already been thoroughly studied based on macroscopic traffic variables derived from road-side infrastructure, e.g., loop detectors [4]–[6]. However, the effectiveness of those detection

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algorithms largely depends on the relative location of the anomaly with respect to the loop detectors. If a disruption takes place far away from the loop detector location, then the anomaly may not be detected and/or a long delay may be present before the anomaly is eventually identified.

Recent advances in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless communications have increased the potential of real-time measuring of microscopic traffic variables [3], [7]–[12]. However, only a few studies have explicitly investigated the potential of using microscopic traffic variables for anomaly detection. Among these studies, only our previously proposed algorithm in [3] and an algorithm proposed in [10] have been designed for real-world applications, whereas others either rely on localized measurements of an individual vehicle, which increase the likelihood of having too many unnecessary alarms [7], [11], or assume that fine-grained information can be obtained through a specialized infrastructure that may not be applicable with typical traffic monitoring systems [8], [12].

We have recently proposed an anomaly detection algorithm in [3]. In this paper, an extension of this algorithm to include anomaly classification is presented. We also carry out a more extensive set of assessments of the proposed algorithm.

The contributions of this paper can be summarized as follows: We propose a novel anomaly detection and classification algorithm that explicitly utilizes the temporal changes in variance and the changes in spatial covariances of microscopic traffic variables, namely, relative speed, intervehicle time gap, and lane changing. We apply a novel method using the smallest eigenvalue of covariance matrix to capture changes in microscopic characteristics as well as to assess their severity. The performance of the proposed algorithm is also assessed under partial availability of individual vehicle information.

This paper is organized as follows: Review of related studies is provided in Section II. Section III describes the analysis framework of this study. The proposed detection and classification methodology is presented in Section IV. In Section V, the effectiveness of the proposed algorithm is assessed using a simulation environment. In Section VI, we demonstrate that the proposed algorithm can be used to detect and classify traffic anomalies in real-world scenarios. Finally, Section VII concludes this paper.

## II. RELATED WORK

*Anomaly Detection and Classification Using Macroscopic Traffic Variables:* Macroscopic traffic variables represent the aggregated behavior of vehicles derived based on an analogy

with fluid dynamics, and their relationships are described in the classical Lighthill–Whitham–Richards model [13]. Basic macroscopic traffic variables, notably flow and occupancy, derived from inductive loop detectors, have been extensively employed for traffic incident detection [1], [2]. The majority of those studies focus on detection after a major disruption of traffic has occurred.

Recently, a number of studies have argued that it is more efficient to detect anomalies prior to the occurrence of an incident commonly known as incident precursors [4]–[6]. The majority of these studies have shown that the measures of speed deviation can be used as precursor signals to an incident.

Compared with conventional macroscopic traffic variables, using variation of speeds incorporates more information toward the microscopic level and, subsequently, increases the sensitivity to deviation of traffic patterns. However, most of these approaches are not efficient for the real-time estimation of the likelihood of traffic incident. One of the main problems is that the measured variation of speeds is specific to the detector location and lack microscopic-level characteristics, which capture individual vehicle interaction over time, i.e., the spatial–temporal microscopic characteristics will be lost once the vehicle passes the detector location.

*Anomaly Detection and Classification Using Microscopic Traffic Variables:* Microscopic traffic variables describe individual vehicle behaviors as well as their interactions, which are known to provide fine-grained information of individual vehicle characteristics necessary for certain research areas [9], [13]. However, there have not been many studies that employ microscopic traffic variables for anomaly detection. The study in [14] is among the first to use relative speed and intervehicle spacing to derive a reliability model for freeway traffic flow. However, the model itself is derived to be used with macroscopic traffic variables, e.g., flow and density, and the author did not further propose an algorithm for anomaly detection.

Relative speed, intervehicle spacing, intervehicle time gap, and lane change tracking are microscopic traffic variables that have been used for anomaly detection [3], [10]–[12]. A recent study in [10] has employed lane changing fractions estimated from loop detectors for incident detection, but the effectiveness of this approach is subject to loop detector locations. In Vehicular-based Networking and Computing grid (VGrid) [11], each vehicle only uses its local information to determine if it is in a queue and disseminate information to other vehicles. A more recent system called Wireless local danger warning (WILLWARN) uses onboard sensors to measure microscopic information (e.g., wheel speed, reduced friction) to detect possible hazards [7]. However, the information mainly shared among vehicles are hazard-warning messages. We note that both VGrid and WILLWARN are not explicitly assessed (e.g., in term of false alarm rates) as to whether they can effectively use shared microscopic traffic variables for anomaly detection and classification.

Recently proposed anomaly detection systems, namely, Vehicle Infrastructure Integration with Support Vector Machine (VII-SVM), Vehicle Infrastructure Integration with Artificial Neural Network (VII-ANN) [8], and Notification Of Traffic InCidEnts (NOTICE) [12], are particularly designed to use

speed profile and lane changing behavior of individual vehicles. However, to obtain such fine-grained information, these systems require a specific infrastructure that consists of sensors and wireless transceivers installed uniformly on each road segment [8], [12] and/or on each lane [12]. Such requirements can limit the deployment of VII-SVM, VII-ANN, and NOTICE in the near future as they are not scalable with typical traffic monitoring systems.

### III. ANALYSIS FRAMEWORK

Our framework is based on a distributed traffic monitoring system that could rely on locally shared information among neighboring vehicles to calculate microscopic traffic variables and assess road traffic condition on a freeway segment. It is assumed that a proportion of vehicles are equipped with a capability to measure and share instantaneous speeds and positions through automotive navigation systems and wireless communications [9], [11], [15].

The statistics of microscopic traffic variables are calculated from  $I = PoA * I_{total}$  vehicles, where the percentage of availability  $PoA$  denotes the percentage of equipped vehicles that have the capability to measure its speed and position as well as to communicate with one another on the freeway segment at the time of interest, and  $I_{total}$  is the total number of vehicles on the segment.

In this paper, we consider two types of anomalies: 1) transient anomalies and 2) incident precursors. Transient anomaly is defined as a deviation of traffic patterns that might be followed by minor disruptions of traffic flow, e.g., temporarily drop in speed caused by a distraction on a freeway shoulder. Transient anomalies usually receive less attention in the literature as they are often associated with nonsignificant changes from a macroscopic point of view.

Incident precursor is defined as the traffic pattern that might lead to a major disruption of traffic flow. This type of anomaly has received most attention, where they are often associated with accidents [5], crashes [6], or congestion [1], [4]. It is also important to note that we are only interested in anomalies associated with nonrecurring traffic disruptions, whose occurrence is usually unexpected and random.

In summary, we believe that developing an algorithm that can identify both types of traffic anomalies is the first step to detect, classify, and predict the impact of an incident.<sup>1</sup>

### IV. METHODOLOGY

#### A. Anomaly Detection and Classification Algorithm

This section introduces the proposed anomaly detection and classification algorithm shown in Fig. 1. First, anomaly detection is performed through the detection of temporal changes of variance of microscopic traffic variables (I) using the method described in Section IV-B. If a change is detected, then anomaly is declared on the freeway segment. The algorithm then

<sup>1</sup>Note that alarm in this framework is an early warning signal where traffic should be more closely monitored to decide if response (e.g., dispatching tow trucks) is needed.

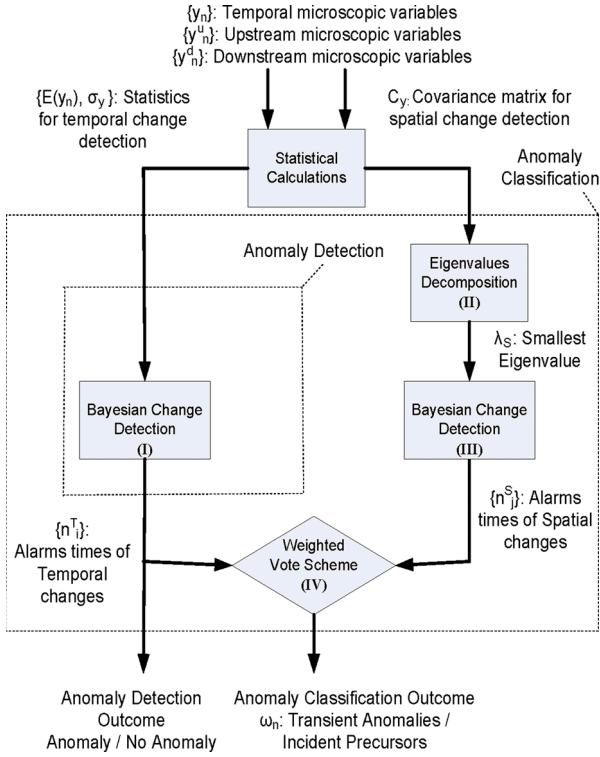


Fig. 1. Proposed anomaly detection and classification methodology.

proceeds with the classification of the detected anomaly, where temporal changes are incorporated with spatial changes obtained from assessing spatial variances of microscopic traffic variables measured upstream and downstream from the freeway segment. In our framework, the positions of equipped vehicles can be measured and shared; therefore, it is possible to determine upstream and downstream microscopic traffic variables.

The classification is performed by first calculating the smallest eigenvalue of the covariance matrix of upstream and downstream microscopic traffic variables (II) using the method described in Section IV-C. Then, we detect the changes of the smallest eigenvalue (III) using the method in Section IV-B. Finally, the detection decisions on temporal changes (I) and spatial changes (III) are assessed using a weighted vote scheme (IV) presented in Section IV-D.

### B. Change of Variance for Anomaly Detection

The proposed anomaly detection scheme in blocks I and III of Fig. 1 is based on a statistical and parametric approach, where the aim is to discover time points at which variance of a microscopic traffic variable changes [3], [16]. Let  $y_n$  denote a microscopic traffic variable of interest at time  $n$ ,  $n = 1, 2, \dots, N$ , where  $N$  is the total number of temporal samples of  $y_n$  used per change detection operation. Let  $L$  denote a predetermined sliding window size, which is used to determine the minimum number of temporal samples of  $y_n$  needed to initiate a change detection operation. Therefore, the change detection is performed by assessing if there is a variance change between two adjacent sliding windows  $W1$  and  $W2$  if there are at least  $L$  samples of  $y_n$  in both windows:  $W1 \geq L$ ,  $W2 = L$ ,  $L < N$ , and  $W1 + W2 \leq N$ .

We model  $y_n$  as a Gaussian process  $N(\mu_n, \sigma_n^2)$ , where  $\sigma_n^2$  denotes the changing variance of  $y_n$ . Let  $n_0 = N - L$  denote the time where the variance of  $y_n$  changes. We compare the null hypothesis  $\{H_0 : \sigma_1^2 = \dots = \sigma_{n_0-1}^2 = \sigma_{n_0}^2 = \dots = \sigma_N^2\}$  against the alternative hypothesis  $\{H_1 : \sigma_1^2 = \dots = \sigma_{n_0-1}^2 \neq \sigma_{n_0}^2 = \dots = \sigma_N^2\}$ .

Now, let  $\Theta^N$  be a vector of variances  $\Theta^N = \{\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2\}$ . Using Bayes' theorem, the probability of the change of variance at  $n_0$  is estimated by the posterior probabilities associated with the hypotheses:  $p(H_q|y_n) = p(y_n|\Theta^N)p(\Theta^N)/p(y_n)$ , where  $p(y_n|\Theta^N)$  denotes the likelihood function, and  $p(\Theta^N)$  denotes the prior probability. The anomaly detection is then performed, where the alarm is raised when  $(\log p(H_0|y_n)/\log p(H_1|y_n)) > 1$ .

### C. Extraction of Spatial Covariance Changes Using Eigenvalues

In this section, we present a method to capture changes using the covariance between the microscopic traffic variables measured upstream and downstream of a disruption in block II of Fig. 1. In a disruption-free traffic condition, the variances of microscopic traffic variables (e.g., lane changing and time gap) measured upstream and downstream from a certain freeway segment are highly correlated as there is nothing to disrupt the transfer of variability in microscopic traffic characteristics from upstream to downstream.

On the other hand, a disruption can reduce the covariance between the upstream and downstream microscopic characteristics. For example, a disruption may cause buildup of a queue upstream that effectively reduces the space for maneuvering upstream of the disruption. Furthermore, the degree of change in covariance will reflect the severity of the disruption itself, which we use to classify transient anomalies and incident precursors.

We propose to capture the degree of changes in covariation using the smallest eigenvalue of the spatial covariance matrix. Let  $\mathbf{Y}_n = \{y_n^u, y_n^d\}$ , where  $y_n^u = \{y_{n,i}^u, i = 1, 2, \dots, m_1\}$  and  $y_n^d = \{y_{n,i}^d, i = 1, 2, \dots, m_2\}$  denote the column vectors of upstream and downstream microscopic traffic variables measured at time  $n$ , respectively. For convenience of presentation, we drop the time notation  $n$ . Given that a total of  $M = m_1 + m_2$  upstream and downstream microscopic traffic variables are taken into account, the spatial covariance matrix  $\mathbf{C}_y$  is obtained as

$$\mathbf{C}_y = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1M} \\ c_{21} & c_{22} & \dots & c_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ c_{M1} & c_{M2} & \dots & c_{MM} \end{bmatrix} \quad (1)$$

where  $c_{ij} = E((y_i - E(y_i))(y_j - E(y_j))^T)$ . Then, a conventional eigenvalue decomposition is employed to find pairs of eigenvalues and eigenvectors  $\{\lambda_i, u_i\} : (\mathbf{C}_y - \lambda_i I)u_i = 0$ . We are interested in the smallest eigenvalue  $\lambda_S$  of  $\mathbf{C}_y$ . For example, for  $M = 2$

$$\lambda_S = \frac{1}{2} \left[ c_{11} + c_{22} - \sqrt{(c_{11} - c_{22})^2 + 4c_{12}^2} \right]. \quad (2)$$

The smallest eigenvalue has previously been used in image processing to identify line, corner, and circle components of an image [17] as it is able to capture abrupt changes of the distribution in the direction of the smallest eigenvector. As (2) demonstrates, reducing the covariance  $c_{12}$  would increase  $\lambda_S$ . In this paper, we apply the same principle to capture uncorrelated spatial changes in variations of microscopic traffic variables.

#### D. Weighted Vote Scheme

In block IV of Fig. 1, we use a weighted vote scheme to classify the detected anomalies. Let  $n_i^T$  denote the clock time that an alarm is raised from assessing temporal changes of a microscopic traffic variable  $i$ , and let  $n_j^S$  denote the clock time that an alarm is raised from assessing spatial changes of a microscopic traffic variable  $j$ . Further, let  $w_i^T$  and  $w_j^S$  be the weights associated with alarms of temporal and spatial microscopic traffic variables  $i$  and  $j$ , respectively. For our classification criterion, we introduce a critical interval  $L_c$  that specifies the interval for the alarms times to be considered as the alarms of the same anomalous event by the weighted vote scheme. Therefore, for each time interval  $[n - L_c, n]$ , our algorithm calculates the total vote  $\omega_n$  by assigning  $w_i^T$  to  $\omega_n$  if  $n_i^T \in [n - L_c, n]$  and  $w_j^S$  to  $\omega_n$  if  $n_j^S \in [n - L_c, n]$ :  $\forall i, j : n_i^T \in [n - L_c, n], n_j^S \in [n - L_c, n]$ , i.e.,

$$\omega_n = \sum_i w_i^T + \sum_j w_j^S. \quad (3)$$

An incident precursor is declared if  $\omega_n$  exceeds a threshold  $\Omega$ ; otherwise, the alarms are determined as signals of transient anomalies. The threshold  $\Omega$  is chosen proportionally to  $\omega_i^T$  and  $\omega_j^S$ , i.e.,  $\Omega \propto \omega_i^T + \omega_j^S$ , to increase the adaptability to the scenarios where there might be only a few alarms due to nonsignificant changes in microscopic variability (e.g., under very low or high vehicle densities). The choices of  $\omega_i^T$  and  $\omega_j^S$  depend on the microscopic traffic variables, which will be discussed in Section V-C2.

### V. PERFORMANCE EVALUATIONS USING SIMULATION

#### A. Performance Evaluation Parameters

Let  $n_{q,p}$  be the time that the  $p$ th alarm is raised for an anomaly occurring at time  $n_q$ . The alarm is considered to be

true alarm if  $n_{q,p} \in [n_q, n_q + n_b]$ ; otherwise, it is considered to be false alarm. A detection interval  $n_b$  is used for evaluation purposes only and should not exceed the anomaly duration. Given  $K$  experiments for each anomaly case, the performance evaluation parameters we consider are the detection rate of anomaly at  $q$   $DR_q$ , the mean time to detection of anomaly at  $q$   $MTTD_q$ , the false alarm rate  $FAR$ , and the classification rate  $CR_q$ , which are calculated in (4)–(7), shown at the bottom of the page, respectively. In this paper,  $FAR$  is calculated by collectively taking into account any alarm that is not in  $[n_q, n_q + n_b]$ . Therefore, it is possible to have  $DR_q = 0$  while  $FAR > 0$ .

#### B. Evaluations on Anomaly Detection

1) *Benchmark Anomaly Detection Algorithms* [5], [10]: As our framework focuses on identifying both transient anomalies and incident precursors that lead to major traffic incidents, we employ the algorithms proposed in [5] and [10] as a benchmark. The reason we compare these with the algorithm in [5] is because it is designed to detect transient changes. We also assess the proposed algorithm on detecting major traffic disruptions by comparing them with an incident detection algorithm in [10].

The first benchmark algorithm, which is referred to as Benchmark-I [5], detects transient changes prior to incidents by examining if the probability that there is an anomaly on the standard deviation of speed  $X$  measured every  $h$  seconds  $P(A|X)$  exceeds a threshold.  $P(A|X)$  is calculated as  $P(A|X = x) = P_A f_X^A(x) / (P_A f_X^A(x) + P_N f_X^N(x))$ , where  $P_A$  is a fraction of  $h$ -second standard deviations of speed associated with anomaly, and  $P_N = 1 - P_A$ . In addition,  $f_X^A(x)$  and  $f_X^N(x)$  are the empirical nonparametric probability density functions of standard deviations of speed associated with anomalous and normal traffic, respectively. The probability density functions are estimated using the kernel density estimator with the Epanechnikov kernel, as in [5].

The second benchmark algorithm, which is referred to as Benchmark-II, is a traffic incident detection methodology proposed in [10] that uses the lane changing fractions and queue length measured from loop detectors. For every  $h$  seconds on each lane  $i$ , hypothesis testing is performed through the modified sequential probability ratio test, which calculates the probability ratio  $\Lambda_i(Z_h) = \prod_{m=1}^h (P_i(Z_m|Z_{m-1}, H_1) / P_i(Z_m|Z_{m-1}, H_0))$ , where  $P_i(Z_m|Z_{m-1}, H_1)$  is the measured conditional probability of lane changes from lane  $i$  to adjacent

$$DR_q = \frac{\text{Number of Anomaly Detected that lie within } [n_q, n_q + n_b]}{K} \quad (4)$$

$$MTTD_q = \frac{\sum_{p=1}^K (n_{q,p} - n_q)}{K}, \quad n_{q,p} \in [n_q, n_q + n_b] \quad (5)$$

$$FAR = \frac{\text{Number of Anomaly Detected that are not in } [n_q, n_q + n_b]}{\text{Total number of Detections}} \quad (6)$$

$$CR_q = \frac{\text{Number of Anomaly Correctly Classified}}{\text{Total Number of Anomaly}} \quad (7)$$

lanes at time step  $m$ , and  $P_i(Z_m|Z_{m-1}, H_0)$  is the predetermined incident-free conditional probability of lane changes from lane  $i$  to adjacent lanes at time step  $m$ .

Based on ten simulated realizations consisting of approximately 11 000 data points, we obtain  $f_X^A(x)$  and  $f_X^N(x)$  for Benchmark-I [5] and  $P_i(Z_m|Z_{m-1}, H_0)$  for Benchmark-II [10]. Furthermore, we ideally place the loop detector station at the position where the disruption originated. In addition,  $h$  is always chosen to be ideally finer than the commonly used 5-min interval [5], [10]. These settings should give better performance than the scenarios in [5] and [10] and any real-world deployed loop detector.

2) *Experimental Setups*: To model a more realistic vehicle mobility, we have implemented Gipps safe-distance car-following model [18] into the microscopic traffic simulation environment Groovenet [19]. On the two-lane freeway segment, each simulated vehicle recorded its timestamp, speed, position, and bearing at every second. In this section, we consider a low-density scenario where  $I_{\text{total}}$  is 16 vehicles/mile/lane on average (approximately 10% of the segment area) as it is usually difficult to detect anomalies using stationary loop detectors under this scenario. Furthermore, we avoid the scenario of having congestion due to the exceeding of the freeway segment capacity by setting an average speed of 70 mi/h and the volume to always be well below a breakdown threshold [20]. This ensures that any change is caused by the simulated disruption only.

As our previous investigation in [3] has shown that using intervehicle spacing can result in very high false alarm rates and may not be suitable for anomaly detection, we focus on using only relative speed for anomaly detection in this paper. The relative speed is calculated as  $v_{k,n} = w_{k-1,n} - w_{k,n}$ , where  $w_{k,n}$  is the speed of a vehicle  $k$  at time  $n$ . Anomaly detection is performed by assessing the variances of sample averages and standard deviations of relative speed. Furthermore, we select flat prior  $p(\Theta_0^N) = 1$  to reflect a real-time application with minimum prior knowledge, where performance depends largely on the analyzed microscopic traffic variables. In addition, for a given  $PoA$ , the vehicles that possess sensors and communication capability are randomly chosen.

3) *Results and Discussions on Transient Anomalies*: In this section, we focus on the detection of short-term transient changes ( $\leq 5$  min) as such kinds of anomalies require a methodology with high sensitivity, making them usually difficult to detect, and keep a low false alarm rate at the same time. Disruptions of traffic flow on a specific location on the freeway are generated by having a designated vehicle decelerated to a low speed of 10 mi/h between  $n_1 = 690$  and  $n_2 = 750$  and then accelerated back to normal speed. Such anomalous behavior causes the average traffic speed to slightly drop, which temporarily disrupts the traffic flow. The aim is to detect changes at  $n_1$  and  $n_2$  since they are the instances where traffic patterns start to change.

Fig. 2 shows the statistics of relative speed of a single simulated realization. The proposed algorithm utilizes the fact that the short-term transient anomalies cause changes in the individual speeds of the vehicles and exacerbates the variation of relative speeds. Table I shows the performance evaluation

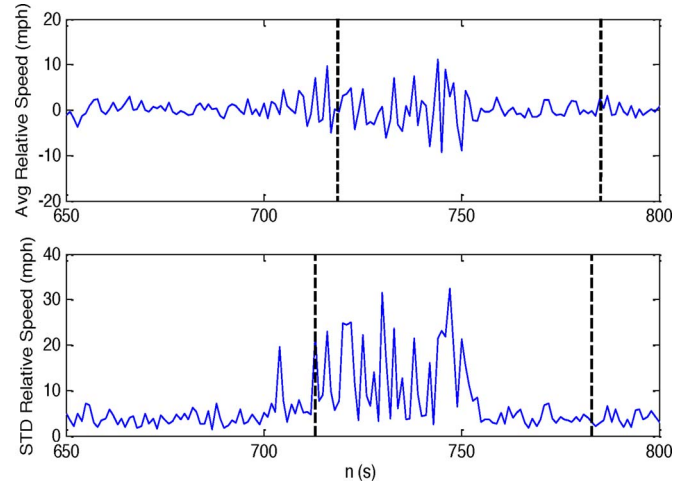


Fig. 2. Single simulated realizations of statistics of relative speed with transient anomalies between  $n_1 = 690$  and  $n_2 = 750$ . Dotted vertical lines denote the alarm times using the proposed algorithm.

TABLE I  
TRANSIENT ANOMALY: PERFORMANCE COMPARISON RESULTS FOR  $n_b = 60s$  AND  $L = 30s$  FROM TEN SIMULATED REALIZATIONS AND UNDER VEHICLE DENSITY OF 10% OF THE SEGMENT AREA (AVG = AVERAGE, STD = STANDARD DEVIATION, RS = RELATIVE SPEED, AND PoA = PERCENTAGE OF AVAILABILITY INTRODUCED IN SECTION III)

Proposed Algorithm (PoA = 50%)	$DR_{n_1}$	$MTTD_{n_1}$ (s)	$DR_{n_2}$	$MTTD_{n_2}$ (s)	$FAR$
AVG RS	1	31.6	1	34.6	0
STD RS	1	31.7	1	32.6	0
Benchmark-I [5]	$DR_{n_1}$	$MTTD_{n_1}$ (s)	$DR_{n_2}$	$MTTD_{n_2}$ (s)	$FAR$
$h = 30s$	1	38.0	0	-	0.33
$h = 60s$	0.9	27.0	0.3	28.0	0.64
Benchmark-II [10]	$DR_{n_1}$	$MTTD_{n_1}$ (s)	$DR_{n_2}$	$MTTD_{n_2}$ (s)	$FAR$
$h = 30s$	0	-	0	-	-
$h = 60s$	0	-	0	-	-

results from applying the proposed algorithm, Benchmark-I, and Benchmark-II to detect changes at  $n_1$  and  $n_2$ . Using the statistics of relative speed as anomaly indicators, the proposed algorithm has relatively higher detection rates with zeros false alarm rates, which outperforms the benchmark algorithms.

As seen in Table I, Benchmark-I detects well the change at  $n_1$  but misses most of  $n_2$  for  $h \geq 30s$ , whereas Benchmark-II fails to detect both  $n_1$  and  $n_2$ . The loop detectors have ideally been placed at the location where the anomaly originates and cause decelerations of individual vehicle speeds; therefore, Benchmark-I can detect  $n_1$  by assessing the standard deviation of speed. However, the disruption does not completely block the lane, so the changes in lane changing fractions and queue length are not significant enough for Benchmark-II to detect  $n_1$ . Furthermore, both benchmark algorithms fail to detect the discharge at  $n_2$  because the change is caused by the moving vehicle that is spatially farther away from the location of loop detectors.

4) *Results and Discussions on Incident Precursors*: For the analysis of incident precursors, we use the simulation environment to generate a lane-blocking disruption that is among the main causes of traffic disruptions [10]. We simulated traffic

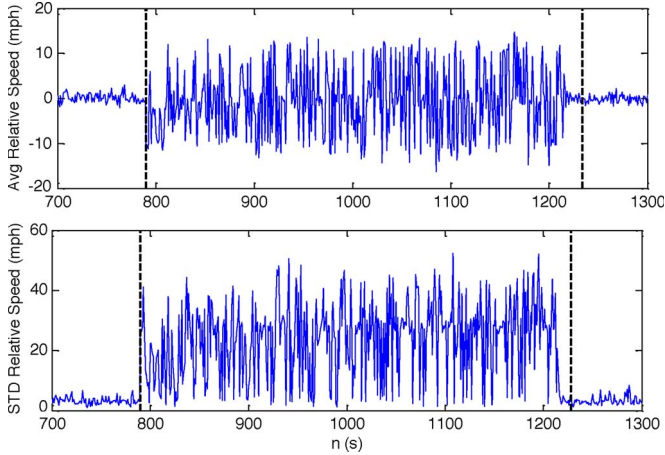


Fig. 3. Single simulated realizations of statistics of relative speed with incident precursors between  $n_1 = 790$  and  $n_2 = 1200$ . Dotted vertical lines denote the alarm times using the proposed algorithm.

TABLE II

INCIDENT PRECURSORS: PERFORMANCE COMPARISONS FOR  $n_b = 120s$  AND  $L = 60s$  FROM TEN SIMULATED REALIZATIONS AND UNDER VEHICLE DENSITY OF 10% OF THE SEGMENT AREA (AVG = AVERAGE, STD = STANDARD DEVIATION, RS = RELATIVE SPEED, AND PoA = PERCENTAGE OF AVAILABILITY INTRODUCED IN SECTION III)

Proposed Algorithm (PoA = 50%)	$DR_{n_1}$	$MTTD_{n_1}$ (s)	$DR_{n_2}$	$MTTD_{n_2}$ (s)	FAR
AVG RS	1	61.5	1	105.0	0
STD RS	1	60.3	1	98.8	0
Benchmark-I [5]	$DR_{n_1}$	$MTTD_{n_1}$ (s)	$DR_{n_2}$	$MTTD_{n_2}$ (s)	FAR
h = 30s	1	80.0	1	83.8	0.44
h = 60s	0.1	80.0	0.9	104.0	0.52
Benchmark-II [10]	$DR_{n_1}$	$MTTD_{n_1}$ (s)	$DR_{n_2}$	$MTTD_{n_2}$ (s)	FAR
h = 30s	1	52.6	0.1	51.0	0.70
h = 60s	1	49.4	0	-	0.65

anomalies between  $n_1 = 790$  and  $n_2 = 1200$  on a specific location on the freeway by having a designated vehicle decelerated to a complete stop, effectively blocking one lane for 5 min, which is the minimum time period commonly used in analyzing traffic characteristics prior to incidents [4]–[6], and then accelerated back to normal speed. The aim is also to detect changes at  $n_1$  and  $n_2$ .

Fig. 3 shows the statistics of relative speed of a single simulated realization, where the proposed algorithm can also use the variation of the relative speeds to detect anomalies. Table II shows the performance evaluation results from applying the proposed algorithm and the benchmark algorithms to detect changes at  $n_1$  and  $n_2$ . With  $PoA = 50\%$ , the proposed algorithm using the statistics of relative speed detects anomalies with much smaller false alarm rates compared with the benchmark algorithms.

In contrast, Benchmark-I [5] misses more than 90% of the change at  $n_1$  for  $h \geq 1$  minute, whereas the discharge at  $n_2$  is detected well because the location of the discharge is fixed, and all the vehicles discharging from a lane-blocking move pass the location of the loop detectors.

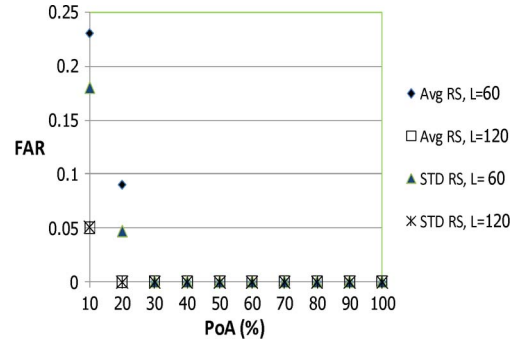


Fig. 4. False alarm rates of the proposed algorithm using statistics of relative speed for different  $PoAs$ .  $L$  is the size of the sliding window in seconds.

Benchmark-II [10] detects well the change at  $n_1$  because the lane blocking causes significant changes in the number of lane changing fractions and queue length. However, Benchmark-II misses the change at  $n_2$  due to the reduction of the significance of the number of lane changing fractions and queue length in the discharge period. Both benchmark algorithms have high false alarm rates because, under a low vehicle density scenario, where the vehicles still have a lot of room to maneuver, these algorithms cannot distinguish well between anomalous and anomaly free traffic patterns. It is clear that anomalies that result in major disruptions would be detected by algorithms like Benchmark-II. However, these algorithms are likely to fail to identify transient anomalies, as previously shown in Section V-B3.

We further assess the impact of  $PoA$  and window size  $L$  on the false alarm rate. Fig. 4 shows the false alarm rates for  $PoA$  ranges from 20% to 100%. With  $PoA$  of 20%, the relative speed statistics are calculated from only four vehicles on average, and there still is a probability of the proposed algorithm obtaining relative speeds from pairs of vehicles with high variations and raising false alarms. With  $PoA \geq 30\%$ , the proposed algorithm can utilize the relative speed from more vehicles on the segment to accurately detect anomalies with zero false alarm rates. Note also that increasing the sliding window size reduces the number of false alarms as the algorithm can assess more relative speed samples in making a decision.

### C. Evaluations on Anomaly Classification

#### 1) Microscopic Traffic Variables for Classification:

For anomaly classification, we employ the algorithm in Section IV-A, which incorporates both spatial and temporal anomaly detections. For the detection of spatial changes, we use the number of lane changes and intervehicle time gaps. The proposed method in Section IV-C is independently employed to extract spatial changes from the number of lane changes and/or intervehicle time gap. Then, the alarms from the number of lane changes and/or intervehicle time gap are assessed together with the alarms from the statistics of relative speed using a weighted vote scheme presented in Section IV-D.

Fig. 5 shows the microscopic traffic variables for a freeway segment consisting of two lanes. Let  $y_{ij}^u(n)$  and  $y_{ij}^d(n)$  denote the number of lane changes from lane  $i$  to an adjacent lane  $j$  at time step  $n$  upstream and downstream of a disruption,

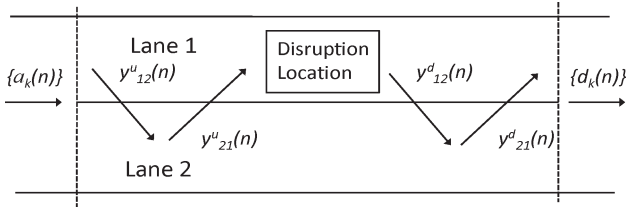


Fig. 5. Upstream and downstream lane changing and intervehicle time gaps.

respectively. For a freeway segment consisting of  $\zeta$  lanes, there are totally  $4(\zeta - 1)$  records on the number of lane changes ( $2(\zeta - 1)$  of  $y_{ij}^u(n)$  and  $2(\zeta - 1)$  of  $y_{ij}^d(n)$ ), and the spatial covariance matrix of the number of lane changes has the dimension of  $4(\zeta - 1) \times 4(\zeta - 1)$ .

We use interarrival time to describe the upstream intervehicle time gap and interdeparture time to describe the downstream intervehicle time gap, as shown in Fig. 5. The interarrival time  $a_k$  is defined as the difference between the arrival time to the beginning of a freeway segment of a vehicle  $k$  and that of the previous vehicle  $k - 1$  that has arrived. Similarly, the interdeparture time  $d_k$  is defined as the difference between the arrival time to the end of a freeway segment of a vehicle  $k$  and that of the previous vehicle  $k - 1$  that has arrived. The spatial covariance matrix of interarrival and interdeparture times has the dimension of  $2 \times 2$ .

2) *Choices of Sliding Window Size  $L$ , Critical Interval  $L_c$ , and Weights:* The effectiveness of our algorithm depends on the sliding window size  $L$  with respect to the critical interval  $L_c$  in Section IV-D. The small window size ( $L \leq L_c$ ) will reduce the classification rate of transient anomalies as all deviations will be taken into account and could be interpreted as incident precursors. On the other hand, increasing the window sizes toward the critical interval ( $L \rightarrow L_c$  and  $L > L_c$ ) will reduce the classification rates of incident precursors as deviations will further be smoothed out and classified as transient anomalies.

The choice of  $L_c$  will depend on the impact of anomalies on the freeway segment, for example,  $L_c$  should be chosen to be between the delays caused by transient anomalies  $D_L$  and incident precursors  $D_H$ , i.e.,  $D_L \leq L_c \leq D_H$ . The weights  $\omega_i^T$  and  $\omega_j^S$  in (3) can be chosen with respect to the average intervehicle spacing that determines the potential impact of the state of the link on each microscopic traffic variable. When the average intervehicle spacing is large, the weights should be equal because the vehicles still have a lot of room to maneuver, and the disruption will have an impact on all the microscopic traffic variables. When the average intervehicle spacing is reduced, the weights of the number of lane change should be lower than those of relative speed and intervehicle time gap because vehicles have less space for lane changing while they can still accelerate or decelerate on a lane.

3) *Results on Classification Using Simulation:* Fig. 6 shows the classification rates on the simulated anomalies. Diamonds and triangles denote classifications rates from using the number of lane changes and intervehicle time gap for spatial change detections, respectively. The colors black and white denote classification rates for transient anomalies and incident precursors, respectively. For each value of  $PoA$ , the classification rates are averaged from ten simulated realizations.  $L$  and  $L_c$  are set to

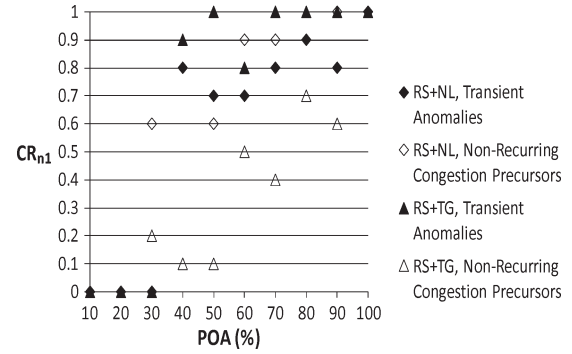


Fig. 6. Classification rates of simulated anomalies. RS = Relative Speed, NL = Number of Lane Changes, and TG = Time Gaps (interarrival and interdeparture times).

be equal to 120 s, which is between the average durations of the simulated transient anomalies of 60 s and the durations of the simulated incident precursors of 300 s. The weights of the microscopic traffic variables in (3) (relative speed, number of lane changes, and intervehicle time gap) are set to be equal since we consider a low vehicle density scenario.

When  $PoA \leq 20\%$ , the microscopic information is too coarse to identify traffic anomalies resulting in misclassifications. Furthermore, as shown in Fig. 6, when more, but still partial, information is available ( $30\% \leq PoA \leq 70\%$ ), the proposed algorithm can utilize more spatiotemporal microscopic characteristics to identify both types of traffic anomalies, whereas incident precursors are more difficult to classify. This is due to the fact that we are assessing a low vehicle density scenario where the vehicles still have a lot of rooms to maneuver, and consequently, the differences between the microscopic variabilities associated with incident precursors and transient anomalies are not very obvious. As more information is available ( $PoA \geq 80\%$ ), changes due to incident precursors can more clearly be identified using both spatial and temporal microscopic traffic variables.

## VI. PERFORMANCE EVALUATIONS USING REAL-WORLD DATA

### A. Descriptions of the Data

The objective of this section is to demonstrate that our proposed algorithm can be used with microscopic traffic variables measured in real-world scenarios. To validate and assess the algorithm, we analyze a freeway segment in which the microscopic traffic variables can also be obtained from a video surveillance camera [21]. The freeway segment we studied is part of the main route that links Bangkok to the Northern provinces of Thailand. The advantage of having video images is that it is possible to determine the times when traffic anomalies and subsequent traffic incidents took place. The traffic anomaly cases analyzed in this paper are based on traffic data collected over 5 mo from August to December 2008, plus an additional 2 mo of postprocessing video information to visually identify anomaly cases.

On the image frame of the camera, virtual entrance and exit lines were drawn at the beginning and end of the segment, respectively. For a vehicle  $k$ ,  $\{t_k^{\text{in}}, t_k^{\text{out}}, w_k^{\text{emp}}\}$  was recorded,

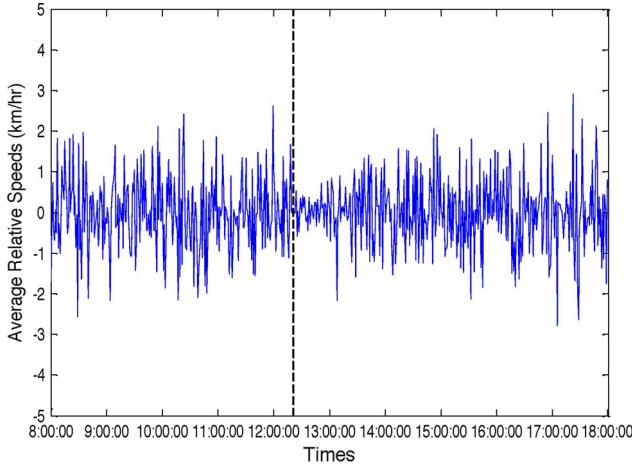


Fig. 7. Average relative speed on December 27, 2008. Dotted vertical lines denote an instance where the variance change is detected by the proposed algorithm.

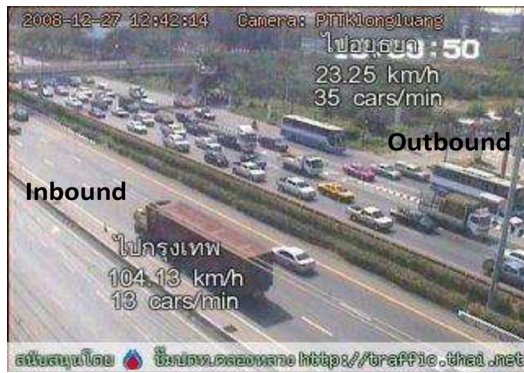


Fig. 8. Video snapshot of an incident on December 27, 2008.

where  $t_k^{\text{in}}$  is the time that the vehicle crossed the entrance line,  $t_k^{\text{out}}$  is the time that the vehicle crossed the exit line, and  $w_k^{\text{emp}} = \text{Segment Length} / (t_k^{\text{out}} - t_k^{\text{in}})$ . A relative speed observed by vehicle  $k$  to its leading vehicle  $k-1$  is calculated as  $v_k^{\text{emp}} = w_{k-1}^{\text{emp}} - w_k^{\text{emp}}$  for  $t_k^{\text{out}} > t_{k-1}^{\text{out}}$ . As the density of the vehicles on the segment can vary with time and can be very low at certain periods, we use  $PoA = 100\%$  to guarantee that there are always enough individual vehicle information for our analysis.

### B. Anomaly Detection on Real-World Data

Fig. 7 shows the detection time of a variance change of relative speed associated with incident precursors. We show one corresponding video snapshot of the freeway segment in Fig. 8, where it can be seen that the disruption was caused by two big trucks that evolved into a state of congestion.

Table III shows the results from using the proposed algorithm with the statistics of relative speed to detect anomalies on the real-world data. The mean time to detection of anomalies (MTTDs) are less than 7 min, which is fast enough for some following actions to be taken. There is one case of incident precursor that is missed by the proposed algorithm using the standard deviation of relative speed. This is a special case that actually took place between two consecutive periods of

TABLE III  
ANOMALY DETECTION ON REAL-WORLD DATA USING THE PROPOSED ALGORITHM WITH RELATIVE SPEED

Transient Anomalies	Number of Cases	Detected Cases	MTTD (s)
AVG Relative Speed	7	7	390
STD Relative Speed	7	7	156
Incident Precursors	Number of Cases	Detected Cases	MTTD (s)
AVG Relative Speed	15	12	300
STD Relative Speed	15	14	210

incidents. The proposed algorithm detects the first incident precursor. Then, there was a discharge period of approximately 30 min before the second incident. However, since there have already been a large number of vehicles on the segment, individual vehicles could only gradually increase their speed, and consequently, there was not enough variability of relative speed for the proposed algorithm to detect.

The missed detections of the other three anomaly cases by the proposed algorithm (when average relative speed is used) also occurred while there was already a high volume of vehicles ( $\geq 2000$  vehicles/hr) on the segment. With such high volume of vehicles, individual vehicles did not have much room to maneuver, and the variability of relative speed was reduced, causing these precursors to be missed by the proposed algorithm.

### C. Anomaly Classification on Real-World Data

For anomaly classification on real-world data in this section, we further analyze the seven cases of transient anomalies and 11 cases of incident precursors that have been successfully detected in Section VI-B. As the lane changing information is not available in our real-world data set, we employ only interarrival and interdeparture times for spatial changes detection, where  $C_y$  has a dimension of  $2 \times 2$ . The interarrival time is calculated as  $a_k = t_k^{\text{in}} - t_{k-1}^{\text{in}}$ , whereas the interdeparture time is calculated as  $d_k = t_k^{\text{out}} - t_{k-1}^{\text{out}}$ . On the freeway segment, the average delay caused by the transient anomaly cases is approximately 15 min, whereas the traffic congestion that followed incident precursors usually persisted beyond 15 min. Therefore, we set the critical interval  $L_c$  to be 15 min. Furthermore, as vehicle density can be low at certain periods, and the simulation results in Fig. 6 show that under low vehicle density and  $PoA = 100\%$ , the proposed algorithm works well with  $L = L_c$  and weights of 0.5, we also use the same setting for classification on real-world data.

The proposed classification algorithm performs considerably well as only one transient anomaly case is misclassified as incident precursor. In fact, this is the case where there was a distraction due to an unexpected appearance of a pedestrian on the shoulder of the freeway, as shown in Fig. 9. This caused the drivers to alter their driving patterns (e.g., reduced speed, changed lane), which impacted the variability of both the relative speed and the covariance between the interarrival and interdeparture times. Both temporal and spatial changes are detected by the proposed algorithm and interpreted as an incident precursor.

We note that, although the proposed algorithm has been assessed only on straight freeway segments, we would expect

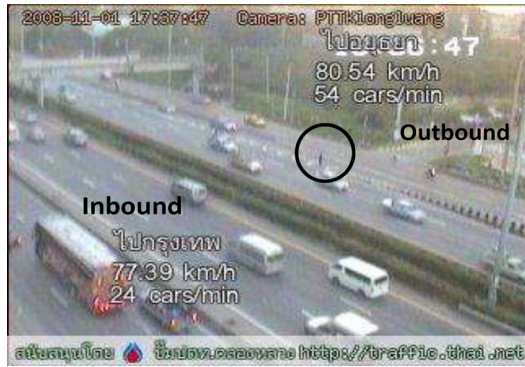


Fig. 9. Distraction caused by a pedestrian on the shoulder of freeway segment.

it to be adaptable to other road geometries. In road geometries such as curves or hills, the change in microscopic variability will be less obvious as vehicles are less likely to change lanes and/or overtake other vehicles when a disruption occurs. The sliding window size  $L$  and the critical interval  $L_c$  should be set to be small (e.g., in the order of seconds) to enable the proposed algorithm to identify changes in variances under these circumstances. The adaptability of the proposed algorithm to different road geometries is worth further investigation.

## VII. FINAL REMARKS

In this paper, we have proposed an anomaly detection and classification algorithm that combines the decisions from the temporal anomaly detection using relative speed and the spatial change detection using the number of lane changes and/or intervehicle time gap. Based on simulation results, the proposed algorithm can detect both transient anomalies and incident precursors with 100% detection rates and zero false alarm rates, which outperforms well-known algorithms [5], [10] running on an ideal setting. Furthermore, it is shown that the proposed algorithm continues to achieve low false alarm rates, even when microscopic traffic information is extracted from as few as 20% of the vehicle population.

The application of our algorithm to real-world data shows that both transient anomalies and incident precursors can be detected and classified using the statistics of relative speed and interarrival and interdeparture times. We also look into how practitioners can fine-tune the proposed algorithm to adapt to the underlying state of the freeway segment being monitored, where the critical interval to incorporate alarms from different microscopic traffic variables has to be chosen according to the impact of anomalies, and the weight of each microscopic traffic variable is chosen based on intervehicle spacing, which reflects the vehicle density of the freeway segment.

The results that we have obtained so far are very encouraging. The continuous advances in wireless and vehicular ad hoc network technologies, together with ongoing research on V2V and V2I communication infrastructure offer a new and interesting area of research and development in anomaly detection and proactive management in vehicular traffic networks. For example, we are currently investigating how to use multiresolution models [22] to extract microscopic changes on different scales. Another interesting aspect worth investigating is to incorporate

information on traffic anomalies (e.g., types, alarm times) from different locations to enhance real-time traffic management actions. Finally, the practical aspect of deploying a distributed anomaly detection solution, using microscopic traffic variables onboard vehicles, is an open area of research.

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